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Three Essays on Spatial Productivity Spillovers across Mexican Regions

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Jesús Antonio López Cabrera

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Dedication

It was a long journey to reach this goal. I would not have reached it without the full support of my family. Baby steps were made every day.

To my MJT, for her unwavering support and priceless complicity in every professional and personal project. All her love was spread through the invaluable talks and tips she gave to me. She inspires me to follow my goals and dreams. You moved me in every sense of my life. Miriam is my name for any tough or unconditional support. I love you more than you can think, and I can see.

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To my daughter, Lilian Helena, all your ideas push me to be better every day. Your beautiful smile and your lion's heart make you my little lovable girl. An invaluable human being that illuminates my way.

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Three Essays on Spatial Productivity Spillovers across Mexican Regions

By

Jesús Antonio López Cabrera

Abstract

This thesis analyzes spatial productivity across Mexican geographical entities. It begins with an introduction chapter addressing productivity, the spatial topic, context, research questions, and the methodology employed. The second chapter presents an essay on the convergence in manufacturing labor productivity in Mexico, from 1993 to 2018. The study follows the tradition of economic growth studies but uses the analytical tools that spatial econometrics has been developing over the last few years. Three econometric models are estimated, the first two with the traditional view, while the third corresponds to a spatial econometric model.

The results allow us to see that there is convergence between states and municipalities, as well as significant spillovers in manufacturing labor productivity between states and municipalities. This means that states or municipalities with high productivity have a positive impact on the productivity of neighboring states or municipalities. Empirical evidence also shows that, on average, a municipality takes 26.5 years to reduce 50% of the initial productivity gap, while it takes 99.4 years for a state, under initial growth conditions.

The third chapter addresses the spatial disaggregation of productivity in a shift-share style model. The chapter analyzes which local components and national factors influence local manufacturing productivity. Results show that regional shifts increase the divergence between national and state-specific performance.

Chapter four presents a study between wages and manufacturing labor productivity. The relationship is analyzed in the context of the state dimension and considers the impact that the productivity of neighboring entities has on local remunerations, given the proximity in geographic space. It is important to mention that the omission of the spatial structure in the estimates can lead to a bias in the estimation of the productivity parameter in relation to wages. The results show that a 1% increase in manufacturing labor productivity would increase wages by 0.1%, on average, in the state in question, while the spatial lag manufacturing labor productivity has an effect of 0.047% on wages. Finally, the last chapter contains conclusions, final remarks, policy implications, and lines of future work.

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Chapter 1. Introduction

Productivity means -in simple terms- how many resources -and how much of them- we use to get an output value: “Productivity is commonly defined as a ratio of a volume measure of output to a volume measure of input use” (OECD, 2001). For example, if we use fewer resources to obtain an output or increase our output value given a fixed use of resources, then we will be more productive. Productivity helps explain diverse phenomena closely related to economic growth such as technological change, efficiency, living standards, and real cost savings (OECD, 2001). So, productivity growth ideally translates into more output and economic growth.

Labor productivity -in simple terms- is how many labor units we use to get a total output. Labor units are usually measured in number of employees used or hours worked. Labor productivity is computed because it does not need to assume a close functional form, in contrast with total factor productivity (TFP),[1] and plays a preponderant role in the growth of an economy and consequently in its total productivity. In addition, labor productivity positively impacts competitiveness and living standards for the whole population (ILO, n.a.). It is also related to knowledge spreading, human capacity boosting, technology adoption, and intergenerational complementarity allowances in human capital (Kremer & Thomson, 1998; Harris 2002). Moreover, labor productivity plays an important role in the innovation diffusion and setting remunerations to labor factor. In the classical economic theory, the labor factor is paid at its marginal product (Ahrend et al., 2022).

Why is it important to study labor productivity for a country like Mexico? Mexico is a country that has shown a low and modest growth in the last 30 years of around 2%, with very low dynamism in labor productivity. Even worse, this modest growth rate significantly dropped during the COVID -19 pandemic, and it has yet to recover. Regardless of the pandemic´s effects on the economy in recent years, if we compare the dynamism of labor productivity in the United States vs. Mexico’s performance[2], instead of closing the gap, as some classical economic theories could say, the gap in terms of productivity still persists and, sometimes, widens. Also, this dynamism has been very low and with high regional differences in Mexico.

[1] To estimate TFP is necessary to adopt a specific production function (for instance, Cobb-Douglas, Leontief or translog). To do so, the assumptions on the functional form must be justified. In contrast, the estimation of labor productivity is a straightforward concept and can easily be achieved with the available public data.
[2] The United States is used because it is the principal trade partner of Mexico.

These three essays contribute to a better understanding of the phenomenon of labor productivity.

Moreover, the studies that have been published on labor productivity are largely detached from a spatial or territorial vision. This is due both to the theoretical development of labor productivity and to the availability of data to test the hypotheses. However, technological progress and the generation of new statistical estimation techniques have made it possible to implement the spatial component in the productivity analysis. In this sense, the arrival of geostatistical data, censuses, and surveys at a more disaggregated geographic level, as well as the availability of different computational packages, both geographic (ESRI, GeoDa) and statistics that implement spatial cutting routines (R, Stata), and, finally, the development of statistical indicators (spatial correlations) and spatial econometrics (spatial lag models, etc.) have contributed to the enrichment of the spatial analysis of productivity.

Recognition of the labor productivity growth gap is rising. The well-being of a territory is closely related to the performance of firms, remunerations to labor factor and distribution of total income (Tsvetkova, et al. 2020). These can be seen through differences in regional income levels (Ezcurra & Pascual, 2007; Mussini, 2019). This means that regions' economic growth and productivity are based on the territory conditions.

Similarly, supply chains and sectoral specialization link territories and reinforce regional productivity. Recent experiences during COVID-19 -such as bottlenecks and goods provision shortages- have highlighted the complex degree of interrelationships reached by value chains (Bolea et al., 2022). This experience shows that supply chains take full advantage of the particular characteristics of regional economies, building intra-firm and extra-firm linkages in the economy (Lüthi, Thierstein & Goebel, 2010). For all the aforementioned reasons, I intend to show in this thesis how productivity analysis can be enriched with a spatial or territorial vision. To design successful policies, a deeper understanding of the spatial dimension of productivity is needed (Tsvetkova et al., 2020). This doctoral work is made up of three essays (running from the second to fourth chapters) whose purpose is to study how labor productivity is influenced by space and, at the same time, impacts it.

The second chapter presents an essay on absolute convergence in the manufacturing labor sector. Economic theories behind convergence are discussed and an applied works literature review about Mexico is presented. The chapter attempts to answer the question:

Is there convergence between the states and municipalities of Mexico? To answer this question, I restricted my study scope to manufacturing labor productivity.

Following Rodrik (2013), the study is looking for convergence between some sectors or areas of the economy to see what the glue of one economy is. It examines the manufacturing sector because the economic paradigm adopted in Mexico in the 80s -based on economic liberalization and the promotion of exports- modifies the dynamics of manufacturing labor productivity. Moreover, the manufacturing sector is chosen because the measurement of value added and input costs is usually precisely delimited, which allows for greater clarity on what specifically is being measured and analyzed.

In summary, the chapter puts forward a labor productivity measure, tests spatial relationships between states and municipalities using common measures of spatial autocorrelation, and proposes the model. The empirical strategy considers a spatial error model to estimate the convergence parameter. Finally, results show that convergence exists in the studied period. That is, when productivity externalities among neighboring states and municipalities are integrated into the econometric analysis, there is positive and significant evidence of convergence in the manufacturing sector in the studied period.

The third chapter delves into spatial spillovers across Mexico´s states regarding manufacturing labor productivity. The related question is: How much of manufacturing labor productivity is explained by its territorial characteristics? A spatial shift-share model is developed to disentangle the indicator. The analysis breaks down the aggregate labor productivity of the manufacturing sector using cluster analysis to find out whether productivity due to industry effects outweighs productivity due to territorial ones. This also makes testing for structural changes in economic activity more accurate. Finally, a multi-factor partitioning analysis is proposed to break down the cumulative regional differential growth paths into their industry-mix (structural effects) and region-specific elements, respectively, while quantifying the industry-region interactive effect (Ledebur & Moomaw 1983; Gardiner et al., 2013). Results shows that regional shifts increase the divergence between national and state-specific performance.

The fourth chapter answers the following two questions: i) At the state level, and within the manufacturing sector, to what extent does the evolution of labor productivity impact the dynamics of remuneration in Mexico? and ii) How does labor productivity in one state influence wages in neighboring states? To answer these questions, previous works were first examined. The chapter begins with an extensive literature review in twofold ways:

productivity – wages relationship, and how spatial productivity impacts in this relationship. A literature review focused on international aspects and restricted to Mexico was also conducted.

Here, the same productivity definition for manufacturing labor productivity is followed and the empirical strategy employed was verified spatial autocorrelation in level and spatial lags using the common spatial statistics test. Then, we ran a spatial econometric lagging the concerned variable: remunerations to labor factor. Results show that the average remuneration for employed personnel is less than the annual value added per employed person (labor productivity) for all census years. However, the levels are not expected to be the same, but they are expected to evolve at similar rates. In the last chapter, conclusions are offered, following a public policy orientation.

In all cases, manufacturing labor productivity was constructed using the data in the economic censuses in Mexico published by INEGI, published every five years (INEGI, 1994, 1999, 2004, 2009, 2014, 2019). Please note that the censuses report the economic activity of the previous year. Other variables used in each analysis are listed in the specific chapter, and treatment and the information source are mentioned.

Chapter 2. Convergence in manufacturing labor productivity

2.1 Introduction

Since the mid-1980s, Mexico has implemented profound economic and structural reforms, which substantially modified its previous pattern of economic development based on import substitution and widespread state intervention in investment and in the allocation of resources. The reforms favored, instead, a market-based approach to development, aimed at making manufacturing exports and private investment the new engines of economic growth (Moreno-Brid & Padilla Pérez, 2012). A key element of the new economic model has been trading policy reform, which began with the unilateral liberalization of international commerce in 1984. By 2023, free-trade agreements had been signed with more than 40 countries, including the European Union and the recently renegotiated agreement with the United States and Canada.

The reforms resulted in noteworthy macroeconomic stability: annual inflation has remained at a single-digit level since 2000 and a long-term fiscal austerity policy was implemented. A second result of the new model was outstanding export performance. Between 1986 and 2021, Mexico's services and goods exports grew at an average annual rate of 8.7% (in current dollars) (ECLAC, 2022). Mexico is by far the largest exporter in Latin America and the Caribbean region, contributing 34.7% of the 2021 total exports (World Bank, 2022)[3]. By June 2022, total goods exports to U.S. reached US$ 160.6 billion, an 18% increase from June 2021. Following the COVID-19 pandemic, U.S. Census Data show that Mexico surpassed China as the United States' top trading partner, with nearly 15% of total U.S. imports (U.S. Census Bureau, 2022).

Despite economic reforms, macroeconomic stability and outstanding economic performance, Mexico has experienced low and volatile economic growth. Between 1990 and 2021, its economy expanded at only 2% annually on average. Several studies have shown a close association between this modest economic growth and slow productivity growth in Mexico (Chiquiar & Ramos Francia, 2009; Kehoe & Ruhl, 2010; Government of Mexico, 2013; OECD, 2013; McKinsey Global Institute, 2014; CEPAL, 2016; López Córdova & Rebolledo Márquez Padilla, 2016, OECD, 2017). Productivity levels diverge significantly

[3] Brazil is in second place, contributing 19.3% of the total performance for Latin America and the Caribbean.

among Mexican states (CEPAL, 2016). These gaps result from a wide array of factors such as sectoral specialization, the stock of financial and human capital, and institutions, among others.

Classical economic theory asserts that when countries open their economies to international trade and financial flows, resulting in the free movement of capital and labor, and there are no barriers to technology dissemination, low-income (and low productivity) countries grow faster than those with high income (and high productivity). This phenomenon is called economic convergence (Solow, 1956, 1957; Jorgenson & Griliches, 1967). That is, poor countries grow faster than rich ones and therefore, in the presence of trade, experience accelerated rates of convergence (Barro et al., 1991; Barro & Sala-I-Martin, 1992; Fischer & Serra, 1996). Yet trade liberalization and international commerce have not always resulted in smaller income and productivity gaps among countries. Some authors suggest that trade accelerates convergence (Parikh & Shibata, 2004), while others suggest the opposite (divergence) (Zhang, 2001).

Aiming at determining whether productivity convergence takes place within a country, various studies have examined this among Mexican states. Some authors have found evidence that productivity gaps have decreased over time (Esquivel & Messmacher, 2002; Asuad Sanén & Quintana Romero, 2008; López González & Cermeño Bazán, 2016; Rodríguez Gámez & Cabrera Pereyra, 2019), while others argue that there has been a divergence (Chiquiar, 2005; Rodríguez-Oreggia, 2007; Garduño Rivera, 2014; Fonseca, Llamosas Rosas & Rangel González, 2018).

To the best of my knowledge, empirical studies that have analyzed productivity convergence in Mexico have not recognized the great importance that high productivity levels in one territory have in the productivity levels of neighboring territories. Productivity externalities may arise from economic and productive linkages between neighboring territories (Vaya et al., 2004; Rey & Le Gallo, 2009; Azorín & Sánchez 2015; Zhang & Ji, 2019; Bufetova, 2020). To examine the impact of such interactions, it is important to conduct the analysis with geographical data that is as disaggregated as possible (municipalities), an approach that has been scantly followed by the existing literature.

This chapter aims to analyze absolute convergence in manufacturing labor productivity among Mexican states and municipalities between 1993 and 2018. The importance of potential spillover effects on manufacturing labor productivity among states and municipalities is acknowledged and a spatial econometrics analysis is conducted. That is, it recognizes that the factors which spur manufacturing labor productivity within a municipality may also have a positive impact on neighboring municipalities. Spatial econometrics allows the estimation of the directions and magnitudes of such impacts.

This chapter focuses on manufacturing activities since: (i) manufacturing productivity has experienced higher growth rates in Mexico than other sectors (Padilla Pérez & Villarreal, 2017); (ii) data for estimating productivity at the municipal level is available only for the manufacturing sector; and (iii) the economic model implemented in Mexico since the mid-1980s has resulted in heterogenous sectoral specialization across Mexico's states, in particular within the manufacturing sector.

The chapter is divided into nine sections. The second section presents some relevant stylized facts and a review of the existing literature. The third section describes the data and offers a descriptive statistics analysis. The statistical methods are presented in the fourth section, in particular exploratory and inferential methods which support the quantitative analysis. The fifth, sixth, seventh and eight section summarizes spatial tests, the results and discusses the model fittingness. The nineth section concludes.

2.2 Background

"Productivity is commonly defined as a ratio of a volume measure of output to a volume measure of input use" (OECD, 2001). Productivity helps explain diverse phenomena closely related to economic growth such as technological change, efficiency, living standards, and real cost savings (OECD, 2001). Labor productivity is computed because it does not need to assume a close functional form, in contrast with total factor productivity (TFP).[4]

Free flows of labor, goods, and services among Mexican states and municipalities, according to economic theory, are expected to lead to closing productivity gaps within the country (Easterly, Fiess & Lederman, 2003). Those flows spur knowledge dissemination and improve productivity in laggard regions. However, divergence or lack of convergence may occur if the labor force is not ready to receive these new inflows, and some basic

[4] To estimate TFP, it is necessary to adopt a specific production function (for instance, Cobb-Douglas, Leontief or translog). To do so, the assumptions on the functional form must be justified. In contrast, the estimation of labor productivity is a straightforward concept and can easily be achieved with the available public data.

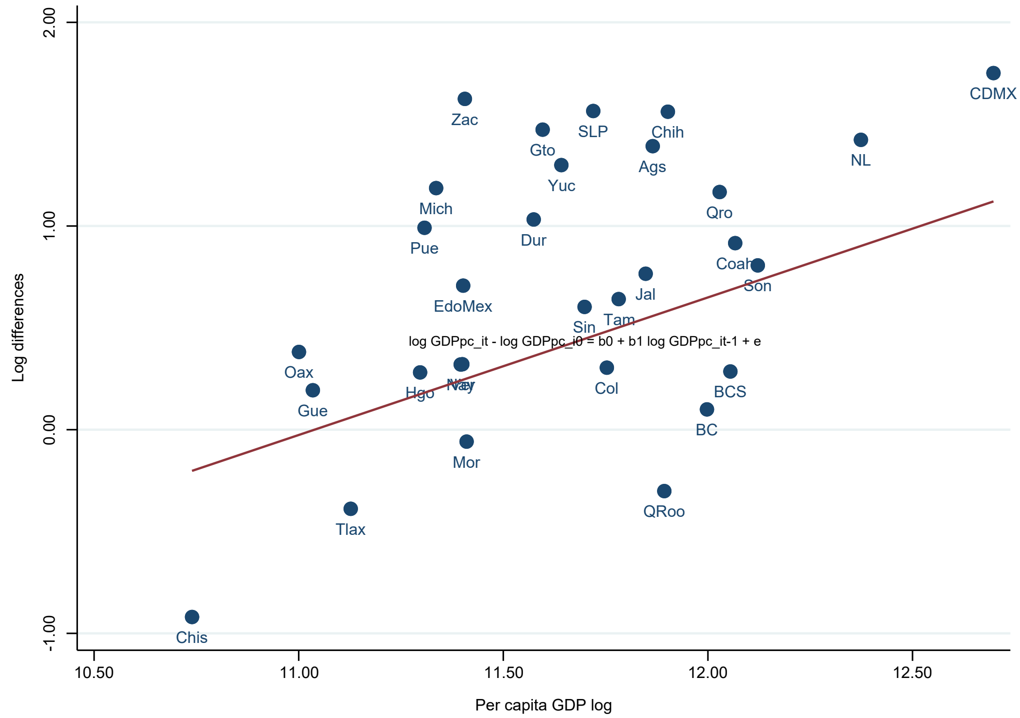
technological capabilities and physical capital are not available in laggard territories (Abramovitz, 1986; Easterly, Fiess & Lederman, 2003).

The existing empirical literature on productivity convergence in Mexico has not yet addressed the importance of productivity externalities among neighboring territories. Productivity externalities diffuse to closely related territories (Krugman, 1991). In other words, productivity spread is likely to be higher between geographically related units than others which are not located near to one another. The availability of advanced infrastructure, human resources, universities and technical schools, and health systems, among other factors, of a territory may have positive effects on the productivity of neighboring territories (Vaya et al., 2004; Rey & Le Gallo, 2009; Azorín & Sánchez 2015; Zhang & Ji, 2019; Bufetova, 2020).

Figure 2.1 presents GDP per capita and its average growth rate between 1993 and 2021 in Mexico's states. A positive slope in the linear regression, depicted in the figure, shows that GDP per capita seems to be converging between the states during this period. Gaps between Mexican regions, for example, the northern and central states, appear to have been closing in recent years.

As a result of economic reforms, in particular openness to international trade and foreign direct investment (FDI) attraction, manufacturing activities in northern and central states have been inserted successfully into global value chains, in high- and medium-technological intensity activities such as automotive, aerospace, electronics, and medical devices (Sánchez & Campos, 2010), while in the south manufacturing has remained concentrated in agribusiness and other natural resource-based manufactures.

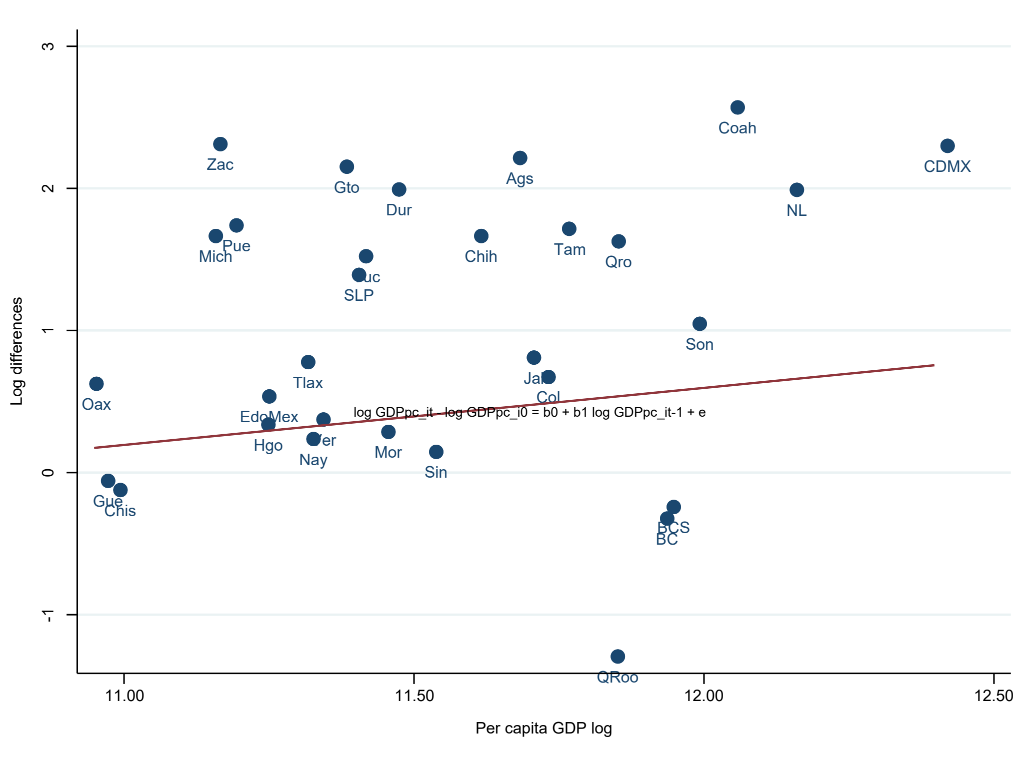
Figure 2.1
Mexico: GDP per capita and its average growth rate, 1993-2021
(Logarithms)



Source: Prepared by the author, on the basis of Instituto Nacional de Estadística y Geografía (INEGI) (2023). "PIB estatal (PIBE). Año base 2013", [online] https://www.inegi.org.mx/programas/pibent/2013/ [date of reference: January 20, 2023]; Consejo Nacional de Población (CONAPO), *Indicadores demográficos 1950-2050*, 2019 [online] https://datos.gob.mx/busca/dataset/proyecciones-de-la-poblacion-de-mexico- and-of-the-federal-entities-2016-2050 [date of reference: May 15, 2019].
Note: The graph excludes the states of Campeche and Tabasco because oil activity makes them outliers.

Figure 2.2 further analyzes the growth-rate gaps and patterns; the analyzed period is divided into three sub-periods: 1993-2003, 2004-2012, and 2013-2021 with the same quantity of years. In all sub-periods (the first years after NAFTA entered into force, previous years of the global financial crisis, and recovered years of the global financial crisis and COVID 19 period), growth rates seem to be diverging, with some outliers in all periods and big gaps between states (Cabral & Castellanos Sosa, 2020). However, further analysis is needed, beyond this graphic method, to obtain a sound conclusion.

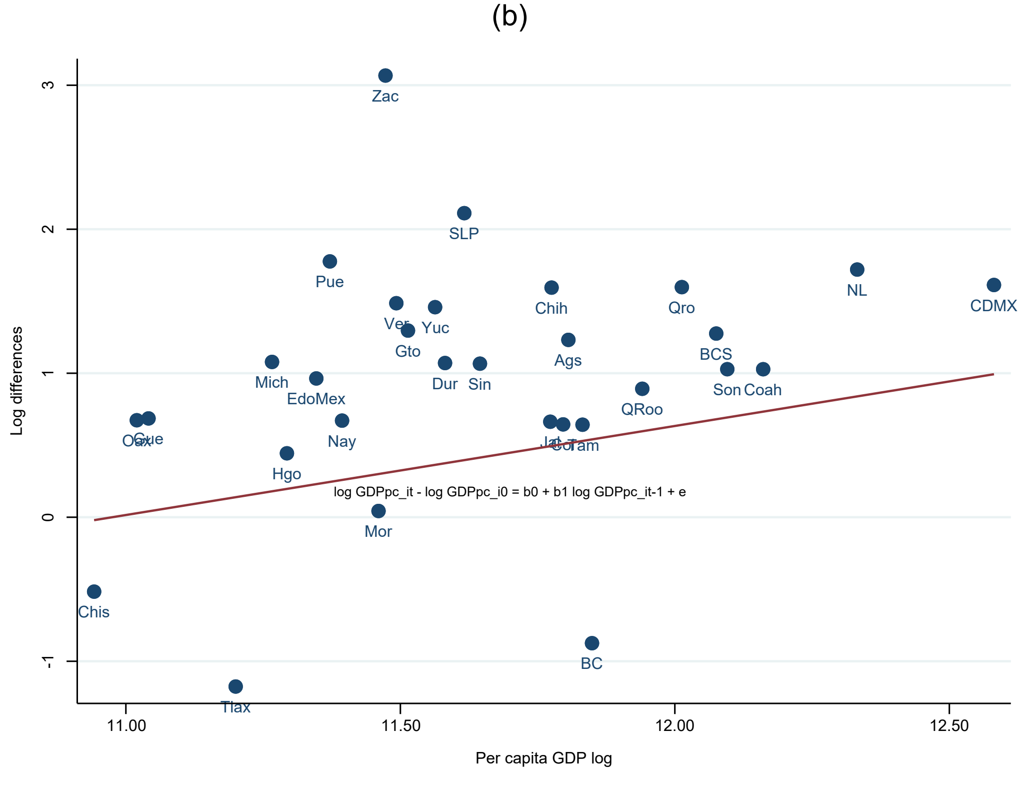
Figure 2.2
Mexico: GDP per capita and its average growth rate, 1993-2021
1993-2002
(a)



Log differences
Per capita GDP log
log GDPpc_it - log GDPpc_i0 = b0 + b1 log GDPpc_it-1 + e
Zac
Gto
Dur
Ags
Coah
CDMX
NL
Mich
Pue
Chih
Tam
Qro
SLP
Son
Oax
Tlax
Col
EdoMex
Hgo
Nay
Mor
Sin
Gue
Chis
BCS
BC
QRoo

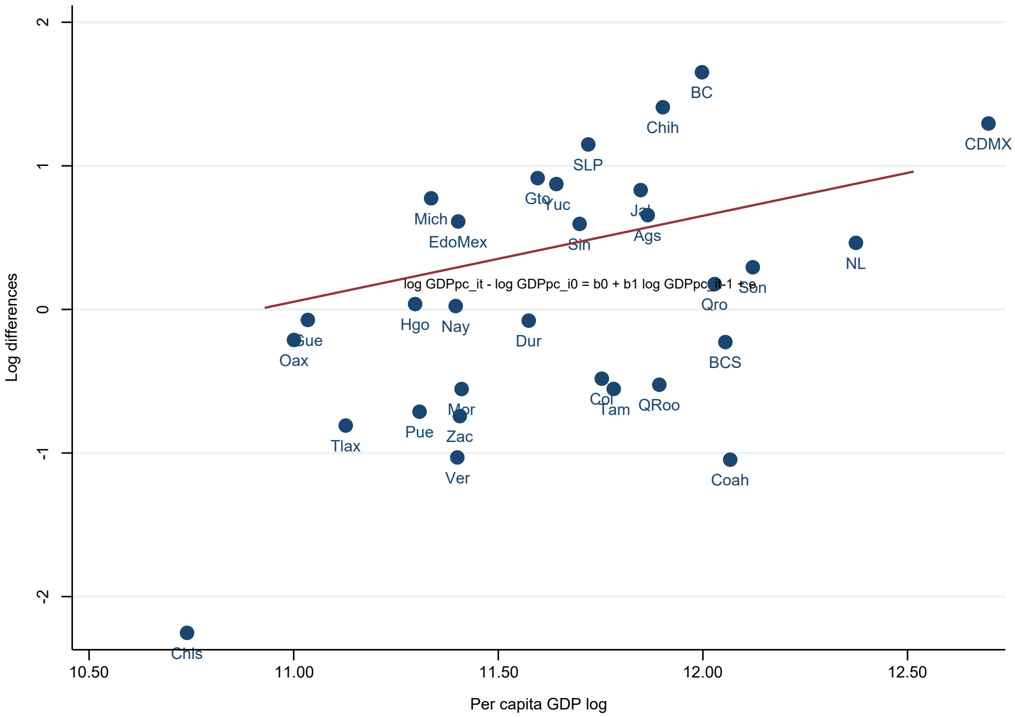
2003-2012

(b)



Log differences
Per capita GDP log
log GDPpc_it - log GDPpc_i0 = b0 + b1 log GDPpc_it-1 + e
Zac
SLP
Pue
NL
CDMX
Chih
Qro
Yuc
Gto
BCS
Mich
EdoMex
Dur
Sin
Ags
Son
Coah
QRoo
Nay
Hgo
Tam
Mor
Chis
BC
Tlax

2013-2021
(c)



Source: Prepared by the author, on the basis of Instituto Nacional de Estadística y Geografía (INEGI) (2023). "PIB estatal (PIBE). Año base 2013", [online] https://www.inegi.org.mx/programas/pibent/2013/ [date of reference: January 20, 2023]; Consejo Nacional de Población (CONAPO), *Indicadores demográficos 1950–2050,* 2019 [online] https://datos.gob.mx/busca/dataset/proyecciones-de-la-poblacion-de-mexico- and-of-the-federal-entities-2016-2050 [date of reference: May 15, 2019].
Note: The graph does not include the states of Campeche and Tabasco because their large oil extraction activity distorts the data comparative analysis.

Several papers show that these patterns of economic growth in Mexico are not random. They respond rather to the quantity and quality of the production factors available in the Mexican states. Therefore, the authors argue that behind this GDP per capita growth gap, there is a similar or higher productivity gap. Yet, the size of this gap is not enough evidence to conclude that productivity within Mexico has followed converging paths over time.

Regional convergence in Mexico has been widely studied. Mallick and Carayannis (1994), Esquivel (1999), Esquivel and Messmacher (2002), and Chiquiar (2005) published seminal papers. The first three documents concluded that there was productivity convergence among Mexican states in the studied period, while the last one found no convergence. These documents make use of different econometric techniques and data, as well as GDP per capita convergence estimations.

Chiquiar (2005) studied GDP per capita convergence before and after the outset of trade liberalization in the mid-1980s, including the first years from when the North American Free Trade Agreement (NAFTA) entered into force. He found that there was no convergence among Mexican states in the studied period. By the same token, Aroca, Bosch and Maloney (2005), and Rodríguez-Oreggia (2007) did not find evidence of convergence. They introduced the club convergence concept, and supplemented econometrics with spatial statistics and transition matrices to estimate productivity performance.

A second wave of studies came along with new econometric approaches and data availability. Asuad Sanén and Quintana Romero (2008) estimated beta and sigma convergence using spatial econometrics, covering a few years after the implementation of NAFTA. In the same way, Sarmiento Reyes (2009) produced his work, using a period covering 1970 to 2006. Carrion-i-Silvestre and German-Soto (2009, 2010) and Cabral and Mollick (2012) used panel data to estimate convergence among Mexican states, concluding that such convergence did exist. In contrast, Baylis, Garduño Rivera and Piras (2009) made use of data at the municipal level and argue that NAFTA resulted in wealthy regions around the border and larger municipalities growing faster than the rest, therefore increasing regional disparities. Ruiz Ochoa (2010) implemented a Weighted Least Squares (WLS) econometric technique to find conditional convergence among states. Gómez-Zaldívar and Ventosa-Santaulária (2012) examined time series and highlighted the stochastic convergence definition.

A third group of studies emerged as more data on trade liberalization and NAFTA became available. Hernández Malvaez and Gómez Zaldívar (2015) lengthened the period of study, as did López González and Cermeño Bazán (2016), Fonseca, Llamosas-Rosas and Rangel González (2018), Rodríguez Gámez and Cabrera Pereyra (2019), and Mendoza-Velázquez et al. (2019). Flores, Andrés-Rosales and Villarreal, (2016) focused on small and medium enterprises in the manufacturing sector, following a sectoral approach. Díaz Dapena et al. (2019) did not expand the time period but instead expanded the disaggregation and examined regional convergence at the municipal level. Rodríguez Gámez and Cabrera Pereyra (2019) applied spatial econometrics, but in a cross-section analysis. Castellanos Sosa (2020) used a panel fixed effects to identify absolute and conditional convergence. However, these studies are not conclusive as some demonstrate regional productivity convergence and some a lack of convergence.

Previous empirical studies have highlighted, in general, a process of regional convergence in Mexico since the economic reforms implemented in the mid-1980s (see table 2.1). After such reforms, most of them show a divergence process.

Table 2.1
Mexico: economic convergence, main studies carried out

Paper published	Principal indicator	Data at level	Type of convergence	Methods	Period	Results
Mallick & Carayannis (1994)	GDP per capita	State level	Absolute convergence	Ordinary Least Squares (OLS)	1970-1985	Converged
Esquivel (1999)	GDP per capita	State level	Absolute convergence and sigma convergence	OLS, Nonlinear Least Squares (NLS) and Seemingly Unrelated Regression (SUR)	1940-1995	Converged
Esquivel & Messmacher (2002)	GDP per capita	State level	Absolute convergence and sigma convergence	OLS	1960-2000	Converged
Chiquiar (2005)	GDP per capita	State level	Conditional and absolute convergence	NLS	1970-2001	Not converged
Aroca, Bosch & Maloney (2005)	GDP per capita	State level	Convergence clubs	Some elements of spatial econometrics	1970-2002	Not converged
Rodríguez-Oreggia (2007)	GDP per capita	State level	Absolute and sigma convergence, conditional convergence	OLS	1970-2001	Not converged
Asuad Sanén & Quintana Romero (2008)	GDP per capita	State level	Beta and sigma convergence	Spatial econometrics	1940-2001	Converged
Carrion-i-Silvestre &	GDP per capita	State level	Stochastics and beta	Panel data	1940-2001	Converged

Paper published	Principal indicator	Data at level	Type of convergence	Methods	Period	Results
German-Soto (2009)			convergence			
Baylis, Garduño Rivera & Piras (2009)	Total value added/ workers	Municipality level	Conditional convergence	Feasible General Least Square (FGLS), Spatial Econometrics	1981-2004	Not converged
Sarmiento Reyes (2009)	GDP per capita	State level	Absolute convergence	OLS	1970-2006	Converged
Ruiz Ochoa (2010)	GDP per capita	State level	Conditional convergence	Weighted Least Squares (WLS)	1900-2004	Converged
Gómez-Zaldívar & Ventosa-Santaulária (2012)	GDP per capita gap	State level	Stochastics and beta convergence	Time series	1940-2009	Converged
Cabral & Varella Mollick (2012)	GDP per capita	State level	Conditional and absolute convergence	OLS, fixed effects and dynamic panel.	1993-2006	Converged
Garduño Rivera (2014)	Production per worker (total value added/L)	Municipality level	Conditional convergence	OLS, Random and Fixed Effects Panel, Spatial Econometrics	1989-2004	Not converged
Hernández Malvaez & Gómez Zaldívar (2015)	GDP per capita	State level	Beta and sigma convergence	Spatial Econometrics, Cross Section	1940, 1976, and 2013	Converged
Flores, Andrés-Rosales, & Villarreal, 2016	Labor productivity	State Level	Conditional and absolute convergence	N.A.	2004-2014	Converged
López González & Cermeño Bazán (2016)	GDP per capita	State level	Convergence clubs	Panel Data, FGLS	1940-2013	Converged
Fonseca, Llamosas-Rosas & Rangel González (2018)	GDP per capita	State level	Conditional and Absolute convergence	Random Effects Panel Data, FGLS	1994-2015	Not converged

Paper published	Principal indicator	Data at level	Type of convergence	Methods	Period	Results
Rodríguez Gámez & Cabrera Pereyra (2019)	Total value added/total pop	State level	Conditional and Absolute convergence	Cross Section, Spatial Econometrics	1999-2014	Converged
Díaz-Dapena, Fernández-Vázquez, Garduño-Rivera & Rubiera-Morollon (2019)	Total value added/ non-agricultural total pop	Municipal level	Regional convergence	Random Effects Panel Data, Two Stages General Least Squares (2SGLS)	1980-2008	Not converged at state level, but clubs converged
Mendoza-Velázquez, German-Soto, Monfort & Ordóñez (2019)	Income per capita	State level	Conditional convergence	Time series econometrics	1940-2015	Not converged, but clubs converge.
Castellanos Sosa (2020)	Labor productivity	State level	Conditional and Absolute convergence	Panel Fixed Effects	1999-2014	Mixed results

Source: Prepared by the author.

An exhaustive search of the current literature yielded no documents that examine productivity convergence in a specific sector (manufacturing), except for the convergence of clubs. By the same token, they have paid scant attention to the importance of spatial effects. The first law of geography emphasizes that all territories or regions can have effects on the object of study, but the closest elements may have greater effects (Tobler, 1970). This chapter aims to address this gap in the extant literature. The hypothesis of this chapter is that when productivity externalities are integrated into the analysis, and spatial econometric techniques are applied, there is significant evidence of productivity convergence among states and municipalities in Mexico.

2.3 Data and descriptive statistics

To test the hypothesis, data on manufacturing labor productivity, disaggregated by state and municipality in Mexico, are used. The source is the Economic Censuses of 1994, 1999, 2004, 2009, 2014, and 2019, which record the previous year's activity (INEGI, 1994, 1999, 2004, 2014, 2019a). The main variables used to estimate labor productivity are gross value added (GVA) and employed population. The consumer price index is used to compute deflation. Table 2.2 shows gross aggregated value and employed population at both state and municipal level.

Table 2.2
Mexico: Gross aggregated average value and average employed population at the state and municipal levels, 1993-2018
(*Value in millions of Mexican pesos, 2018=100*)

Year	Gross Aggregated Average Value at the State level	Gross Aggregated Average Value at the Municipal level	Average Employed population at the State level	Average Employed population at the Municipal level
1993	5,279.6	79.8	100,326	1,387
1998	15,366.7	237.9	130,481	1,763
2003	28,576.4	462.0	131,206	2,037
2008	44,095.4	661.9	145,658	2,101
2013	52,263.9	751.3	158,545	2,202
2018	95,144.7	1,348.4	202,907	7,132

Source: Prepared by the author.

The next step was to analyze annual dispersion of GDP per capita growth rates among states. Since the data are intercensal, this analysis shows the evolution of one of the convergence indicators over time (sigma convergence). The regionalization developed by Chiquiar (2008), followed by Cabral and Mollick (2012), and used in the Banco de Mexico reports (Banco de México, 2022), is useful for this goal[5]. For the complete period, without considering the global financial crisis year, a first stage of economic recovery (2009 to 2010), and the COVID 19 crisis and recovery (2020 to 2021), the standard deviation between northern states is greater (4) than between southern and central states (3.7 and 3.8 in both cases).

Before testing convergence, further dispersion analysis is needed. If we conduct the analysis dividing the studied period into three subperiods (1993-2002, 2003-2012, 2013-2021), we

[5] The northern region includes Baja California, Chihuahua, Coahuila, Nuevo León, Sonora, and Tamaulipas; the central north considers Aguascalientes, Baja California Sur, Colima, Durango, Jalisco, Michoacán, Nayarit, San Luis Potosí, Sinaloa, and Zacatecas; the central is made up of Mexico City, State of Mexico, Guanajuato, Hidalgo, Morelos, Puebla, Querétaro, and Tlaxcala; and the south consists of Campeche, Chiapas, Guerrero, Oaxaca, Quintana Roo, Tabasco, Veracruz, and Yucatán.

will find different dispersions. Between 1993 and 2002, the standard deviation of northern states is 2 points higher than that of southern states (6 versus 4). The standard deviation in central north and central states averages 4.5 and 5.3, respectively. Between 2003 and 2012, the dispersion in northern states decreases to 5.3 standard deviations, while it also decreased to 3.5 in the central north, 4 in central and 3.4 in the south. In the last subperiod (from 2013 to 2021), the standard deviation in northern states was 4, 4.7 in the central, 5.7 in the central north, and 6 in the south. Thus, the dispersion in the northern states decreases over time, but not in the other regions.

2.4 Empirical strategy

To analyze the convergence between Mexican states and municipalities, manufacturing labor productivity is defined as follows:

$$y_{i,t} = \frac{VAB_{i,t}}{PO_{i,t}} \qquad (2.1)$$

where $\mathbf{VAB_{i,t}}$ corresponds to the value added of the manufacturing sector of the state or municipality i in year t, while $\mathbf{PO_{i,t}}$ is the number of workers employed in the manufacturing sector.

This estimate considers potential spatial correlation among geographical administrative units. States or municipalities with high or low productivity may influence, positively or negatively, the productivity of their neighboring states or municipalities. Therefore, before estimating convergence, it is necessary check that there is spatial correlation among geographical administrative units.

First, a spatial weight matrix (W) is estimated. This matrix allows the implementation of any type of spatial cut estimate (Baronio, et al. 2012; Drukker et al., 2013). The W Matrix is defined as follows:

$$W = \begin{bmatrix} \mathbf{0} & \boldsymbol{w_{1,2}} & \cdots & \boldsymbol{w_{1,n}} \\ \boldsymbol{w_{2,1}} & \mathbf{0} & \dots & \boldsymbol{w_{2,n}} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{w_{n,1}} & \boldsymbol{w_{n,2}} & \dots & \mathbf{0} \end{bmatrix} \quad (2.2)$$

where W is an NxN spatial matrix. There are two main types of matrices on which the analysis can be based: contiguity and distance matrices. The former is built with the contiguity of geographic polygons of the spatial units, while the latter is based on the distances between geographic points. Due to the type of data available for the analysis, the contiguity matrix is used to perform the analysis.

Second, global spatial correlation statistics were used: Moran´s I, Geary´s C and Getis and Ord's G (Pisati, 2001). Moran's I is a technique for capturing the global spatial correlation as follows:

$$I = \left(\frac{N}{\sum_i \sum_j w_{i,j}}\right) \frac{\sum_i \sum_j w_{i,j}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2} \quad (2.3)$$

where $\boldsymbol{w_{i,j}}$ is an element of the matrix of spatial weights; $(\boldsymbol{X_j} - \bar{\boldsymbol{X}})$ $(\boldsymbol{X_j} - \bar{\boldsymbol{X}})$ is the covariance between states labor productivity; and $\sum_{\boldsymbol{i}}(\boldsymbol{X_i} - \bar{\boldsymbol{X}})^2$ is the variance. Since firm-level data are not available, the state contiguity matrix is used. Two indices were also used, in addition to the Geary’s C and the Getis and Ord's G. Geary's C is an overall measure of dissimilarity, while the latter makes use of agglomeration measures. Geary's C is calculated as follows:

$$C = \left(\frac{\boldsymbol{N-1}}{\sum_{\boldsymbol{i}} \sum_{\boldsymbol{j}} \boldsymbol{w_{i,j}}}\right) \frac{\sum_{\boldsymbol{i}} \sum_{\boldsymbol{j}} \boldsymbol{w_{i,j}}\left[(\boldsymbol{X_i} - \bar{\boldsymbol{X}}) - (\boldsymbol{X_j} - \bar{\boldsymbol{X}})\right]^2}{\boldsymbol{N} \sum_{\boldsymbol{i}} (\boldsymbol{X_i} - \bar{\boldsymbol{X}})^2} \quad (2.4)$$

where the elements of the equation are the same as those described above (equation 2.4). In addition, Getis and Ord's G is calculated as follows:

$$G = \frac{\sum_{\boldsymbol{i}} \sum_{\boldsymbol{j}} \boldsymbol{w_{i,j}}(\boldsymbol{X_i})(\boldsymbol{X_j})}{\sum_{\boldsymbol{i}} \sum_{\boldsymbol{j}} (\boldsymbol{X_i})(\boldsymbol{X_j})} \quad (2.5)$$

where X only takes positive values, and $\boldsymbol{w_{i,j}}$ corresponds to the array of spatial weights. Once spatial correlation has been verified, the specification of the spatial econometrics model is presented.

The first assumption is that the manufacturing sector produces according to a Cobb-Douglas function. In addition, it is assumed that this same relationship between production factors occurs in all states of Mexico (CIDAC, 2011). Following the generalization of Mankiw, Romer and Weill (1992) and Islam (1995), and to examine convergence from a spatial econometric outlook (Ertur & Koch, 2007; Elhorst, 2009), the absolute convergence equation can be described as the Spatial Error Durbin model (SDEM)[6]:

$$\begin{aligned}\boldsymbol{\Delta y_{i,t}} &= \boldsymbol{\alpha + \rho lny_{i,t-1} + v_{i,t}} \\ \boldsymbol{v_{i,t}} &= \boldsymbol{\gamma \sum_{j=1}^{N} w_{i,t}\, v_{i,j,t} + e_{i,t}}\end{aligned} \quad (2.6)$$

where $\boldsymbol{\Delta y_{i,t}}$ corresponds to per capita productivity growth rate of state i in time t; $\boldsymbol{lny_{i,t-1}}$ is the natural logarithm of lagging per capita productivity; and $\boldsymbol{w_{i,t}}$ is an element of the N x N matrix of spatial weights W, which captures the spatial structure throughout the Mexican states. The productivity growth rate is measured as the logarithmic difference of per capita income in respect to its own lag ($\boldsymbol{\Delta y_{i,t} = \ln y_{i,t} - \ln y_{i,t-1}}$). The W matrix is designed to capture two different structures: a contiguity structure or a distance-based weight structure. Absolute convergence is observed when ρ is negative and significant. The convergence rate, λ, can be obtained from ρ, such that $\boldsymbol{\lambda = -\frac{\ln(1+\rho)}{t}}$, and t is the time period.

A first approach for testing absolute convergence is derived from the inclusion of time and state-specific effects in equation (2.6). This allows different states or municipalities to converge towards various levels of productivity, depending on their own condition and the influence of their neighboring states. As a result, SDEM takes the following specification:

$$\boldsymbol{\Delta y_{i,t} = \alpha + \mu_i + \eta_t + \rho lny_{i,t-1} + v_{i,t}} \quad (2.7)$$

[6] Appendix A provides a taxonomy of Spatial Econometric Models based on Belotti, Hughes & Piano (2017).

In sections 2.7 and 2.8, the last equation (2.7) is estimated using alternative econometric techniques employing data for Mexico at the state and municipal levels.

Results are not discussed or compared between states and municipal level because of the Modifiable Area Unit Problem (MAUP). The MAUP is a statistical effect which means that when a sample from a given area is used to represent certain information, it may be different when the boundaries of the study area are changed (Altaweel, 2018). The area limits are arbitrary, producing very different results, unpredictable in their intensity and effects, depending on the form and scale chosen for the statistical analysis (Fotheringham & Wong, 2016).

2.5 Spatial data testing at state level

To begin the spatial exploration of the data, the neighboring weights matrix at the state and municipal level shows that states have up to eight neighboring elements, while all states have at least one contiguous state. The contiguity relationships that are the basis for estimating the W matrix are shown on map 2.1.

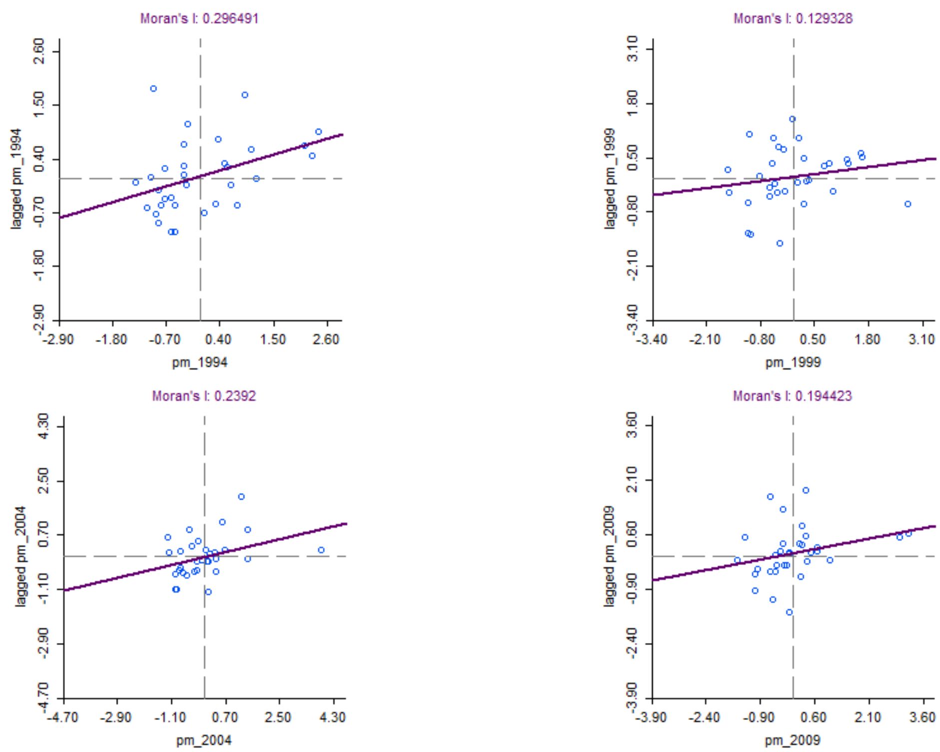
Map 2.1
Mexico: States Contiguity Relations

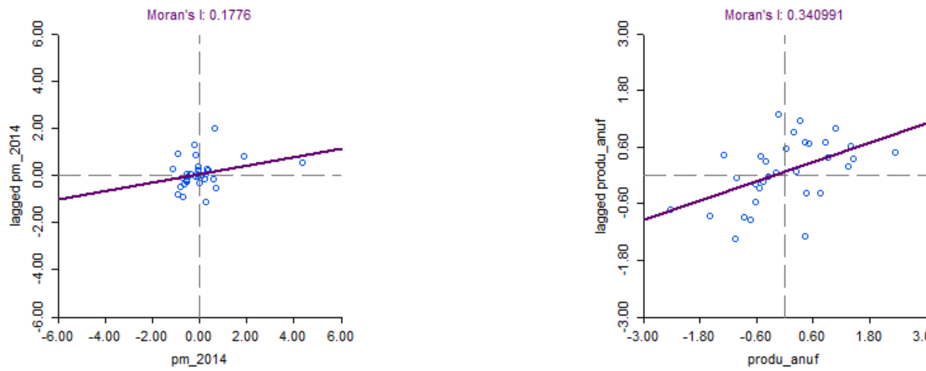
Source: Prepared by the author, based on L. Anselin, I. Syabri, & Y. Kho (2006). GeoDa: An introduction to spatial data analysis, *Geographical Analysis*, 38 (1), pp. 5-22.

The estimation of global spatial correlation statistics shows that there is indeed spatial correlation in the data, and, therefore, the estimation of productivity convergence should consider spatial effects. However, this spatial correlation might be not originated directly in the variable of interest (labor productivity). For example, the global correlation statistic of state-level manufacturing labor productivity, Moran's I, shows that spatial autocorrelation is not explicitly defined.

Figure 2.3 shows the dispersion diagrams of manufacturing labor productivity versus its spatial lag for different censuses (1994, 1999, 2004, 2009, 2014, and 2019). The results of Moran's I global spatial autocorrelation tests, in levels, show that for 1994, 2004, and 2019, with a 95% confidence level, the null hypothesis of spatial randomness is rejected, while in 2009 and 2014 it is rejected with a 90% confidence level. For 1999, there is insufficient information to rule out the null hypothesis of spatial randomness.

Figure 2.3
Mexico: cross-section diagnostic tests for spatial correlation in manufacturing labor productivity,
at the state level, 1993-2018
(Logarithms)





Source: Prepared by the author, based on L. Anselin, I. Syabri, & Y. Kho (2006). GeoDa: An introduction to spatial data analysis*,* *Geographical Analysis*, 38 (1), pp. 5-22.

Productivity spatial randomness can be also tested through a linear regression. The global spatial correlation statistic applied on residuals (such as Moran´s I, Geary´s C, Getis and Ord’s G, as well as Lagrange multipliers) show that there is spatial correlation. That is, the residuals show that there is a spatial structure behind it (see Table 2.3). When the test is applied, it rejects the null hypothesis that the residuals do not have a spatial correlation, but it is inconclusive to reject the null hypothesis on the spatially lagged dependent variable. Therefore, a model with a spatial error should be applied (Shehata, 2016).

The spatial dimension comes from the economic and productive interaction between neighboring states and municipalities (trade of goods and services, employment and education-related commuting, joint production activities). Human resources, infrastructure, education and research organizations, and health systems, among others, of a state or municipality may have positive effects on the labor productivity of neighboring states and municipalities. As a result, statistics applied to residuals show high spatial correlation (see Table 2.3).

Table 2.3

Diagnostic tests for spatial correlation from a linear regression at state level

Statistic	Standardized value	P value
Spatial error		
Moran´s I	0.3813	0.0000
Geary´s C	0.4966	0.0082
Getis and Ords´s G	-1.5969	0.0000
Spatial Lag		
Lagrange Multiplier (Anselin)	38.4115	0.0000
Robust Lagrange Multiplier	1.4656	0.2260

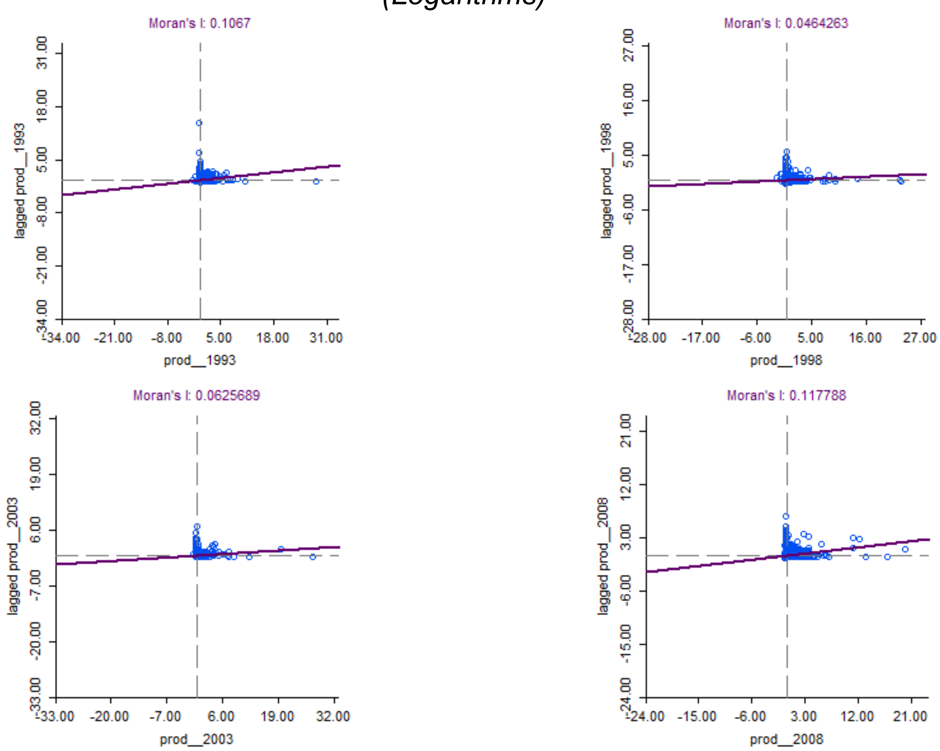
Source: Prepared by the author, based on Pisati, M. (2001). Tools for spatial data analysis. Stata Technical Bulletin, No. 60, pp. 21-37. Retrieved from: http://www.stata.com/products/stb/journals/stb60.pdf.

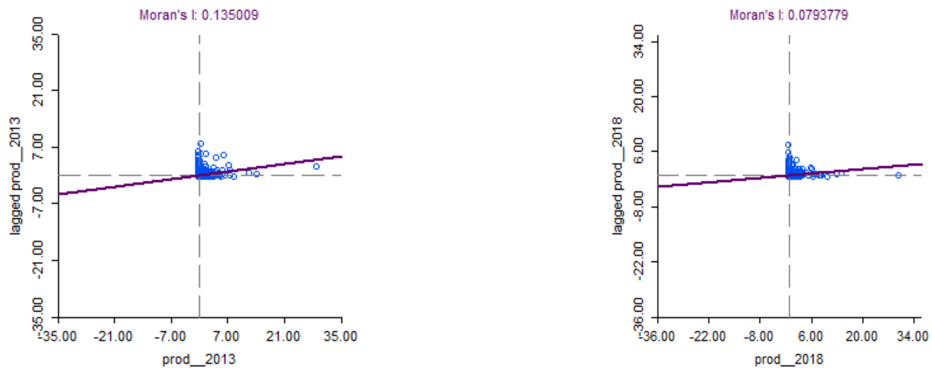
Note: In the residual's spatial correlation tests, the Ho: λ = 0, where λ is the interaction coefficient between the explanatory variable and the spatial weights matrix. The hypothesis test on spatial lag is Ho: ρ = 0, where ρ is the coefficient of interaction between the explanatory variable and the matrix of spatial weights.

2.6 Spatial data testing at the municipal level

In the same way, spatial correlation at municipal level should be examined. The global spatial correlation statistics show that there is spatial correlation in each of the studied years, and therefore the estimation should consider spatial effects. Moran´s I of global spatial correlation is calculated for manufacturing labor productivity at the municipal level, for each year, as shown in Figure 2.4. The results demonstrate that there is spatial autocorrelation. Specifically, when Moran´s I statistics with a spatial delay are applied to the variable of interest, the test results are conclusive, and the non-autocorrelation null hypothesis is rejected.

Figure 2.4
Mexico: cross-section diagnostic tests for spatial correlation in manufacturing labor productivity, at the municipal level, 1993-2018
(Logarithms)





Source: Prepared by the author, based on L. Anselin, I. Syabri, & Y. Kho (2006). GeoDa: An introduction to spatial data analysis, Geographical Analysis, 38 (1), pp. 5-22.

The statistical inference can be strengthened by estimating productivity through a linear regression and applying several spatial correlation statistics (Moran´s I, Geary´s C, Getis and Ord's G, as well as Lagrange multipliers) on residuals, as was done at the state-level. Table 2.4 shows spatial correlation indicators at the municipal level.

Table 2.4

Diagnostic tests of spatial correlation from a linear regression at the municipal level

Statistic	Standardized value	P value
Spatial Error		
Moran´s I	2.33	0.020
Geary´s C	3.54	0.060
Getis and Ords´s G	6.11	0.013
Spatial Lag		
Lagrange Multiplier (Anselin)	0.35	0.56
Robust Lagrange Multiplier	2.92	0.09

Source: Prepared by the author.
Note: In the residual's spatial correlation tests, the Ho: $\lambda = 0$, where λ is the interaction coefficient between the explanatory variable and the spatial weights matrix. In the spatial lag tests, the null hypothesis is Ho: $\rho = 0$, where ρ is the interaction coefficient between the explanatory variable and the spatial weights matrix.

Since the analysis conducted above shows that there is spatial correlation among states and municipalities, this must be considered in the econometric model to examine convergence. A second conclusion is that an error model should be implemented, since the spatial error test rejected the null hypothesis (no spatial interaction), at a 5% significance level.

2.7 Results at the state level

Table 2.5 shows the results of the state-level productivity convergence estimation. It presents three estimates of the absolute convergence parameter, making use of different techniques: linear regression of combined data (Pooled OLS), panel data and fixed effects, and spatial panel data (Pisati, 2001; Belotti, Hughes & Piano Mortari, 2016; Shehata, 2016). The first two models are used as a benchmark to compare the results when spatial panel data are introduced (third model). The absolute magnitude of the coefficient increases as more structure is incorporated into the estimation. Pooled OLS and panel data does not show convergence among Mexican states. However, when spatial correlation is considered, the regression coefficient indicates absolute convergence. The errors spatial correlation coefficient, $\boldsymbol{\gamma}$, is statistically significant at 5%. Therefore, when productivity externalities among states are included in the econometric analysis, absolute convergence is demonstrated.

Table 2.5
Mexico: estimates of the absolute convergence parameter, at the state level, 1993-2018

Parameters	Pooled OLS	Panel data, fixed effects	Spatial panel data, fixed effects
ρ	0.05	0.07	-0.16**
	(0.07)	(0.09)	(0.09)
μ_i	0.47*	0.50*	
	(0.09)	(0.10)	
γ			0.13*
			(0.02)
σ_ϵ^2			0.37*
			(0.16)
Speed of convergence (b)[a]	0.2%	0.3%	0.7%
Half life[b]	355.17	256.12	99.39
R^2 adj	0.01	0.01	0.01
Akaike Information Criteria (AIC)	297.85	290.25	255.66
Bayesian Information Criteria (BIC)	303.55	295.95	264.22

Source: Prepared by the author.
Notes: * Statistically significant coefficients at 95% confidence level.
** Statistically significant coefficients at 90% confidence level.
[a] The convergence rate is calculated as $b = -\frac{\ln(1+\rho)}{T}$.
[b] The half-life indicator is calculated as $v_{media} = \frac{\ln(2)}{b}$.

The convergence speed rate and the half-life indicator are two statistics commonly calculated in the convergence literature. The former estimates how fast the manufacturing sector converges into the equilibrium state, while the latter computes how long it would take to fill half of the initial gap, at that given rate (Arbia, 2006). The convergence speed is within the parameters set up by Barrow's empirical regularity, called "iron law", of 2%. The computations also show that, with these convergence rates, the states that present the largest productivity lags would take 99.4 years to reach half of the lag.

The adjusted R square and Akaike and Bayesian information criteria were used to verify the goodness of fit. The criteria are used to determine which model is best explained by the included variables. Although the variables included in the regression models are the same, it is appropriate to evaluate the adjustment to different models, as well as considerations of the data generation process (DGP). The adjusted R square is barely modified since, in all models, the variance explained by the independent variable is the same. However, as noted in all specifications, the statistic improves as the spatial correlation of the data is modeled. In addition, when the regression model based on data groups is adapted to a panel model, the information criteria improved. The model with the lowest information criteria is chosen. In both cases, the Akaike and Bayesian criteria suggest that the spatial correlation model of errors provides the best fit.

2.8 Results at municipal level

Table 2.6 shows the results of productivity convergence at the municipal level. As in the state-level analysis, three estimates of the absolute convergence parameter are presented: linear regression of pooled data (Pooled OLS), panel data with fixed effects, and spatial panel data with fixed effects (Pisati, 2001; Belotti, Hughes & Piano Mortari, 2016; Shehata, 2016). The size of the coefficient increases as more effects are incorporated into the regressions. Similarly, spatial regression coefficients show absolute convergence, in contrast to pooled OLS and panel data fixed effects. The convergence parameter estimator increases by one hundredth, in absolute terms, compared to the fixed effects estimator. The errors spatial correlation coefficient, $\boldsymbol{\gamma}$, is statistically significant at 5%.

Table 2.6

Mexico: estimates of the absolute convergence parameter, at the municipal level, 1993-2018

Parameters	Pooled OLS	Panel data, fixed effects	Spatial panel data, fixed effects
ρ	1.04*	1.01*	-0.48*
	(0.02)	(0.02)	(0.01)
μ_i	3.55	3.51	

Parameters	Pooled OLS	Panel data, fixed effects	Spatial panel data, fixed effects
	(0.08)	(0.09)	
γ			0.12*
			(0.00)
σ_{ϵ}^{2}			1.84*
			(0.03)
Speed of convergence (b)[a]	2.85%	2.79%	2.62%
Half life[b]	24.31	24.82	26.50
R^2 adj	0.32	0.32	0.26
Akaike Information Criteria (AIC)	54 068.97	29 199.14	26 401.17
Bayesian Information Criteria (BIC)	54 082.96	29 212.51	26 421.89

Source: Prepared by the author.
Notes: * Statistically significant coefficients at 95% confidence level.
** Statistically significant coefficients at 90% confidence level.
[a] The convergence rate is calculated as $b = -\frac{\ln(1+\gamma)}{T}$.
[b] The half-life indicator is calculated as $v_{media} = \frac{\ln(2)}{b}$.

The convergence rate is within the parameters established by Barrow's empirical regularity of 2%. In addition, if the OLS results are used the municipality with the largest productivity gap would need 24.3 years on average to reach half of the lag. In the panel regression, 24.8 years would be needed, while with third estimate the time is increased to 26.5 years. To assess the goodness of fit, adjusted R square and information criteria such as Akaike and Bayesian are used. R squared decreases when the spatial error model is used. These information criteria indicate that the third model adjusts the data better than the other two.

2.9 Conclusions

The empirical data shows that after profound economic and structural reforms, there has not been convergence among Mexico’s states in terms of economic growth rates. The existing literature presents heterogenous results regarding convergence in productivity levels. Yet previous studies have not considered the importance of spatial correlation to examine productivity convergence.

This chapter aims to assess whether there is convergence in manufacturing labor productivity between 1993 and 2018 among Mexican states and municipalities, through panel-type estimation techniques (fixed effects and fixed effects with spatial errors). The econometric analysis shows that there is manufacturing labor productivity convergence in the studied period, when spatial panel data analysis is applied, in contrast to previous studies that have made use of alternative techniques such as pooled OLS and panel data fixed effects.

That is, when productivity externalities between neighboring states or municipalities are integrated into the econometric analysis, there is positive and significant evidence of convergence in the manufacturing sector in the studied period. In effect, Rodrik (2013) argues that non-conditional convergence can occur in certain sectors of the economy. Depending on the sector, this could lead other sectors, regions, or states towards economic convergence, contingent to the linkages that the sector has with all the other sectors of the economy. Also, this spatial model of absolute convergence is possibly capturing elements that enable the estimation of conditional convergence, instead. By incorporating spatial elements, the spatial distribution is being conditioned to the economic units under analysis.

In terms of public policy, there is a need for regional strategies that stimulate productivity in territories that have been less favored. These strategies should go beyond administrative boundaries, given the importance of productivity externalities among neighboring territories. More infrastructure is also needed to facilitate linkages and connection among states and municipalities. Fostering links between high- and low-productivity economic sectors or activities, for instance manufacturing and agriculture, could lead to increasing convergence.

Lines of future research are the analysis of σ convergence, and conditional convergence, to unravel the conditions under which convergence is taking place. The study of the impact of the current economic and social crisis due to the COVID-19 pandemic on convergence among states and municipalities is also a line of future research.

Chapter 3. A shift-share analysis with spatial econometrics

3.1 Introduction

Among other things, it is recognized that Mexico has macroeconomic stability, a long-term fiscal austerity, and an outstanding export performance. But Mexico has experienced low and volatile economic growth, with its economy expanding at only 2% annually on average between 1990 and 2021. Several studies have shown a close association between this modest economic growth and slow productivity growth in Mexico (Chiquiar & Ramos Francia, 2009; Kehoe & Ruhl, 2010; Government of Mexico, 2013; OECD, 2013; McKinsey Global Institute, 2014; CEPAL, 2016; López Córdova & Rebolledo Márquez Padilla, 2016, OECD, 2017). Also, even when productivity levels diverge significantly among Mexican states (CEPAL, 2016), there are some sectors of the economy that perform well. For example, chapter 2 shows that manufacturing labor productivity converges across states and municipalities.

Productivity levels and growth come from a complex interrelation between technological progress and production methods, new product and service development, and allocation of resources (Cuadrado-Roura, Mancha-Navarro & Garrido-Yserte, 2000). So, how can the different levels of State productivity and manufacturing labor productivity convergence be explained? State inequality might be related with one of the two circumstances: aggregate productivity differs because there are differences among output per worker across sectors that comprise the whole economy or because of its intrinsic characteristics. The former is a result of the variability in the industry mix component of the national economy (Ezcurra, Pascual & Rapún, 2007).

In contrast, how much of manufacturing labor productivity can be explained by its territorial characteristics? The gaps among Mexican states may be a result of a wide array of factors such as sectoral specialization, the stock of financial and human capital, and institutions, among others (Galindo & Ríos, 2015). If this is the circumstance that determines inequality, then the principal factors of regional inequality in productivity would be the aggregation of these factors impacting in all sectors (Ezcurra, Pascual & Rapún, 2007).

Chapter 3 examines in greater depth spatial spillovers of manufacturing labor productivity across Mexico´s states. A classical and multifactor partitioning shift-share model and spatial econometrics are developed to disentangle the indicator. The chapter analyzes which local components and national factors influence local manufacturing productivity. The shift-share analysis is proposed to break down the regional differential growth paths into their industry-mix (structural effects) and region-specific elements, respectively, while quantifying the industry-region interactive effect (Gardiner et al., 2013). Results show that regional shifts increase the divergence between national and state-specific performance, but this is not the case for sectoral shifts.

The chapter is divided into nine sections. The second section presents and discusses a relevant literature review. The methods are presented in the third section, in particular, exploratory and the shift-share methodology which support the quantitative analysis. The fourth section describes the data and offers a descriptive statistics analysis. The fifth, sixth, seventh, and eight sections summarizes and discusses spatial data testing and the results. The nineth section concludes and offers a public policy recommendation for the short term.

3.2 Literature review

The neoclassical theory of economic growth posits that, assuming the free mobility of capital and labor, diminishing returns to scale in production, and the absence of barriers to technological diffusion, lower-income countries will have higher economic growth rates than the richest countries, in such a way that they reach an equilibrium level of income in the long run (Solow, 1956, 1957; Jorgenson & Griliches, 1967). This approach is known as economic convergence. In the case of regions, states or municipalities within a country, national economic growth should be such that the entities that comprise it converge in the same way, since there are no administrative or legal barriers to prevent said process. However, some empirical studies have shown that there is not always convergence within a sector, country, or region.

This lack of internal convergence causes heterogeneity within a country, sector, or region. In turn, heterogeneity manifests itself in income inequality. We see entities in which economic growth is high (and therefore, greater wealth) while other entities grow less (or do not grow) and are poor, even within the same country. This situation suggests that there are endogenous forces in the countries, regions or municipalities that drive growth. The theory of endogenous growth exposes its approach around this argument (Romer, 1990; Barro & Sala-i-Martin, 1992; Klenow & Rodríguez-Clare, 1997).

The best-known notions of convergence come from these two opposing arguments. It is said that when a country or region converges in growth or productivity towards a steady state[7], there is absolute convergence or β convergence, regardless of the initial conditions (Islam, 2003). Working in this same sense, some authors have suggested that convergence is a necessary condition, but not sufficient, since attention must also be paid to the convergence distribution. Thus, if there is a decrease in the dispersion of economic growth or productivity over time, then the process tends towards convergence. This approach is known as the σ convergence. The σ convergence is reproduced regardless of the initial conditions (Islam, 2003).

On the other hand, one theory postulates that, derived from the lack of absolute convergence, conditional convergence can exist. We can then say that, although there is a lack of absolute convergence, there may be a convergence conditional on a series of factors (controlled by the specifications of the model) between a group of countries, regions, or sectors. Conditional convergence is delineated by similar factors or structures shared by some geographic units or economic sectors. Note that conditional convergence gives way to convergence clubs. Conditional convergence and convergence clubs show similar initial and structural conditions (López González & Cermeño Bazán, 2016).

A third postulation is that, beyond an absolute, conditional convergence or aggregate-type clubs, we must seek a convergence between some sectors or areas of the economy (Rodrik, 2013) to see what the glue of one economy is, for example. As already mentioned, neoclassical economic growth theory hypothesizes that identical access to technology, markets, capital, and labor should force convergence in income. Low income and high productivity should lead states, regions, or municipalities to grow faster than their counterparts, defining a stable and long-term common path. This reinforces the convergence hypothesis.

However, the empirical work conducted so far does not fully support this proposition. For example, if growth rates are under a conditional rather than unconditional convergence process, then economies will tend towards a different income level in the long run. The lack of empirical work supporting unconditional convergence has strengthened models of exogenous technological change. These models do not necessarily show convergence, so

[7] Economic growth and productivity are closely related. The increase in productivity has a positive effect on economic growth, since productivity implies a higher quality of the labor force, better organization of the company, deepening of capital or technological change, or a combination of these.

the empirical work focuses on the variables that make convergence possible. In this sense, we affirm that unconditional convergence exists, but it occurs in certain areas of the economy, rather than in the whole economy. In this case, we evaluate the manufacturing sector.

Convergence in Mexico has been studied since the papers by Mallick and Carayannis (1994), Esquivel (1999), Esquivel and Messmacher (2002) and Chiquiar (2005). Studies have evolved over time, using several econometrics techniques, data, time periods, and disaggregation levels. Chapter 2 shows an extensive literature review about this topic. Most of these studies lack spatial interactions, such as in spatial econometrics, and none of them delve into sectorial and regional contributions to convergence.

To disentangle the relationship between sectoral and regional contributions to employment, or productivity in our case, Dunn (1960) wrote in his seminal article that the shift share analysis could identify such relationships. As he explains, regional development runs at different rates than national development. The basic pillar of the statistical technique of shift-share analysis is the calculation of geographical changes in economic activity. The computation is based on data describing the geographical distribution of an economic dimension for different periods. Three effects are described: the regional effect, the sectoral effect, and the mix effect. The first describes differences between regional and national phenomenon, while the second between the whole economy and each sector. Finally, the last computes a mixture of both effects.

Since then, many papers have applied the technique to employment or productivity analysis. A summary literature review was conducted by Stevens and Moore (1980) in the 80s, following the papers of Selting and Loveridge (1992), Loveridge and Selting (1998), and Dinc, Haynes and Qiangsheng (1998) in the 90s. Recently, Lahr and Ferreira (2020) delve more deeply into the history of shift-share analysis, decomposing the literature review since its initial developments until its forecasting phase and more profoundly into its components.

As an example of the literature developed in the beginning stages, Reynolds (1980) is one of the first to introduce the effects of changes in the sectoral labor force and in the growth of total factor productivity at the regional level in Mexico. Moreover, Ledebur and Moomaw (1983) compare labor productivity and labor productivity growth in the manufacturing sector for various regions of the United States, finding that the sectoral effect plays an important role in productivity. Haynes and Dinc (1997) assess the fundamentals of economic performance and employment change in six snow-belt and six sun-belt regions, and evaluate the so-called snow belt to sun belt regional shift in the manufacturing. They support the thesis of the change from the snow-belt to the sun-belt states.

A major improvement was made by Esteban-Marquillas (1972), which identifies an additional effect to those proposed by Dunn (1960), the location effect, but it is in Esteban (2000) that the spatial structure within the shift-share analysis is introduced. Nazara and Hewings (2004) developed a comprehensive taxonomy for the decomposition structure alternatives. Since then, several authors have proposed new approaches to this technique: Le Gallo and Kamarianakis (2011) use a shift analysis to decomposes labor productivity and explore the industry mix effect and regional structural differences through spatial econometrics; Mayor and López (2008) use nonparametric techniques to refine its shift share analysis; Ezcurra and Pascual (2007) and Mussini (2019) combine shift-share with techniques from the income distribution literature. Both use a Gini and Theil index, but the second decomposes a Gini index into the components of the shift-share analysis, separating each contribution into neighboring and non-neighboring components[8]. Montania, et al. (2021) offer a good discussion about several approaches to spatial shift-share analysis.

The quantity of applied shift-share studies is quite extensive. One of the more important, and relevant to our work, is Matlaba, et al. (2012), which examines classical and spatial shift share analysis to decompose employment in Brazil using the 27 states. Another study that is closely related to our work is Ezcurra, Pascual and Rapún (2007). They use spatial shift-share analysis along with income distribution analysis to identify the causes of regional differences in output per worker among regions of the European Union. They also use a methodology to classify regions according to labor productivity, output, and employment. Results indicate a decrease in regional disparities, but the process was not continuous during their sample period of 1977 and 1999.

One of the most relevant studies for Mexico is Flores, Medellín and Villarreal (2018). Their methodology is based on the spatial shift-share analysis for employment and spillover effects. Following a taxonomy based on innovation, their results suggest a competitive effect for some sectors, such as those related to science and specialized suppliers, scale-intensive industries, and dominated suppliers, which leads to the formation of industrial corridors from neighboring states that connect the central region with the northeastern region of the country. A microregional study on the State of Mexico was conducted by Rendón Rojas, et

[8] The Gini index is not decomposable, even though several authors do so, because of its lack of additivity. Liu, Sickles and Zhang (2016) offer an excellent discussion on this topic.

al. (2013), examining the diminishing production growth rate in this central Mexican state compared with the North of Mexico, as we infer in our introduction. As a result of this performance, the share of state GDP in the national GDP decreased from 11.1% in 1985 to 9.5% in 2008, while the state manufacturing sector experienced a loss in dynamism and economic momentum compared to other sectors.

Finally, chapters 2 and 3 differentiate from previous contributions since the first explore absolute convergence for Mexico and then the lats disentangle labor productivity with the shift-share for Mexico to understand the sources of regional differences. They also examine the degree to which State-related and industry-related factors contribute to productivity performance in the manufacturing sector.

3.3 Methodology

A multi-factor partitioning analysis is proposed to break down the cumulative regional differential growth paths into their industry-mix (structural effects) and region-specific elements, respectively, while quantifying the industry-region interactive effect (Gardiner et al., 2013). First, we propose a classical shift-share analysis, as a benchmark, to study regional productivity in the manufacturing sector. The classical shift-share equation becomes:

$$\dot{Y}_{ij,t+1} - \dot{Y}_{ij,t} = \Delta\dot{Y}_{ij,t+1} = NS_{ij,t+1} + IM_{ij,t+1} + RS_{ij,t+1} \quad (3.1)$$

where $\dot{\boldsymbol{Y}}_{\boldsymbol{ij,t}}$ are manufacturing labor productivity in the *ith* manufacturing sector and region *jth* in year *t*. The terms are:

$$\boldsymbol{NS_{ij,t}} = \dot{\boldsymbol{Y}}_{\boldsymbol{ij,t}} * \boldsymbol{g_n} \quad (3.2)$$

$$\boldsymbol{IM_{ij,t}} = \dot{\boldsymbol{Y}}_{\boldsymbol{ij,t}} * (\boldsymbol{g_{in}} - \boldsymbol{g_n}) \quad (3.3)$$

$$\boldsymbol{RS_{ij,t}} = \dot{\boldsymbol{Y}}_{\boldsymbol{ij,t}} * (\boldsymbol{g_{ij}} - \boldsymbol{g_{in}}) \quad (3.4)$$

In the equation (3.2), the national share $\boldsymbol{NS_{ij,t}}$ is equal to manufacturing labor productivity in the *ith* manufacturing sector and region *jth* in year *t* multiplied by its national percentual growth. Likewise, industry mix ($\boldsymbol{IM_{ij,t}}$) is the same indicator multiplied by the difference between its *ith* sectoral percentual growth at the national level and the total national percentual growth. Finally, the regional shift is defined by manufacturing labor productivity multiplied by the difference between the regional percentual growth and the national percentual growth of the *ith* sector.

There has been some debate about this classical shift-share analysis approach. The debate focuses on the initial structural distribution of the employment or output, which is assumed to be constant across the entire study period (Vasquez López, 2018). Ray, Lamarche and Beaudin (2012) proposed a standardized version of this partitioning form, named multi-factor. Here, the Gardiner, et al. (2013) version is followed. The regional growth rate becomes:

$$\bar{\bar{g}}_j = \sum_j g_{ij} \frac{PO_{in,t}}{PO_{n,t}} \tag{3.5}$$

where the manufacturing labor productivity of the *ith* sector in the *jth* region $(\boldsymbol{g_{ij}})$ in time *t*, is weighted by the proportion of the sectoral employment $(\boldsymbol{PO_{in,t}})$ over the national employment $(\boldsymbol{PO_{n,t}})$ in time *t*.

Now, the sectoral is:

$$\bar{\bar{g}}_{in} = \sum_j g_{ij} \frac{PO_{j,t}}{PO_{n,t}} \tag{3.6}$$

where the manufacturing labor productivity of the *ith* sector in the *jth* region $(\boldsymbol{g_{ij}})$ in time *t*, is weighted by the proportion of the regional employment $(\boldsymbol{PO_{in,t}})$ over the national employment $(\boldsymbol{PO_{n,t}})$ in time *t*.

And the national rate is drawn from:

$$\bar{\bar{g}}_n = \sum_i g_{in} \frac{PO_{in,t}}{PO_{n,t}} = \sum_j g_j \frac{PO_{j,t}}{PO_{n,t}} \tag{3.7}$$

where equation (3.7) can be obtained from regional or sectoral growth rate.

Thus, the shift share becomes:

$$\begin{aligned} \dot{Y}_{j,t}(g_j - g_n) = \sum_i \dot{Y}_{ij,t}\left(\bar{\bar{g}}_j - \bar{\bar{g}}_n\right) + \sum_i \dot{Y}_{ij,t}\left(\bar{\bar{g}}_{in} - \bar{\bar{g}}_n\right) \\ + \sum_i \dot{Y}_{ij,t}\left(g_{ij} - \bar{\bar{g}}_{in} - \bar{\bar{g}}_j + \bar{\bar{g}}_n\right) + \sum_i \dot{Y}_{ij,t}\left(\bar{\bar{g}}_n - g_n\right) \end{aligned} \tag{3.8}$$

In the last equation, the left-hand side is the difference between the total growth of the regional and national manufacturing labor productivity; the first term of the right-hand side is the regional effect $(\widetilde{\boldsymbol{RS}})$, following the industry mix effect $(\widetilde{\boldsymbol{IM}})$. Finally, an interaction effect and allocation effect $(\widetilde{\boldsymbol{ALL}})$ are proposed in equation 3.8. The allocation effect accounts for competitive disadvantage or advantage (Herzog & Olsen, 1977).

Several approaches to introduce spatial interactions have been proposed and are detailed in the literature review section. Most of them incorporate a spatial weights matrix in each of the shift-share components (Fernández & Menéndez, 2005). These methodological approaches are deterministic in themselves. But recent developments -based on spatial econometrics- incorporate stochastic components into the shift-share analysis (Le Gallo & Kamarianakis, 2011). In this context and answering which components influence local manufacturing productivity, the following empirical model is proposed to account for spatial correlation:

$$\begin{aligned} \Delta\dot{\boldsymbol{Y}}_{ij,t+1} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\,\widetilde{\boldsymbol{IM}}_{ij,t+1} + \boldsymbol{\beta_2}\,\widetilde{\boldsymbol{RS}}_{ij,t+1} + \boldsymbol{\beta_3}\,\widetilde{\boldsymbol{ALL}}_{ij,t+1} + \boldsymbol{v}_{ij,t+1} \\ \boldsymbol{v}_{ij,t+1} = \boldsymbol{\gamma}\sum_{j=1}^{N} \boldsymbol{w}_{ij,t+1}\,\boldsymbol{v}_{ijh,t+1} + \boldsymbol{e}_{ij,t+1} \end{aligned} \tag{3.9}$$

where $\widetilde{\boldsymbol{IM}}_{\boldsymbol{ij,t+1}}$, $\widetilde{\boldsymbol{RS}}_{\boldsymbol{ij,t+1}}$ and $\boldsymbol{ALL}_{\boldsymbol{ij,t+1}}$ are the components developed in equation 3.8. Equation 3.9 follows a Spatial Error Model because it considers spatial correlation between variables omitted in the equation.

In addition to the formulas, an issue arises from census sectoral codification. The names and codes of manufacturing subsectors change between the 1994 and 1998 Censuses -and then the following Censuses- in order to implement the North American Code System (NACS). We follow Castaldi's (2009) innovation-based taxonomy to establish the set of homogeneous manufacturing subsectors under study. The taxonomy proposed and applied to the census categories are depicted in Appendix B.

A final issue to address that will allow us to complete the empirical strategy concerns region-specific variations in oil production accounting. For example, Tabasco is one of the principal oil producers among all Mexican states, and Pemex, the Mexican oil company, monopolizes production. The monopoly's income increases or decreases Tabasco's revenues significantly for the entire study period, with the exception of 2018. Gross value added (GVA) in Tabasco for 2018 is negative. In 2017, the Mexican government introduced a new pricing system for gasoline and diesel, distorting inputs and final outputs. This new system affects GVA and hence the productivity data in the manufacturing industry and could therefore lead to a distortion in our analysis. To prevent this problem, we estimate the 2018 GVA for Tabasco using regression analysis.

3.4 Data and descriptive statistics

Empirical findings of productivity performance are based on a panel of State-level observations on a five-year basis. We utilize data from the Mexican Economic Censuses published by the Mexican Institute of Geography and Statistics (INEGI, by its Spanish acronym) (INEGI, 1994, 1999, 2004, 2009, 2014, 2019). The principal variables used to estimate labor productivity are gross value added (GVA) and employed population. The 2018 consumer price index is used to compute constant values (INEGI, 2018).

Table 3.1. displays the manufacturing labor productivity by state indicator for each census, with Tabasco (20.7%), Chiapas (12.5%), and San Luis Potosi (7.1%) showing the most notable growth rate for the whole period. But as we stated, Tabasco labor productivity is distorted, and Chiapas grows in the nineties and then decreases over time. Also, Chiapas

(23.28) shows the greatest volatile GVA measure by standard deviations, while Guerrero (9.4%), Campeche (6.7%), and Yucatan (4.0%) are the lowest over the whole period.

For the exploratory descriptive analysis that follows, regions were formed as proposed by the Central Bank of Mexico in its regular quarterly publication (Banco de México, 2022). If we classify the indicator by these regions (Table 3.1), the south region shows the highest heterogeneity in the labor productivity growth rate. Almost 40% of the variability is inside this region. After the south, is the north center (35.6%), northern (11.1%), and center (15.8%) region.

Table 3.1
Mexico: Annual labor productivity in the manufacturing sector, at the state level, 1993-2018
(in pesos of 2018)

State	1993	1998	2003	2008	2013	2018[a/]	Average Growth Rate [b/]	Standard deviation	Regions
Aguascalientes (AGS)	42,488	135,612	233,535	384,474	307,974	768,918	18.6%	3.30	North center
Baja California (BC)	30,004	94,839	159,002	221,598	212,692	364,646	8.8%	2.74	Northern
Baja California Sur (BCS)	26,153	63,691	111,122	131,918	136,337	245,444	4.8%	1.24	North center
Campeche (CAM)	15,985	36,160	68,533	73,987	99,273	147,908	2.7%	0.87	South
Coahuila (COAH)	55,244	182,274	250,852	477,524	488,897	728,894	18.0%	3.13	Northern
Colima (COL)	27,474	158,286	310,556	271,216	166,927	295,119	22.4%	17.20	North center
Chiapas (CHIS)	26,975	71,196	440,371	383,555	531,294	7,985	33.4%	23.28	South
Chihuahua (CHIH)	26,475	77,906	204,892	216,375	198,724	296,480	8.8%	3.42	Northern
Mexico City (CDMX)	71,929	127,474	173,546	351,439	343,102	507,109	8.3%	0.64	Center
Durango (DUR)	29,512	95,167	130,185	235,277	201,719	319,913	8.5%	3.15	North center
Guanajuato (GTO)	41,411	141,232	254,257	286,871	298,956	523,713	13.8%	3.62	Center
Guerrero (GRO)	19,900	38,213	76,804	37,300	45,976	90,399	2.3%	1.75	South
Hidalgo (HGO)	49,829	134,844	331,746	346,600	321,841	452,017	12.8%	2.70	Center
Jalisco (JAL)	66,981	151,453	212,730	284,836	347,365	470,126	8.4%	0.71	North center

Sate of Mexico (EDOMEX)	73,605	204,564	295,232	392,836	393,922	637,944	14.2%	1.84	Center
Michoacan (MICH)	44,178	113,015	137,854	260,321	157,424	288,566	7.9%	2.19	North center
Morelos (MOR)	115,065	222,462	457,827	347,925	400,715	746,409	15.0%	1.29	Center
Nayarit (NAY)	34,755	119,004	129,185	143,868	212,781	151,601	7.9%	4.62	North center
Nuevo León (NL)	63,143	173,918	298,341	421,005	436,344	665,541	14.2%	1.67	Northern
Oaxaca (OAX)	103,030	105,783	447,361	115,440	279,981	253,878	21.2%	10.06	South
Puebla (PUE)	36,994	108,838	260,677	288,186	404,477	512,048	12.4%	2.58	Center
Queretaro (QRO)	63,853	225,747	265,220	416,282	323,419	613,439	19.6%	4.51	Center
Quintana Roo (Q.ROO)	36,834	69,450	104,553	228,585	108,455	228,043	6.0%	1.95	South
San Luís Potosi (SLP)	58,953	209,522	250,084	366,440	420,151	976,969	24.0%	4.17	North center
Sinaloa (SIN)	35,253	107,719	141,535	198,804	202,479	274,694	7.4%	2.63	North center
Sonora (SON)	48,943	142,094	188,986	340,815	513,194	592,064	13.0%	1.92	Northern
Tabasco (TAB)	75,364	307,304	808,351	900,217	1,512,283	2,573,236	61.5%	5.40	South
Tamaulipas (TAM)	42,986	97,587	181,647	254,487	302,727	365,893	7.0%	0.88	Northern
Tlaxcala (TLAX)	37,287	112,019	204,845	257,552	243,039	407,688	9.9%	2.48	Center
Veracruz (VER)	108,600	183,135	333,637	831,752	837,230	471,622	17.8%	2.24	South
Yucatan (YUC)	26,176	63,382	103,192	126,181	153,490	194,385	3.9%	1.06	South
Zacatecas (ZAC)	25,504	97,655	233,101	289,676	366,642	508,482	13.6%	4.98	North center

Source: Prepared by the author, based on Instituto Nacional de Estadística y Geografía (INEGI) (1994). Censos Económicos 1994 [online], Aguascalientes, México. Retrieved from: https://www.inegi.org.mx/programas/ce/1994/#Microdatos; INEGI (1999). Censos Económicos 1999 [online], Aguascalientes, México. Retrieved from: https://www.inegi.org.mx/programas/ce/1994/#Microdatos; INEGI (2009). Censos Económicos 2009 [online], Aguascalientes, México. Retrieved from: https://www.inegi.org.mx/programas/ce/2009/; INEGI (2014). Censos Económicos 2014 [online]. Aguascalientes, México. Retrieved from https://www.inegi.org.mx/programas/ce/2014/); and INEGI (2019). Censos Económicos 2019 [online], Aguascalientes, México. Retrieved from https://www.inegi.org.mx/programas/ce/2019/).
Note: a/ The 2018 Tabasco labor productivity is estimated by regression analysis.
b/ The weighted average growth rate.

3.5. Results from classical shift-share analysis

The census years introduced here are five snapshots of important events in Mexico and the world in the study period. 1998 is four years after the North American Free Trade Agreement (NAFTA) came into effect. Then, a second moment is the 2003, covering a period of global growth: oil prices rose, flow trade expanded, and the economy was relatively stable. A third picture is depicted in 2008: data collected in that year is at the initial stage of the worst moment of the global financial crisis (GFC). Then, 2013 is presented, when the economy was recovering from the GFC. Finally, 2018 is a year when the world recession drifted in the air. Throughout the 2010-decade, flow trade never recorded the pre-GFC levels, the economy's growth was insufficient, and global demand was still cautious.

Figure 3.1 presents results from the classical shift-share equation for the 32 Mexican states and the scale intensive sector. Appendix B shows Castaldi's (2009) innovation-based taxonomy, while appendix C displays results from the classical shift-share analysis for the science-based, specialized supplier and supplier-dominated sector. The scale intensive sector is composed of items classified as consumer durables and processed raw materials. In addition, this sector includes mostly large firms that acquire advanced capital goods from science-based and specialized supplier manufacturing firms.

Queretaro, Guanajuato, and Tabasco are the first three states to gain in the manufacturing labor productivity across the short period between 1994 and 1998. The regional share is becoming the greatest provider in this time. For the next period, 2003, Tabasco, Oaxaca, and Chiapas are the states with major gains. These outcomes possibly result not only from oil prices, but also from a deliberate public expenditure effort. After 1994, a revolt organized by the Zapatista army in Chiapas focused the national government's attention on these places. Chiapas also houses the most important electrical plants in Mexico. Furthermore, a development agenda was boosted by the Puebla-Panama Plan. Here, regional shares mark the difference between states, and sectoral shifts are negative, as in the previous period.

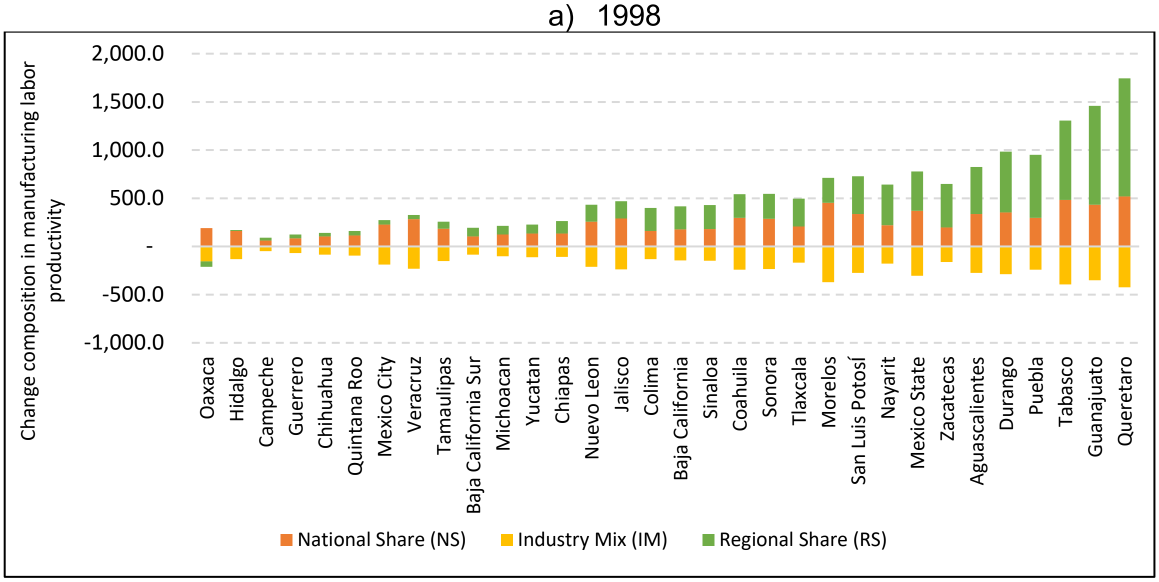
Veracruz, Quintana Roo, and Mexico City appear as the following gainers in the next snapshot, 2008. Also, throughout those years, Pemex followed an effort to implement a reconfiguration scheme for the refineries located in Veracruz and Oaxaca, and to reengineer its process in Tabasco. The regional share makes a difference here too. Sectoral shifts are negative but, in some cases, regional shifts are negative. After the GFC, data for 2013 show that Tabasco, Oaxaca, and Sonora perform better than others. But regional share becomes negative for the majority of the states, while sectoral decomposition is positive for all states. Finally, in the 2018 data, San Luis Potosi, Aguascalientes, and Morelos are the top three. Regional share becomes the greatest part of the composition change, and sectoral shows as negative for all states.

Figure 3.1

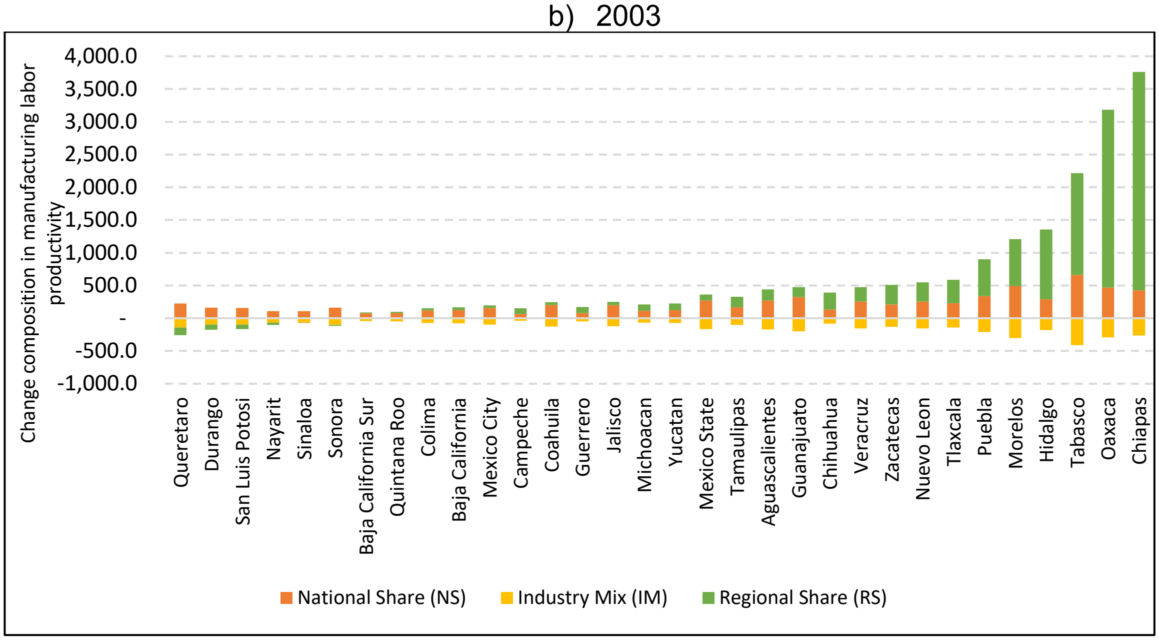
Mexico: manufacturing labor productivity performance across censuses, classical shift-share, scale intensive sector, 1998-2018

(in thousands of pesos of 2018)

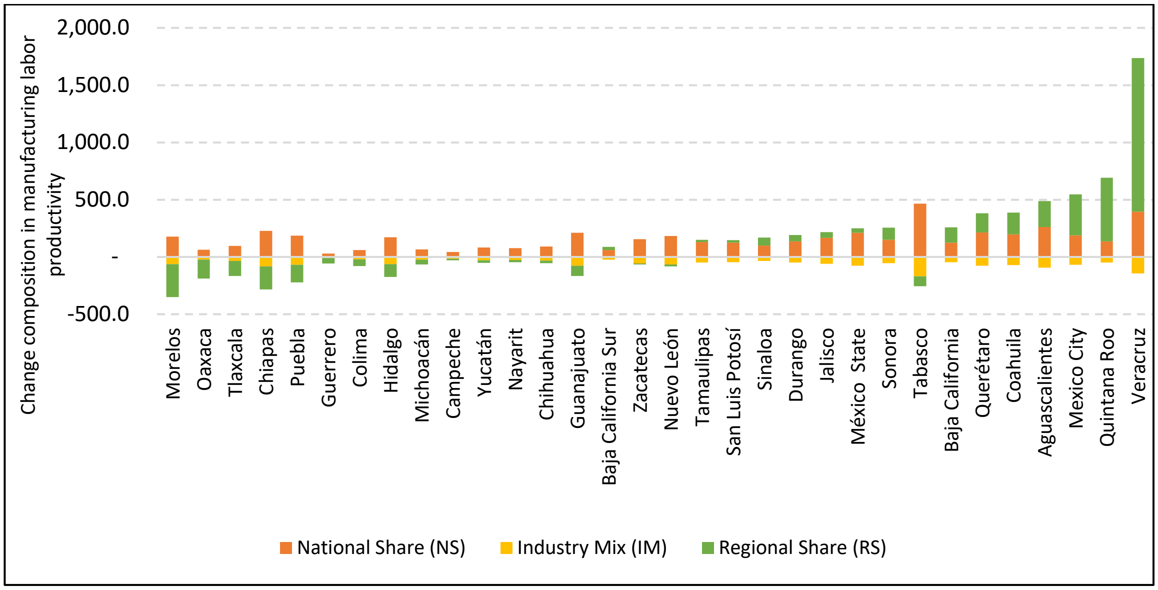
a) 1998



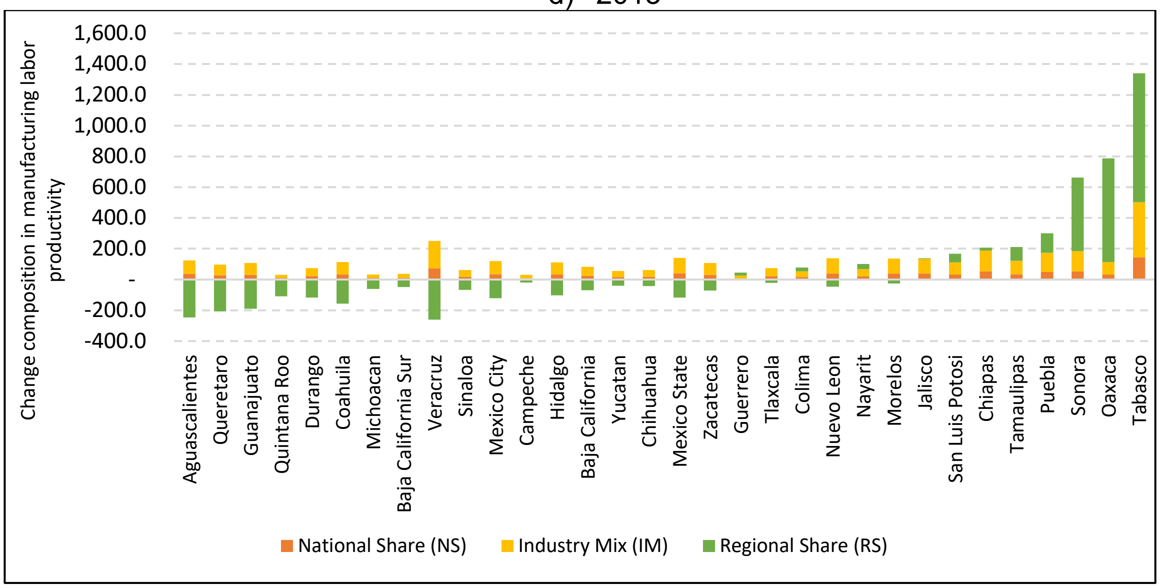
b) 2003



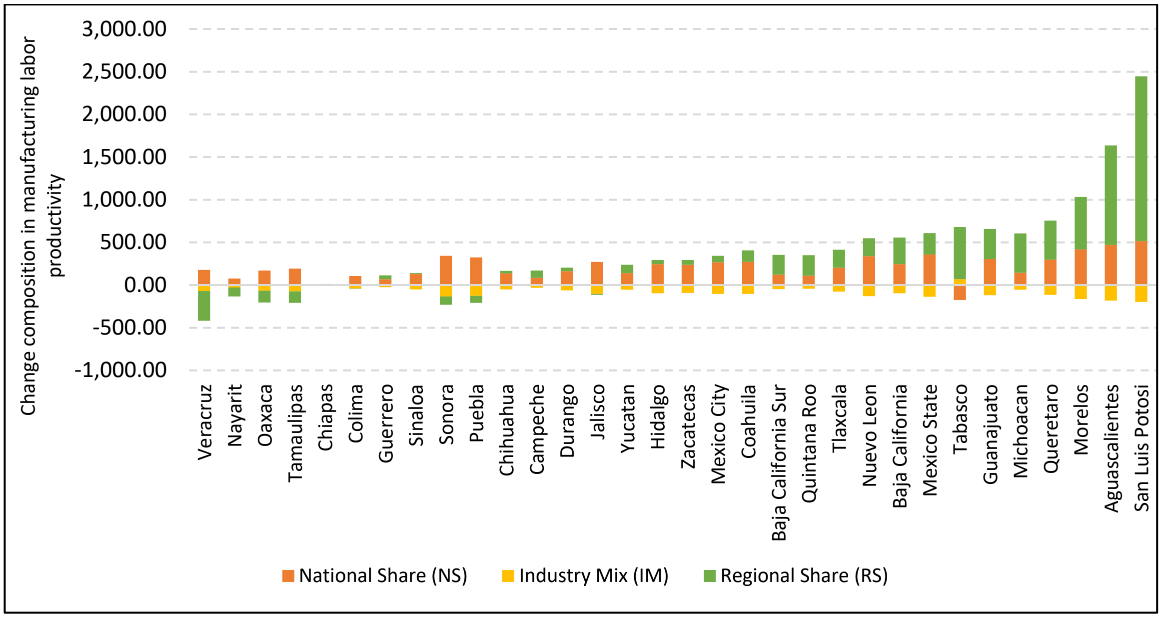
c) 2008


Change composition in manufacturing labor productivity
2,000.0
1,500.0
1,000.0
500.0
-
-500.0
Morelos
Oaxaca
Tlaxcala
Chiapas
Puebla
Guerrero
Colima
Hidalgo
Michoacán
Campeche
Yucatán
Nayarit
Chihuahua
Guanajuato
Baja California Sur
Zacatecas
Nuevo León
Tamaulipas
San Luis Potosí
Sinaloa
Durango
Jalisco
México State
Sonora
Tabasco
Baja California
Querétaro
Coahuila
Aguascalientes
Mexico City
Quintana Roo
Veracruz
National Share (NS)
Industry Mix (IM)
Regional Share (RS)

d) 2013


Change composition in manufacturing labor productivity
1,600.0
1,400.0
1,200.0
1,000.0
800.0
600.0
400.0
200.0
-
-200.0
-400.0
Aguascalientes
Queretaro
Guanajuato
Quintana Roo
Durango
Coahuila
Michoacan
Baja California Sur
Veracruz
Sinaloa
Mexico City
Campeche
Hidalgo
Baja California
Yucatan
Chihuahua
Mexico State
Zacatecas
Guerrero
Tlaxcala
Colima
Nuevo Leon
Nayarit
Morelos
Jalisco
San Luis Potosi
Chiapas
Tamaulipas
Puebla
Sonora
Oaxaca
Tabasco
National Share (NS)
Industry Mix (IM)
Regional Share (RS)

e) 2018



Source: Prepared by the author.

3.6 Results from multifactor partitioning shift-share analysis

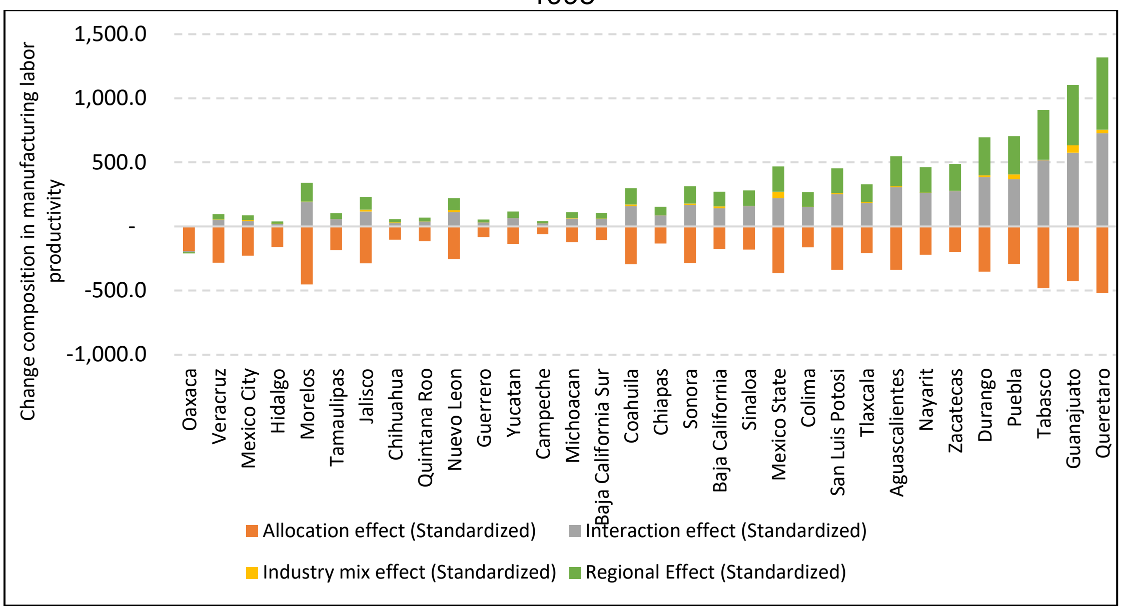
Figure 3.2 shows the multifactor partitioning of manufacturing labor productivity for the scale intensive sector. Appendix D displays the analysis for the rest of the sectors. As stated in the previous section, the growing rates are decomposed into four parts: regional share, industry mix, allocation effect, and an interaction effect. The rates are weighted by the employment structure of the current year.

The graphs for 1998 in figure 3.2 show that the states' order list remains the same as in the classical shift-share. But now, the decomposition accounts for two new elements: the allocation effect and the interaction effect. We can see that the regional share plays an important and positive role across all states, except for Oaxaca. The allocation effect becomes negative in the change, but this is because of the way it is computed. Nevertheless, the allocation effect appears to be greater in magnitude than in the regional share. This means that firms in the sector are located in these states because of their competitive characteristics.

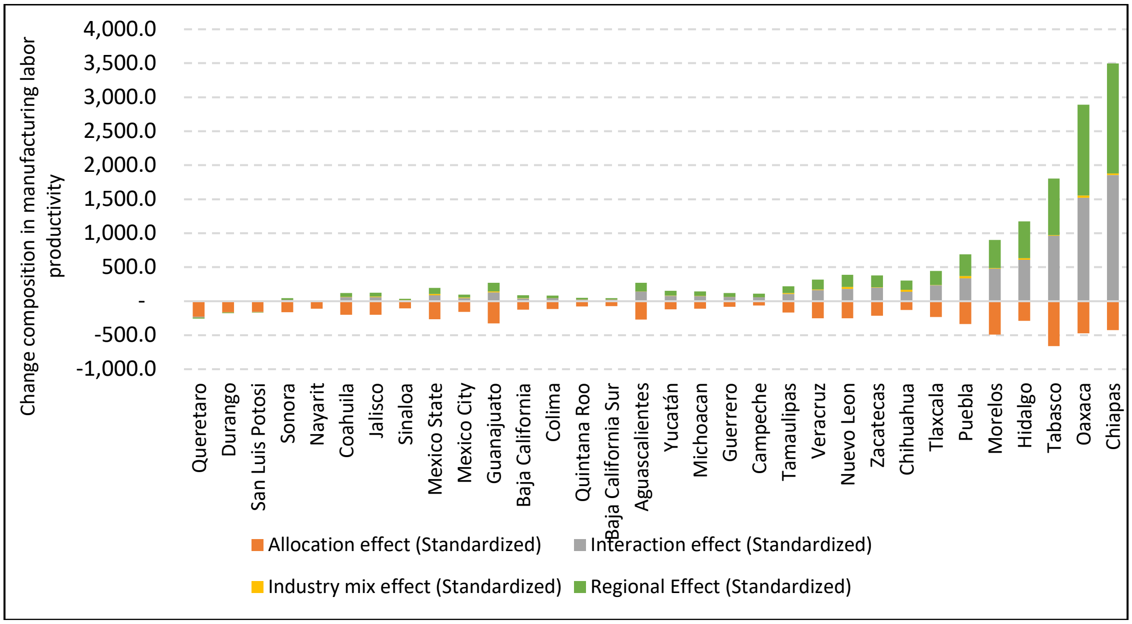
For 2003, allocation goes down but regional goes up. The industry mix is a tiny portion of the change. Compared with the classical analysis, the regional share is less here because of the industry mix and interaction effect. In the 2003-2008 change period, the regional share goes down and the competitive effect remains the same.

For the 2013 graph, the allocation effect is less than the regional in all states. This sector looks appears to be losing its competitive factor. The regional share is a lesser portion than in the classical analysis because the interaction and industry mix effect are occupying its space. The picture for 2018 illustrates a regional share growing more than the allocation effect.

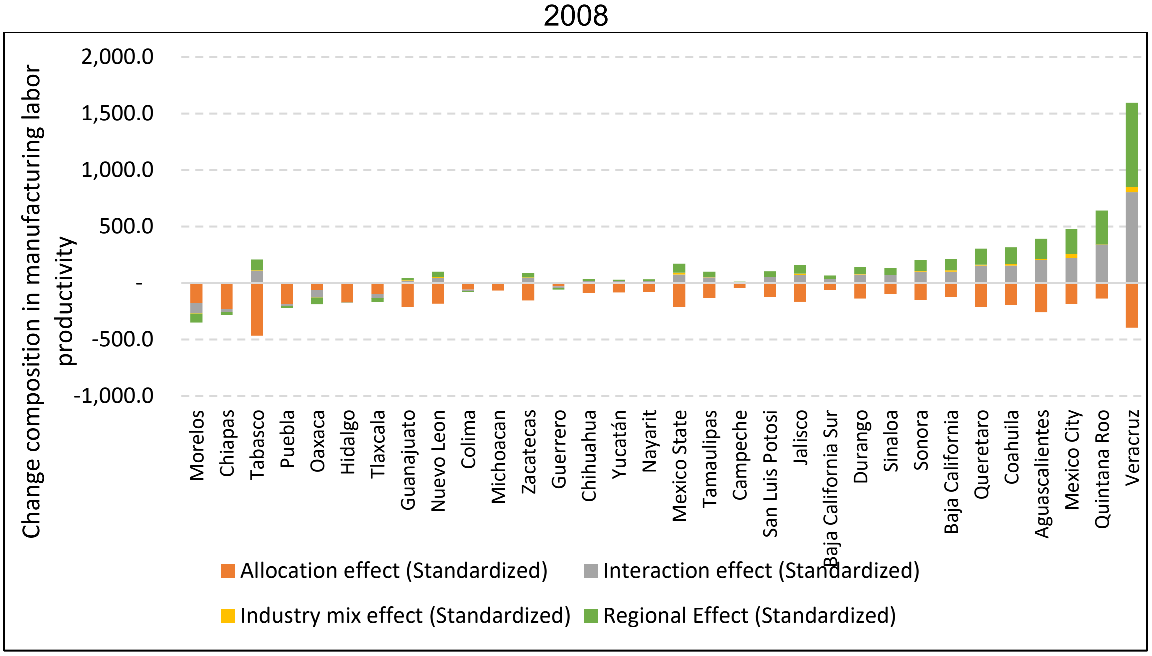
Figure 3.2
Mexico: manufacturing labor productivity performance across censuses, multifactor partitioning, scale intensive sector, 1998-2018
(in thousands of pesos of 2018)
1998



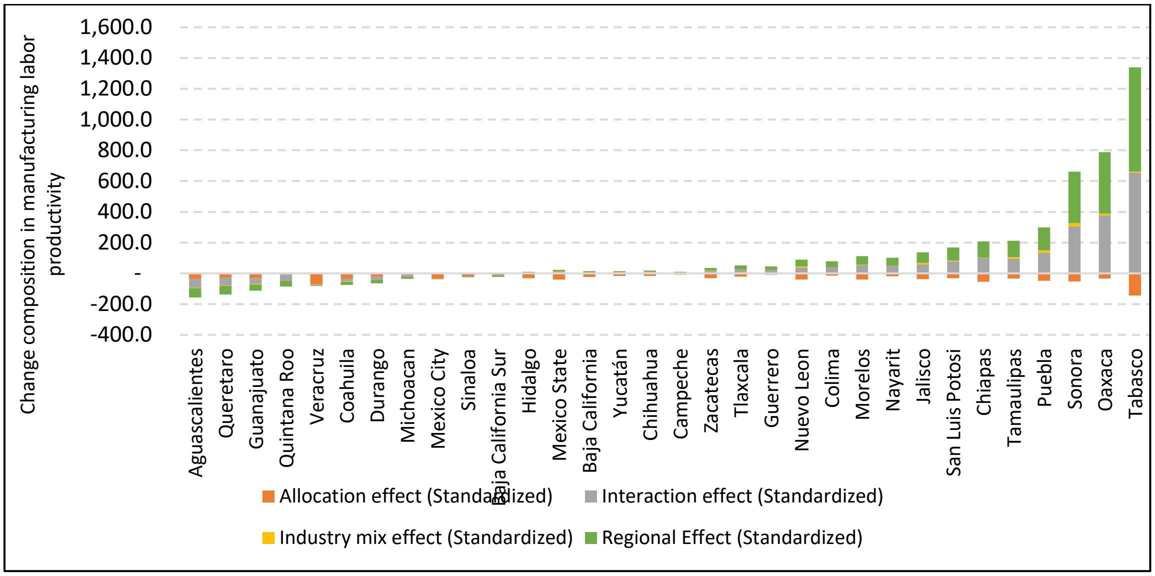
2003


Change composition in manufacturing labor productivity
4,000.0
3,500.0
3,000.0
2,500.0
2,000.0
1,500.0
1,000.0
500.0
-
-500.0
-1,000.0
Queretaro
Durango
San Luis Potosi
Sonora
Nayarit
Coahuila
Jalisco
Sinaloa
Mexico State
Mexico City
Guanajuato
Baja California
Colima
Quintana Roo
Baja California Sur
Aguascalientes
Yucatán
Michoacan
Guerrero
Campeche
Tamaulipas
Veracruz
Nuevo Leon
Zacatecas
Chihuahua
Tlaxcala
Puebla
Morelos
Hidalgo
Tabasco
Oaxaca
Chiapas
Allocation effect (Standardized)
Interaction effect (Standardized)
Industry mix effect (Standardized)
Regional Effect (Standardized)

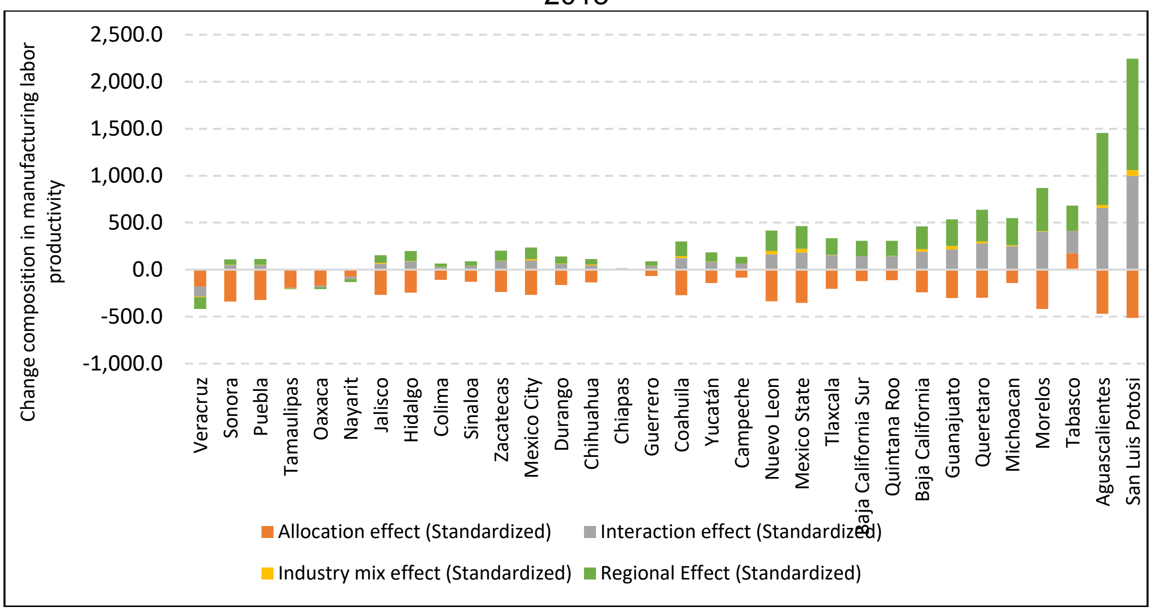
2008


Change composition in manufacturing labor productivity
2,000.0
1,500.0
1,000.0
500.0
-
-500.0
-1,000.0
Morelos
Chiapas
Tabasco
Puebla
Oaxaca
Hidalgo
Tlaxcala
Guanajuato
Nuevo Leon
Colima
Michoacan
Zacatecas
Guerrero
Chihuahua
Yucatán
Nayarit
Mexico State
Tamaulipas
Campeche
San Luis Potosi
Jalisco
Baja California Sur
Durango
Sinaloa
Sonora
Baja California
Queretaro
Coahuila
Aguascalientes
Mexico City
Quintana Roo
Veracruz
Allocation effect (Standardized)
Interaction effect (Standardized)
Industry mix effect (Standardized)
Regional Effect (Standardized)

2013



2018



Source: Prepared by the author.

3.7 Spatial data testing

Before running the regressions, several tests for spatial global correlations were applied. Results are those described in Section 2.5. Here, few remarks are presented. First, manufacturing labor productivity shows spatial correlation for most of the years, but not for 1999. Second, spatial diagnostics test applied to residuals from regressions show global spatial correlation. Third, results showed in Table 2.3 suggest an error model. Thus, the panel spatial error model by sector proposed in equation 3.9 was run.

3.8 Results from spatial econometrics

Results from equation (3.9) are displayed in the table 3.2. Equations are run by sector, as in 3.9, resulting in several matters to discuss. First, the scale-intensive sector does not have an error spatial correlation, such as the gamma coefficient (γ) and Wald test displayed in the last row shows. The other equations have error spatial correlations at a 95% confidence level. Second, the regional share and the industry mix coefficients are not statistically significant in the last specifications. The allocation effects are significant in all specifications. Third, the magnitude of regional share is the greatest in all specifications, except in number four. This confirms deductions from the shift-share analysis: the regional share impacts more than the sectoral and allocations effects, generally speaking. Finally, marginal effects are not displayed because there are no indirect effects.

Table 3.2

Mexico: estimates of the shift-share components, at the state level, 1993-2013

Parameters	Scale-intensive sector coefficients (std errors) (1)	Supplier dominated sector coefficients (std errors) (2)	Science-based sector coefficients (std errors) (3)	Specialized supplier sector coefficients (std errors) (4)
$\widetilde{\boldsymbol{IM}}_{ij,t+1}$	1.27*	-0.17	-0.46	0.11
	0.06	1.35	0.98	0.18
$\widetilde{\boldsymbol{RS}}_{ij,t+1}$	-2.86*	-2.39	-1.60	0.06
	1.13	7.08	5.85	2.18
$\boldsymbol{ALL}_{ij,t+1}$	0.42*	-1.23**	-0.96**	-0.32
	0.08	0.70	0.53	0.24
$\boldsymbol{\gamma}$	0.07	-0.35*	-0.39*	-0.32*
	0.21	0.16	0.16	0.16
∑ error	88.35	253.55	253.03	252.58
	5.52	15.88	15.85	15.81

Wald test of spatial terms:	chi2(1) = 0.11 Prob > chi2 = 0.7356	chi2(1) = 5.08 Prob > chi2 = 0.0243	chi2(1) = 5.97 Prob >chi2 = 0.0146	chi2(1) = 4.30 Prob > chi2 = 0.0382

Source: Prepared by the author.

Note: * Statistically significant at a 95% confident interval

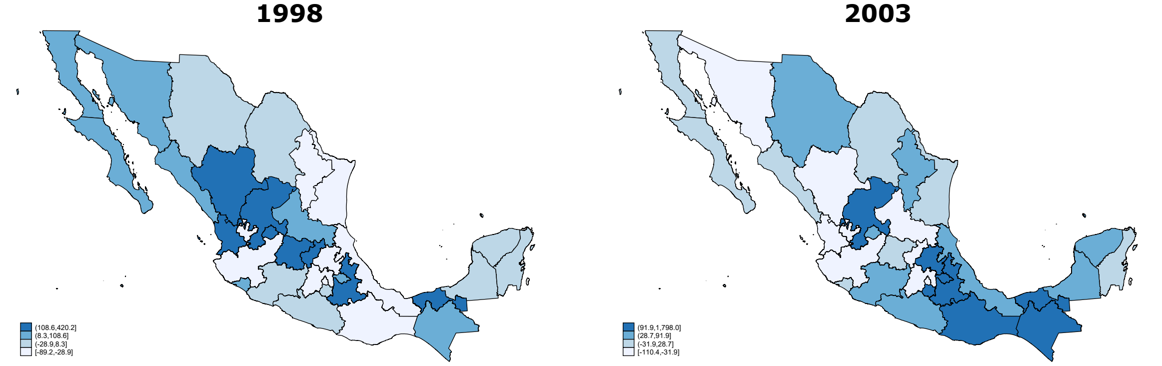
** Statistically significant at a 90% confident interval

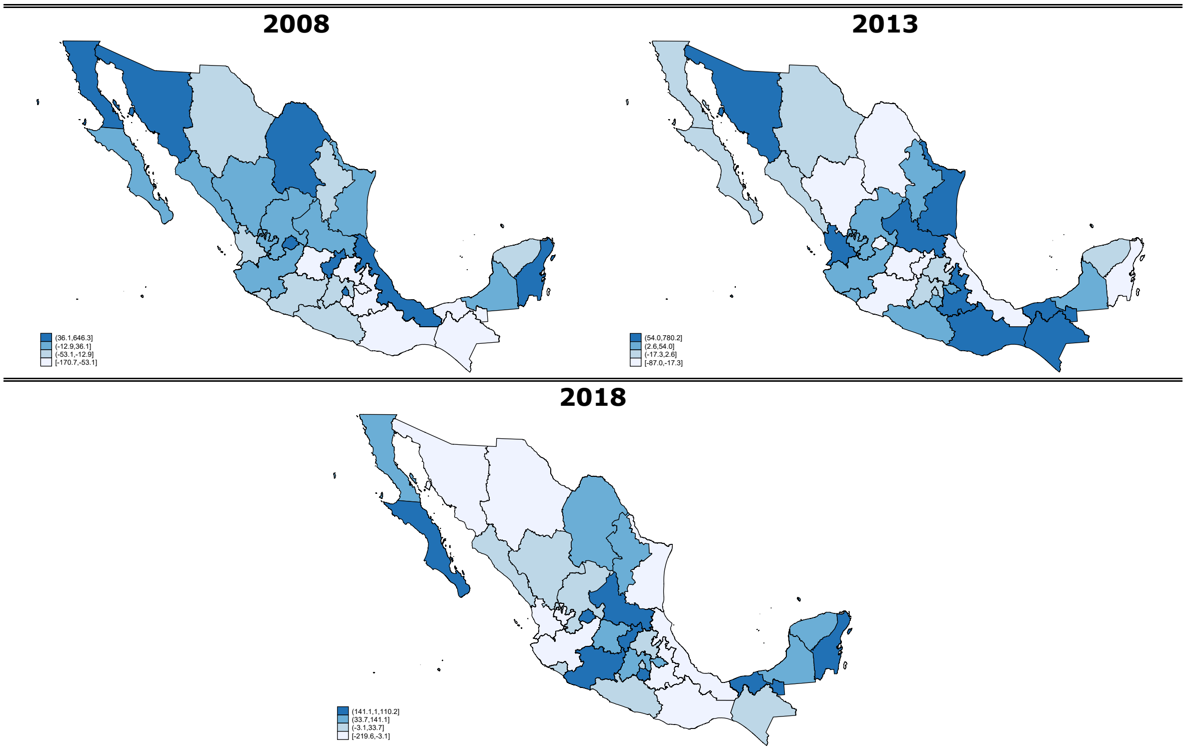
To delve into more spatial patrons and in order to validate our results from spatial regressions, maps for the sectoral fitted values are displayed in the following set of maps. The maps in 3.1 display the fitted values for the difference between the total growth of the regional and national manufacturing labor productivity from the scale-intensive sector since 1998 to 2018, running every five years. For the supplier dominated sector, the science-based sector, and the specialized supplier sector, maps are shown in Appendix E. Maps are in blue and divided into quartiles. The highest differentials, in dark blue, are at the top of the quartiles. There seems to be a grouping pattern in central and south states for 1998 and 2003, because they share the same shade of blue. But as times goes on, the pattern fades across Mexico.

Remember that the scale-intensive sector includes large firms related to the chemical, automotive, cement and oil sectors (see Appendix B). In Mexico these results are distorted by Pemex and CFE. Pemex's principal plants from the initial phase of the value chain are located in the gulf states. Guanajuato and Tamaulipas have oil refineries as well. Otherwise, CFE has hydroelectric plants accounting for around 30% of the total national production in Chiapas (SEMARNAT, 2018).

Maps 3.1

Mexico: Fitted values for the differential total growth of the manufacturing labor productivity in the scale-intensive sector, 1998-2018





Source: Prepared by the author.

3.6 Conclusions

The goal of this chapter is to disentangle manufacturing labor productivity into sectoral and regional effects. The previous chapter shows that there is convergence, but the question still remains regarding the different levels of manufacturing labor productivity. Two circumstances could be possible. One is that aggregate productivity differs because there are differences among output per worker across sectors that comprise the whole economy, and the other is because of its own characteristics. Results from the shift-share analysis show us that the regional component impacts the heterogeneity that we see, even when sectoral and allocation effects play a role.

Moreover, the results of the spatial econometrics equations shed light on spatial correlation between sectors and states. The magnitude of regional effects outweigh other components in all sectors. The aforementioned confirms that regional effects play a major role in manufacturing labor productivity growth differences. The scale-intensive sector does not show spatial effects, but supplier dominated, science-based, and specialized supplier do. Maps depicting the fitted values for the differential total growth of the manufacturing labor productivity confirms the spatial econometrics results.

In terms of public policy, there is a need for regional strategies that boost productivity in less-favored territories. It is concerning that the main gains in the science-based sector remain in the same regions and states. Regional strategies should go beyond administrative boundaries, given the importance of productivity externalities between neighboring territories. A combination of quality of schooling, public expenditure, and FDI would have a positive impact to reduce regional differences, boost manufacturing labor productivity, and reinforce convergence. Regional analyses show that the states located in the south need active public policies to reduce their poor performance. But even in other regions, state differences play an important role in manufacturing labor productivity.

In this context, some key policy areas could be: providing government incentives to increase the population's schooling years; improving public infrastructure to facilitate linkages and connection across territories; fostering links between high-and low-productivity economic sectors or activities, for instance manufacturing and agriculture; promoting firm innovation and technological capabilities, with emphasis on technological issues; and encouraging integration processes at the regional level to attract FDI, which leads to intensifying convergence between the Mexican and U.S. economies. It is also necessary to reinforce the quality of education through good education evaluation systems—which the 2013 law intended to do. Only this will ensure the quality of the Mexican education system, increasing the country's productivity and making it more competitive to attract investment returning from Asia.

Moreover, the manufacturing sector has the highest levels of integration in value chains and backward linkages between Mexico and the U.S. For that reason, proposing regional strategies to boost manufacturing labor productivity will allow reshoring or nearshoring processes. The formulation of strategies will make it possible to allocate production in Mexico closer to the U.S. markets. In this sense, technological and geopolitical trends affecting the U.S. economy require a good diagnosis and an active regional public policy to positively impact manufacturing labor productivity growth in Mexico.

Recently, large businesses have been relocating parts of the global value chains from faraway to nearby the principal markets they are supplying. Supply chain interruptions are one of the principal arguments in favor of this relocation. The growing cost of doing business overseas, building supply chain resiliency, and the arrival of tax benefit programs are additional arguments explaining why businesses favor reshoring and nearshoring their activities. For this reason, and at this particular moment, any policy boosting productivity is highly recommended, especially in local border economies, which are seeking to recover from the COVID19 pandemic period by adding new business opportunities in manufacturing, reflecting their proximity to the Mexican-U.S. border. Lines of future research could improve the spatial decomposition of the shift-share components.

Chapter 4. Spatial relationship between labor productivity and wages

4.1 Introduction

The relationship between wages and productivity is a key determinant of the quality of life of the employed population, and of the distribution of income between work and capital, also known as the remuneration of factors of production. If wages grow at the same rate as productivity, the share of wages in national income remains essentially unchanged (Feldstein, 2008). In this sense, it is essential to consider what the Economic Commission for Latin America and the Caribbean and the International Labor Organization (CEPAL & OIT, 2012) say about labor productivity: it is an important measurement of development conditions, by relating production elements with socio-labor aspects.

To move towards a more inclusive development, the benefits of the increases in productivity must be distributed in a more equitable way between workers and employers, through increases in remuneration that correspond in a greater proportion to that currently observed with workers' productivity gains. However, this transmission does not occur automatically and there are often various mechanisms that limit it.

Among the most significant factors associated with a lower share of wages in national income, we can mention aspects linked to financial and economic globalization, as well as institutional factors, such as the weakening of the power of workers in collective bargaining (CEPAL & OIT, 2012). It is possible to design and apply measures to improve wages, without affecting the competitiveness of a country in the international environment, by means of improvements in labor productivity, which translate into higher wages in companies, while allowing them to maintain their profit margins and achieve better levels of competitiveness (Guerrero de Lizardi, 2009).

Productivity growth in an economy should provide the potential to increase living conditions over time (Bivens & Mishel, 2015), although this assumption is not always fulfilled. The divergence between compensation and productivity means that most workers do not benefit from productivity growth. Understanding the link between the two variables, as well as their mechanisms, makes it possible to develop more appropriate policies towards a sustained increase in productivity, but at the same time, this growth will produce better living conditions for workers and their families.

The analytical perspective of some economic theories establishes that the compensation received by the workers of a country varies according to the changes experienced by productivity measured in labor terms (the production achieved per worker or per hour worked). For example, the marginal productivity theory postulates that a wage must be equal to its marginal productivity (Clark, 1899), while the efficiency wage theory argues that there is a relationship between the income of the worker and his productivity (Leibenstein, 1958). Considering that labor income is the main way by which the living conditions of workers' families are maintained or modified, it is highly relevant to review whether this postulate is empirically manifested in Mexico with the most recent information available. This work seeks to contribute to a better understanding of the link between the dynamics of productivity in Mexico and changes in compensation paid to workers.

There are different situations that prevent an adequate estimation of the relationship between wages and productivity in developing countries, such as: a) the scarcity of reliable, uniform, and periodic data to measure the relationship; b) the volatility and distortions in the economic and employment environment; and c) high inflation, which can cause difficulties in correctly equating wage increases with productivity growth (Van Biesebroeck, 2015). In this sense, the different price indices to deflate the nominal levels of the variables would cause distortions (Bosworth, Perry & Shapiro, 1994). In the same way, there are structural conditions that affect the relationship between the two variables: market concentration, macroeconomic policies applied to contain wages, and as an anchor so that agents' expectations do not affect the price level, and the decrease in public net investment, among others (Peñaloza & Peñaloza, 2020).

This chapter explores the relationship between productivity and wages, with a particular focus on the impact that the productivity of one state has on the productivity and wages of its neighboring states. In other words, it explores whether there are productivity spillover effects at the state aggregate level which are transmitted through various mechanisms and sectoral linkages that impact own wages, as well as the productivity and wages of neighboring states.

This chapter seeks to answer the following two questions:

i) At the state level, and within the manufacturing sector, to what extent does the evolution of labor productivity impact the dynamics of remuneration in Mexico?

ii) How does labor productivity in one state influence wages in neighboring states?

Additionally, according to Sherk (2016), the remuneration of workers and productivity, however, move in a one-to-one relationship so that there is a link between them. This author observes that some of the barriers that restrict the diffusion of the benefits generated by the increase in productivity in some sectors on wage improvements for workers, both in the most productive and least productive sectors, lose strength when performing the analysis at the subnational level, especially with reference to geographic scope barriers. Thus, the impact of the increase in productivity in one or more sectors of an entity can exert an influence on salary remunerations, not only of the workers from those sectors and of that entity, but also of the workers from the adjoining entities.

Through the answer to the research questions posed above, the aim is to assess, on the one hand, if the strength of the link between productivity and remuneration is significant, considering the substantial variations from one entity to another and, on the other, whether or not the divisions' state policies prevent the transfer of the benefits of increased productivity in one entity to the remuneration of another with which it shares territorial limits.

This essay includes a second section discussing the relationship between productivity and remuneration, according to various economic theories, in which the influence of the spatial proximity variable at the state level is also added, seeking to provide the reader with greater clarity regarding the analytical context in which this work is inserted. Subsequently, a literature review is presented to identify the contributions, the results of each of them, the data, and the methodology used. The fourth section of this work, which is the central part, involves the details of the methodology and the data used. The sixth section shows spatial data tests as well as seventh and eighth sections present and analyze both the results obtained and the main contributions and limitations.

4.2 Productivity, wages, and spatial proximity

4.2.1. Productivity and wages

Labor productivity is defined as the relationship between the product generated and the amount of work necessary to obtain it in each period. Thus, the labor factor is commonly measured by hours worked or the number of employed workers, and production by its gross value or value added (CEPAL, 2016). The measurement of productivity through these variables normally makes it possible to have available and up-to-date data on production, employment and hours worked at the sector level.

Regarding remuneration, several authors agree that it is not enough to include only raw wages in the analysis, but rather total compensation must be measured, including additional income to wages and which may even be in kind or non-monetary (Feldstein, 2008; Bivens & Mishel, 2015), arguing that considering only wages instead of total compensation underestimates the true payment that is transferred to workers. According to Feldstein (2008) due to the increase in the benefits derived from non-monetary payments, wages have not grown at the same rate as total labor compensation, which is why using the latter in the analysis instead of wages is suggested.

Neoclassical economics postulates that, in the long term, the increase in productivity in the workplace has a positive effect on the growth of real wages, in such a way that the rate of growth of productivity determines the rate of increase in average income (Mankiw, 2015). Thus, under this theoretical perspective, the rates of variation of productivity should be the same as the rates of real remuneration of workers.

For the neo-Keynesian economic theorist, although the approaches of its exponents are not homogeneous, there are imperfections or rigidities in the markets that prevent or distort the way in which companies adjust workers' wages based on prices, production, and distribution. These imperfections partially block the transmission of movements in labor productivity towards workers' remunerations. On the other hand, an interesting element in the analysis of the relationship between wages and productivity (especially due to the variation in the approach in which this relationship is addressed), within the neo-Keynesian thinkers, is given by efficiency wages, which imply remunerations higher than the equilibrium salary of labor supply and demand. Companies are willing to pay these higher wages by virtue of the increased effort of workers to perform their tasks better, thus increasing their productivity (Vadillo, 2013; Mankiw, 2015; Sherk, 2016).

Structuralists emphasize the existence of power relations that permeate the functioning of markets. The political power of the State and other political, social, and cultural institutions exerts a decisive influence on the labor market and, with it, on the distribution of the benefits generated by the production of goods and services in a country. Thus, the relationship between wage movements and productivity variations is unequivocally affected by power structures. As Polanyi (1944) pointed out, in a market economy, public policies and the political conditions of a country affect the costs and the product of labor (considered as a fictitious commodity), and with this they would affect the link between productivity with workers' compensation. In this relationship, the concept of transaction, conceived by the structuralist thinking of Latin America, is especially useful, among other things, because it allows the capacity or bargaining power of workers to be incorporated into the analysis (Di Filippo, 2018).

Understanding the link between productivity and remuneration, as well as its mechanisms, will allow the development of the most appropriate policies, as well as a deeper understanding of the extent to which variations in productivity trigger the growth of workers' real wages. For the International Labor Organization, "in the long term, the increase in labor productivity (the average value of goods and services produced by workers) is what allows wages to be increased sustainably" (OIT, 2017).

ECLAC has promoted the debate about the link between productivity and wages, as well as the dissociation between these variables in recent years, which has led to a decreasing relative weight of wages within national income. For several years, ECLAC has also promoted an agenda to encourage advances in productivity, but also with a view to reducing inequality and overcoming structural gaps in the region. One of the necessary mechanisms to reduce inequality in countries is to increase the weight of wages in national income, reducing the gap between increases in productivity and wage increases.

ECLAC and the ILO found that, between 2002 and 2008, for 13 of 21 countries in Latin America and the Caribbean the share of wages in GDP decreased, which indicates an unfavorable redistribution of income for workers. In this context, two concerns stand out: the first is of a moral nature in the face of a trend of inequitable redistribution of wealth, and the second is related to the risk that this situation generates on the sustainability of economic growth and social stability, and with-it democratic governance (CEPAL & OIT, 2012).

In summary, following the approach of Van Biesebroeck (2015), there are three means to analyze the strength of the relationship between wages and productivity: a) employers generally have monopsony power that allows them to manage the hiring conditions of the workers, with salaries lower than those that marginal productivity would demand of them; b) the productivity-wage relationship becomes more fragile or more robust according to certain characteristics of the workers, for example, young workers are usually paid a wage below their marginal productivity; and c) it registers a gradual decline in the labor share of national income.

It is important to make progress in the implementation of public policies aimed at avoiding the continuity of the lag between wage increments related to the increases achieved in productivity in Latin America and the Caribbean. These can be considered for economies as a whole or for specific sectors. For example, one of the measures that has been debated in various countries of the region and has been implemented in some of them, is that the fixing and updating of minimum wages should consider not only inflationary aspects, but also elements of improvements in productivity (CEPAL & OIT, 2012).

4.2.2. Spatial proximity and its relationship with productivity and remuneration

The competitive advantages and, with-it, the level of productivity of a region or of the states or provinces of a country, are created and maintained in a localized process of spatial proximity. There are important differences in the industrialization and development of local economies, at different geographical levels, because of the dominance of a certain number of activities and sectors specific to each locality and each entity. Thus, the level of productivity and remuneration of each entity or locality is linked to the maturity and modernization of the dominant activities (Unger, Flores & Ibarra, 2014).

According to the perspective of the competitive advantages of a territory, the productivity level of a region is essentially determined by a set of capacities, infrastructure, knowledge, institutions, and public policies, among other factors. The productivity level of a region significantly influences remuneration, as well as the level of prosperity and development of each region (Unger, Flores & Ibarra, 2014).

There are various economic geography models that allow a better understanding of the role of the spatial proximity variable considered in this research, the most representative being the center and periphery model and the mobile capital model. Essentially, economic geography provides a reference framework that makes it possible to understand how spatial proximity, concentration, and the variety of industries present in a region have a determining influence on the levels and dynamics of productivity, of the accumulation of capital, both physical and human, and of the scale of production (Baldwin, R. et al. 2003; Mayer, 2006). The underlying idea is that capital gains and better remuneration are strengthened and transmitted in modern and homogeneous environments, which consolidates the most favorable scenarios for the competitiveness of the regions and states, over the scenarios of other regions and states. The competitiveness of a region or a state reflects the conditions of productivity and remuneration within it (Unger, Flores & Ibarra, 2014).

In recent decades, various studies have focused on the spillover effects of productivity on geographic space. Coe and Helpman (1995), in their seminal article, investigate the spillover effects that the productivity of one country has on another. They do this by checking the relationship between each country's research and development (R&D) capital stock and the total factor productivity (TFP) of its main trading partners. The results suggest that there is a relationship between productivity and R&D capital stock, not only of national capital, but also of foreign capital. In a subsequent review, Coe, Helpman & Hoffmaister (2009) confirm their findings, even after controlling for variables by levels of human capital (schooling) and institutional differences between nations (such as patents, legal system, etc.).

Other authors have investigated the sectoral productivity spillovers that exist between countries. Badinger and Egger (2008) carried out a spatial econometric estimation in which they distinguish between and estimate the intra- and inter-sectoral spillover effects of two TFP transmission channels: domestic and imported. One of the most outstanding results is that the data analyzed (from thirteen OECD countries and fifteen manufacturing industries) show a significant effect of knowledge spillovers, referring to research and development, on productivity, both horizontally (intra-sectoral) and vertically (inter-sectoral). Similarly, Tsai and Lin (2005) explore spatial, temporal, and sectoral productivity spillovers, with one of the main objectives being to assess the contribution of these different types of spillover mechanisms, and their interdependence, on productivity growth.

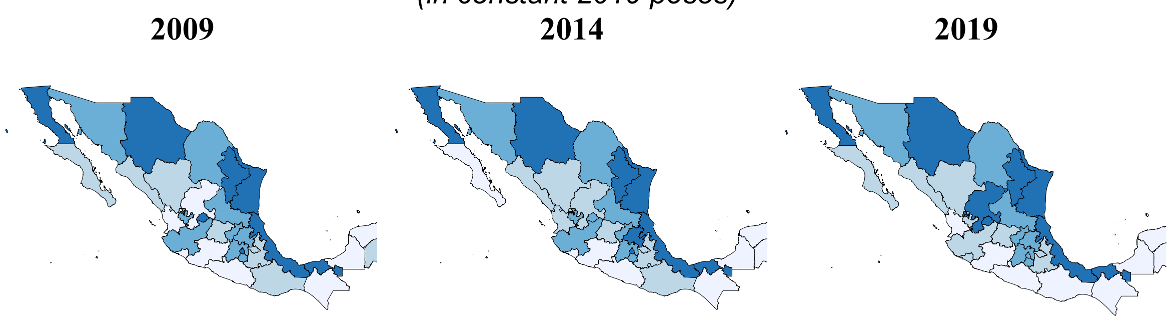
An additional strand that explores the spillover effects of productivity in space is constituted by the works that investigate the effects of productivity decomposition. Haini (2020) disaggregates the direct and indirect effects of the TFP increase across Chinese provinces, while Glass and Kenjegalieva (2019) analyze the banking sector, breaking down TFP at the firm level. Escobar and Mühlen (2019) work in the same direction, in a sectoral manner and exploiting the internal differences of Mexico.

The work by Cabral and Varella Molick (2017) examines the impact that the performance of the United States economy has on the labor market in Mexico. Relevant to the purpose of this paper, these authors confirm the influence of the cycles of the US economy on wages in Mexico, especially in neighboring states. In Mexico, as in other countries, the states have reached different levels of development and there are in turn diverse conditions for the development and performance of the manufacturing industry. The differences between the states in Mexico in terms of their competitiveness and productivity are very clear.

The most competitive states have structures that generate improvements in productivity; these improvements are transferred to the population, to a greater or lesser extent, through higher wages and are transmitted between activities in geographically close environments (Unger, Flores and Ibarra, 2014). According to the approach of the present work, these improvements in a state's productivity have the capacity to permeate beyond its political-administrative limits, towards the neighboring states.

By computing for Mexico, at the state level, variation rates for both wages and labor productivity (in the manufacturing sector) and evaluating the relationship between these rates, a deeper analysis of this relationship at the state level is possible. The inclusion in the analysis of the variable of spatial proximity between the states is the most relevant innovation of this document, since, through this variable, the influence that the productivity of a state exerts on the remunerations of neighboring states is evaluated. Studies such as Coe and Helpman (1995), Badinger and Egger (2008), Tsai and Lin (2005) and Coe, Helpman, and Hoffmaister (2009) have found spillover effects between productivity levels across space and sectors. This document considers that this relationship also exists between productivity and wages. Map 4.1 shows the average annual wages of the employed population by federal entity. In the first instance, important regional differences are observed within the country.

Map 4.1
Mexico: average annual wages per employed population, at the state level, 2009, 2014 and 2019
(in constant 2019 pesos)



Source: Prepared by the author, based on Instituto Nacional de Estadísticas y Geografía (INEGI) (2009). Censos Económicos 2009 [online], Aguascalientes, México. Retrieved from: https://www.inegi.org.mx/programas/ce/2009/; INEGI (2014). Censos Económicos 2014 [online]. Retrieved from https://www.inegi.org.mx/programas/ce/2014/). Aguascalientes, México; and INEGI (2019). Censos Económicos 2019 [online]. Retrieved from https://www.inegi.org.mx/programas/ce/2019/), Aguascalientes, México.
Note: Values are deflated by the Manufacturing Producer Price Index (2019=100).

4.3. Literature review

This section presents a review of various works focused on studying the relationship between productivity and remuneration, from various approaches and objectives, with the purpose of finding elements of analysis that facilitate understanding of the relationship between variables, as well as the various factors that intervene in that relationship. In the first instance, international documents are reviewed and later studies referring specifically to the country under study in this document, Mexico, are listed and analyzed.

4.3.1. International literature

Table 4.1 lists some of the international works that address the relationship between productivity and workers' wages, while the following paragraphs show a brief analysis of the main results and contributions of each of them.

Table 4.1

Productivity and salaries: most relevant international bibliography

Authors	Year	Title	Period covered
Hellerstein, J. Neumark, D. & K. Troske	1999	Wages, productivity, and worker characteristics: evidence from plant-level production. Functions and wage equations	1989-1990
Crepon, B., Deniau, N. & Pérez-Duarte, S.	2002	Wages, productivity, and worker characteristics: a French perspective	1994-1997
Bojnec, S.	2004	Labor Market Flows, Labor Productivity, and Wages in Slovenia	1987-2001
Long, M., Dziczek, K., Luria, D. & Wiarda, E.	2008	Wage and productivity stability in U.S. manufacturing plants	1987-1997
Feldstein, M.	2008	Did wages reflect growth in productivity?	1970-2006
Broadberry, S. & Burhop, C.	2010	Real Wages and Labor Productivity in Britain and Germany, 1871-1938: A Unified Approach to the International Comparison of Living Standards	1871-1938
Jacobson, M. & Occhino, F.	2012	Labor´s Declining Share of Income and Rising Inequality	1947-2010
CEPAL & OIT	2012	Coyuntura Laboral en América Latina y el Caribe: productividad laboral y distribución	2002-2012
Bivens, J. & Mishel, L.	2015	Understanding the historic divergence between productivity and a typical worker´s pay	1973-2014
Van Biesebroeck, J.	2015	How Tight Is the Link between Wages and Productivity?	N.A.
Lawrence, R.	2016	Does Productivity Still Determine Worker Compensation? Domestic and International Evidence”	1970-2013

Sharpe, A. & Uguccioni, J.	2017	Decomposing the productivity wage nexus in selected OECD countries, 1986-2013	1986-2013
Schwellnus, C., Kappeler, A. & Pionnier, P.	2017	Decoupling of wages from productivity: Macro-level facts	N.A.
Stansbury, A. & Summers, L.	2017	Productivity and pay: is the link broken?	1948-2016
OIT	2017	Informe mundial sobre salarios, 2016/2017: la desigualdad salarial en el lugar de trabajo	1999-2001

Source: Prepared by the author.

In summary, several of the studies reviewed report, with data from different countries, a widening of the gap between the evolution of productivity and increases in wages in real terms. In some of them, the probable underlying causes for this greater decoupling between the variables are exposed. Other documents point out the heterogeneity that exists within the countries in the analysis of the variables in question, in such a way that the strength of their relationship is greater or lesser depending on certain groups, sectors, or conditions. Some of these studies focus on the exogenous factors that affect the relationship between productivity and wages. Another group of studies agrees that there is or may be a positive correlation between productivity and wages depending on the fulfillment of certain conditions. In a couple of studies, the reliability of the database and the way of measuring the variables and their deflators are emphasized as necessary elements to verify the positive correlation, while another document points out the relevance of the public policies implemented at the national level, in terms of productivity and income distribution, on the strength and direction of the variation.

A first group of studies finds a weak relationship between the evolution of productivity and wages. CEPAL and OIT (2012) analyzed data from 2002 to 2011 for several selected countries in Latin America and the Caribbean and found that workers' real wages did not increase in line with increases in labor productivity. Sharpe and Uguccioni (2017) reviewed information for 11 countries belonging to the Organization for Economic Co-operation and Development (OECD) and analyzed the hypothesis that, in the long run, productivity growth leads to growth in real wages in the economy in the same proportion. They found that in 8 of the 11 countries the link is not met. Another document made by Jacobson and Occhino (2012) focuses on analyzing for the United States the evolution of the participation of labor income in the total income of the country and they registered a significant decrease in that participation since the decade 1980. Likewise, the International Labour Organization (OIT, 2017) found that in the period 1999-2001 the growth of average labor productivity was more than twice that of average wages, in a sample of 36 developed countries, and highlights - based on this result- that the decline in the labor income share is a global trend, although with some exceptions.

In addition to finding results that support a gap between the dynamics of productivity and wages, Bivens and Mishel (2015) and Stansbury and Summers (2017) suggest the factors that cause this dissociation. The former use data from the United States since 1973 and record a gap between increases in productivity and increases in real wages that is widening, especially since 2000, which is linked to the extraordinary increase in inequality in the entry. For them, one of the most likely causes of the decoupling between wages and productivity is that the bargaining power of workers has been intentionally undermined by a set of policies aimed particularly at benefiting those with greater wealth and power.

For their part, Stansbury and Summers (2017) investigate the relationship between productivity and wages for each decile of the wage distribution in the United States, thus generating information segmented by income distribution. The data used covers from 1948 to 2016 and finds a clear breaking point in 1973, since before that year productivity and wages had a parallel growth, but since then the gap has opened in the evolution of the two variables. They suggest as an explanation for the results obtained that in recent decades various factors have undermined the link between the variables, such as technological progress, education and specific skills, and globalization, as well as institutions and their power over the market. For his part, Bojnec (2004) uses data from Slovenia and finds, as one of the main results, that the increase in labor productivity explains only in part the increase in real wages in that country (70%), so there is a relevant role of other factors not considered or explained in the model, which affect the formation of wages.

A second group of works finds heterogeneous results, according to the groups of workers or the productive sectors. Hellerstein, Neumark, and Troske (1999), using data for the United States, analyze data for different groups of workers and argue that for most of these groups wage differentials are significantly linked to productivity differentials. Crepon, Deniau, and Pérez-Duarte (2002), with data from France, and grouping the workers according to age and sex, find significant differences between the groups in terms of the proportion of wage increases with respect to increases in productivity. Long, et al. (2008), using data from manufacturing plants in the United States, note two important points. On the one hand, they find a great heterogeneity in the condition of productivity as a predictor of wages, according to the type of industry and, on the other, they find an important variability in the magnitude of the connection between wages and productivity over a few years, even within the same industries. Broadberry and Burhop (2010) compare historical data on changes in both real wages and productivity in Germany and Great Britain. These authors identify significant differences in the relationship between the evolution of wages and increases in productivity between these two countries, but they also observe very important differences within them, according to the sectors and the qualification level of the workers.

A third group of studies points to a positive relationship between the evolution of productivity and wages. Lawrence (2016) conducted a data analysis of 32 countries from a World Bank database, for the manufacturing sector. This author found a close relationship between average productivity and average wages, with an explained variance of 87%.

Feldstein (2008) found evidence that in the United States the share of national income going to workers was roughly the same in 2006 as it was in 1970. He emphasizes that real compensation should be measured using the same price index that is used to calculate productivity. When studied in this way, the increase in compensation has been very similar to the increase in productivity.

After conducting an analysis of temporary movements in labor participation and wage inequality, with data from OECD countries, Schwellnus, Kappeler, and Pionnier (2017) found that various country-specific factors, including the implementation and adjustment of public policies, play a significant role in shaping the relationship and trend between the variables. In other words, the characteristics and scope of various national public policies related to the distribution of remuneration, as well as those related to the promotion of productivity, exert an important effect on the strength and direction of the correlation of these variables.

The work of Schwellnus, Kappeler, and Pionnier (2017) focuses on a quantitative description of the movements in labor participation and wage inequality in OECD countries. According to the authors, various country-specific factors, including public policy adjustments, could play a significant role in shaping the effects of global trends between variables.

4.3.2. Economic literature in Mexico

In recent years, valuable research has been carried out in Mexico on the relationship between productivity and wages, as well as the relationship between employment and productivity and wages. Table 4.2 presents some representative works on this subject.

Table 4.2

Mexico: the most relevant literature on productivity and remuneration in the country

Authors	Year	Title	Period covered
Valle, A.	2003	El comportamiento de los salarios y la productividad en México y EUA	1982-to 1991
Verhoogen, E.	2008	Trade, quality upgrading, and wage inequality in the Mexican manufacturing sector	1984-2001
Rodríguez Espinosa, M. & Castillo Ponce, R.	2009	Empleo, productividad y salarios en México: un análisis de corto y de largo plazo para el sector manufacturero	1994-2007
Castellanos, S.G.	2010	Desempleo y determinación de salarios en la industria manufacturera de México. Un análisis mediante paneles dinámicos	1994-2002
Liquitaya Briceño, J.	2013	Crecimiento, empleo y productividad en la industria manufacturera mexicana	2007-2013
Unger, D. Flores, K. & Ibarra, J.	2014	Productividad y capital humano. Fuentes complementarias de la competitividad en los estados de México	2004 and 2009
Ruíz Ramírez, H.	2015	La productividad laboral en México, la producción, el empleo y los salarios	N.A.
Lechuga Montenegro, J. & Gómez García, C.	2015	Relaciones analíticas entre salarios, productividad y precios. La canasta básica y su consumo en México, 1993-2011	1993-2011
López Machuca, J. & Mendoza Cota, J.	2017	Salarios, desempleo y productividad laboral en la industria manufacturera mexicana	2007-2015
López Macías, E.M. & Mojica Gutiérrez, A.A. (2018).	2018	Empleo, salarios y productividad en México: un análisis de la situación laboral en México, con predicciones para el futuro	2005-2017
Almonte, L.J & Murillo Villanueva, B.	2018	Salario y productividad laboral en la manufactura	2009-2017
Munguía, L.F.	2019	Productividad, salarios y trabajo digno en México	2005-2018

Source: Prepared by author.

The main contributions of the work carried out with data from Mexico that were reviewed are briefly detailed in the following paragraphs. These documents use different methodologies and different data sources, as well as different temporary scenarios. The results are not uniform, because while some a correlation between the variables is observed, in other cases the reported findings show a clear disconnection between productivity increases and salary evolution in Mexico. Additionally, two papers whose contribution is based on the proposal of various elements of analysis for public policy are integrated into this review.

Valle (2003) finds that between 1982 and 1991, although productivity increased moderately, real remuneration fell sharply. Castellanos (2010) uses data from the Monthly Industrial Survey from 1994 to 2002, which has establishments in the manufacturing sector as its unit of analysis, except for those engaged in export maquila. With these data, the author analyzes for Mexico the relationship between (nominal) wages, unemployment, and labor productivity, through a model that uses a generalized method of moments for dynamic data panels. Among the results obtained, she highlights that a decrease of 1% in labor productivity reduces the annual rate of increase of nominal wages by approximately 0.3% in the short term, and by approximately 0.47% in the long term.

Liquitaya Briceño (2013), also with information from the manufacturing industry, as well as from the National Consumer Price Index, performs Granger causality tests, cointegration analyses, and regression analyses in levels and in growth rates, and build the error correction model. Among the results, employment unidirectionally causes economic activity and productivity, and there is feedback between the latter two. A 1% increase in economic activity requires an increase in employment of only 0.57%, with the rest derived from increases in productivity and capital.

Using information from the Central Bank of Mexico's statistical database, from the first quarter of 1994 to the fourth quarter of 2007, Rodríguez Espinosa and Castillo Ponce (2009) estimate a cointegration equation and a common cycle equation. In the short term, a common cycle between the variables could not be observed. However, in the long term, the authors detect that those wages share a common variation with productivity and employment, that is, wages are positively related to productivity and negatively to unemployment. These results are similar to those obtained by López Macías and Mojica Gutiérrez (2018).

With data from the National Institute of Statistics and Geography (INEGI), the Mexican Social Security Institute (IMSS), and the National Minimum Wage Commission (CONASAMI), Ruíz Ramírez (2015) carried out a descriptive and graphic analysis, relating the variables of labor productivity, production, employment, and wages. According to the information analyzed, she found that increases in productivity do not lead directly and unequivocally to increases in wages. Similarly, through a descriptive analysis of graphs, Almonte and Murillo Villanueva (2018), with data from the IMSS and INEGI, analyze the evolution of wages and labor productivity in manufacturing, at the national level and by state. Among the results, the marked heterogeneity at the state level stands out in terms of real wages and productivity levels, although it can be clearly observed that productivity tends to grow above the increase in wages in the country.

López Machuca and Mendoza Cota (2017) carry out a comparative analysis of the 32 states in the country in which they evaluate the relationship between labor productivity and unemployment with real wages in Mexico. Based on the wage curve model, the methodology used employs econometric techniques designed for static, dynamic, and long-term cointegration functional structures. They find that wages react to variations in productivity, but contrary to expectations, these variations are in the opposite direction, since they detect that wages decrease with increases in productivity. Munguía (2019) analyzes information from 2005 to 2018 on labor productivity and wages in Mexico, highlighting that, for the manufacturing industry, productivity has grown above wages, especially in some subsectors. Particularly since 2009, labor productivity has registered sustained growth, but wages have not experienced a recovery from that year's crisis. The author even notes a mirror movement, in which when there are increases in productivity, a greater decrease in wages is observed, similar to the findings of López Machuca and Mendoza Cota (2017).

A paper by Verhoogen (2008) focuses on the empirical implications of the relationship between trade and wage inequality, using panel data on manufacturing plants in Mexico. In the analysis, the manufacturing plants are grouped according to their level of productivity, and the most productive plants are found to pay higher wages than the less productive plants to maintain a higher quality workforce, although a clear differentiation is established between occupational categories.

Some of the main results of the work by Lechuga Montenegro and Gómez García (2015) show that wages have not grown at the same rate as labor productivity, due, among other factors, to the fact that a structural heterogeneity persists in the sectors that produce consumer goods, such as the basic basket. Likewise, the authors find that, due to an unfavorable relationship between productivity, wages, and prices in the country, real wage deterioration is maintained as the logic on which the rate of profit operates. Meanwhile, through a cluster analysis Unger, Flores and Ibarra (2014) review the role of the Gross Domestic Product, labor productivity, employment, and average wages, as characteristics of economic competitiveness. The main contribution of the aforementioned document to this work is the emphasis on the relevance of incorporating the regional or territorial dimension in this type of analysis.

4.3 Data and methodology

It is important that the analysis of the relationship between productivity and wages should control the effect that unemployment may be exerting on the first two variables. This impact on one of the two variables, or on both, has been widely observed in the economic literature, in various contexts (Castellanos, 2010; López Machuca & Mendoza Cota, 2017; Stansbury & Summers, 2017).

In Mexico, two phenomena have been observed in the relationship between unemployment, productivity, and wages. The first is that the influence of productivity and unemployment on wages is sensitive to economic cycles, that is, it varies between periods of stability and of crisis, while unemployment has a more significant effect when there is economic stability. The second is that the impacts present differences in their significance in the analysis by states. In states whose economy is strongly linked to the performance of manufacturing activity, labor productivity is more significant than the unemployment rate in determining workers' remuneration (López Machuca & Mendoza Cota, 2017).

This work focuses on the analysis of the manufacturing sector in Mexico, and data on the wages of the employed population are used, instead of information only on wages. As mentioned above, considering total remuneration -and not wages- allows the analysis to incorporate additional elements to the salary received by workers as compensation for their work, which often represent a considerable amount of the total received. Moreover, additional elements usually have a different variability than the salary in the revisions and adjustments of remuneration. Thus, the variable used in this case refers to the total remuneration per worker in a working year.

Manufacturing labor productivity, on the other hand, is calculated as the added value generated by a worker, in the sector, in one year. To calculate it, the value of production is divided by the labor input (Van Biesebroeck, 2015). The labor productivity of the manufacturing sector was chosen because the measurement of value added and the costs of inputs are generally narrowly defined, which provides greater clarity about what is specifically measured and analyzed.

The data for the estimate comes from the 2009, 2014, and 2019 economic censuses of the National Institute of Statistics and Geography (INEGI, 2009, 2014, 2019a). The figures correspond to the economic activity of the previous year. The variables used are the gross value added (GVA) of production and employed personnel in the manufacturing sector, at the state level. To deflate the values, the producer price index (INPP, base 2019) published by the INEGI (2022a) was used.

Variables such as the unemployment rate, manufacturing exports per worker, manufacturing foreign direct investment (FDI) per worker, and average schooling (in years) at the state level were also used to control for the conditions of each one. We use the unemployment rate because various authors (Alexander, 1993; Fernández and Montuenga, 1997; Nikulin, 2015; López Machuca and Mendoza Cota, 2017; Kugler, 2019) consider it to be a factor that affects the remuneration-productivity relationship, at the aggregate level. The unemployment data source is the National Occupation and Employment Survey (INEGI, 2019b).

Schwarzer (2018) considers that there is a differentiated behavior in labor productivity between exporting and non-exporting companies, while Driffield and Taylor (2006), Girma and Wakelin (2007) and Mullen & Williams (2008) think that FDI has a differentiating effect on the demand and remuneration of the labor factor. Finally, Choudhry (2009), and Fallahi et al. (2010) consider education as a determinant of productivity. The data source of the manufacturing exports is the Quarterly Exports by State (INEGI, 2022b), while the manufacturing foreign direct investment (FDI) comes from the Secretary of the Economy (Government of Mexico, 2021), and average schooling from the Secretary of Public Education (SEP, 2021).

Regarding the methodology used in this research, a spatial fixed effects panel model is proposed, in which the spatial and temporal effects of the data are incorporated. Thus, the analysis is based on a spatial model, since it is recognized that data collected in nearby spatial units tend to be more similar than those that are further away geographically (Tobler, 1970).

The following equation is proposed, following the model developed by López Machuca and Mendoza Cota (2017), to estimate wages from labor productivity, in a context of spatial econometrics (Elhorst, 2014)[9], we have:

$$\begin{aligned} \boldsymbol{ln\,remun_{i,t}} = {} & \boldsymbol{\emptyset_1 W\, ln\,remun_{i,t} + \beta_1 lnpl_{i,t} + \beta_2\, ln\,des_{i,t} + \beta_3\, ln\,exp_{i,t}} \\ & \boldsymbol{+ \beta_4\, ln\,ied_{i,t} + \beta_5\, ln\,escol_{i,t} + \rho_1 W\, ln\,X_{i,j,t} + \alpha_i + u_{i,t}} \end{aligned} \tag{4.1}$$

[9] Appendix A provides a taxonomy of Spatial Econometric Models based on Belotti, Hughes & Piano (2017).

where $\boldsymbol{ln\,remun}_{\mathrm{i,t}}$ is the logarithm of remunerations in state i, for period t; while $\boldsymbol{lnpl_{i,t}}$ is the logarithm of manufacturing labor productivity in state i, for period t; $\boldsymbol{ln\,des_{i,t}}$ is the logarithm of the unemployment rate in state i, for period t; $\boldsymbol{ln\,exp_{i,t}}$ represents the natural logarithm of manufacturing exports per worker; $\boldsymbol{ln\,ied_{i,t}}$ is the natural logarithm of manufacturing foreign direct investment (FDI) per worker in state i, for period t; $\boldsymbol{ln\,escol_{i,t}}$ is the average schooling in years in state i, for period t; and $\boldsymbol{u_{i,t}}$ is the error term. The terms $\boldsymbol{WlnX_{i,j}}$ are the whole set of explanatories and explain spatially lagged variables.

This model includes a remuneration spatial lag $\boldsymbol{W\,ln\,remun_{i,t}}$ which represents a linear combination of remunerations values coming from neighbors' states, own characteristics ($\boldsymbol{lnpl_{i,t}}$, $\boldsymbol{ln\,des_{i,t}}$, $\boldsymbol{ln\,exp_{i,t}}$, $\boldsymbol{ln\,ied_{i,t}}$, $\boldsymbol{ln\,escol_{i,t}}$), and characteristics of neighbors' states ($\boldsymbol{W\,ln\,X_{i,j,t}}$). This setting is proposed because global spillover arises from shared manufacturing inputs and workers between states (LeSage, 2014). For example, one of the manufacturing clusters in the north, called La Laguna, is in a metropolitan area comprised of Torreón, Matamoros and Madero in Coahuila, and Gómez Palacio and Ciudad Lerdo, in Durango. The same for other regions, such as the Puebla-Tlaxcala automotive cluster.

For this chapter, manufacturing labor productivity is defined as:

$$\boldsymbol{pl_{i,t}} = \frac{\boldsymbol{VAB_{i,t}}}{\boldsymbol{PO_{i,t}}} \tag{4.2}$$

where $\boldsymbol{VAB_{i,t}}$ is the gross census value added in entity i in period t, while $\boldsymbol{PO_{i,t}}$ is the employed population in the same entity i and period t.

This specification is relevant because it is based on the hypothesis of causality from productivity to wages. The theory of distribution postulates that, without friction, each factor of production will be remunerated in the same amount that they create (Clark, 1899), that is, the labor factor should be remunerated according to its marginal productivity (Robinson, 1967). It is also based on the approaches of the relationship of efficiency wages. Solow (1979), conceptualizes and formalizes the theory of efficiency wages, and proposes a model that assumes a direct relationship between wages and worker productivity.

Two things were carried out before estimating the model. First, we verified whether or not there is spatial correlation between the elements. Tests were performed to consider the influence of spatial location not only on manufacturing remunerations and labor productivity, but also on the other variables.

The procedure was implemented in two steps. In step one, we tested the spatial correlation in levels on the variables of interest. The three spatial statistics used are Moran's I, Geary's C and Getis and Ord's G running in Stata 16 (Pisati, 2001). Moran's I is the most commonly spatial statistic indicator used. It is used to determine whether or not the data presents spatial randomness. Moran's I is computed as:

$$I = \left(\frac{N}{\sum_i \sum_j w_{i,j}}\right) \frac{\sum_i \sum_j w_{i,j}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2} \tag{4.3}$$

where $\boldsymbol{W_{i,j}}$ is the spatial weight matrix, while $(\boldsymbol{X_i} - \overline{\boldsymbol{X}})(\boldsymbol{X_j} - \overline{\boldsymbol{X}})$ is the covariance between the variable of interest at the state level, and $\sum_{\boldsymbol{i}}(\boldsymbol{X_i} - \overline{\boldsymbol{X}})^{\mathbf{2}}$ is the variance.

Geary's C is a global measure of dissimilarity, while Getis and Ord's G uses agglomeration measures. Usually, both measures indicate the existence of clusters in the spatial distribution of the variable, for example high values with high values or low paired with low values. Geary's C is computed as:

$$C = \left(\frac{N-1}{\sum_i \sum_j w_{i,j}}\right) \frac{\sum_i \sum_j w_{i,j}\left(\left[(X_i - \bar{X}) - (X_j - \bar{X})^2\right]\right)}{N \sum_i (X_i - \bar{X})^2} \tag{4.4}$$

where the elements of the equation are the same as described above. If Geary's C is greater than 1, then the distribution of the variable is characterized by a negative spatial autocorrelation. In contrast, if Geary's C is less than 1, then it is a positive spatial autocorrelation.

The Getis and Ord's G indicator is computed as:

$$G = \frac{\sum_{i \neq j} w_{i,j}(Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_{i \neq j}(Y_i - \bar{Y})(Y_j - \bar{Y})} \tag{4.5}$$

In the second stage, a linear regression for the whole dataset was run by ordinary least squares (OLS) to verify the spatial autocorrelation using the errors and spatial lagged dependent variables and model selection (Shehata, 2016). In addition to the previous statistics, Lagrange Multiplier (LM) Lag tests, non-robust and robust versions, were used to test spatial autocorrelation and model selection. If the latest are more statistically significant than the previous, and the robust LM lag test is significant, but the error test is not, then a spatial lag model is a better fit. Moreover, if error tests are more statistically significant than LM lag tests and error statistics are significant but robust LM lag is not, then a spatial error model fits better (Anselin and Florax, 1995; Shehata, 2012).

A second issue was a negative gross census value added for Tabasco in 2018. A geographically weighted regression (GWR) model was then applied for the outlier data (i.e., Tabasco) using GWR Stata commands (Pearce, 1998). Geographically Weighted Regressions (GWR) are a statistical technique that aims to establish prediction processes for both independent and dependent variables, with a spatial approach forming the best linear unbiased predictors. The use of this technique presents an advantage in the conformation of the modeling because it captures the spatial heterogeneity in the territories and makes them functional in the regression equation of each observation. At the same time, the results consider the spatial effect of parameter estimation, tending to normalize the observations (Fotheringham et al., 2002; Harris et al., 2011).

Furthermore, exponential kernel functions were used to obtain an efficient specification of the prediction derived from the GWR. Exponential functions are defined as those based on spatial approximation, that is, functions that permit smoothing degrees of spatial influence to be generated. Their presence allows us to consider that the effects present in a geographic location of region i tend to decrease as one moves away from it. The usefulness of this assumption makes it possible to determine different spatial behaviors and standardize the predictions established in the modeling structure (Fotheringham et al., 2002; Harris et al., 2011; Bidanset & Lombard, 2014).

Finally, Stata 16 is employed to estimate equation 1 using the Panel Fixed Effects (Cameron & Trivedi, 2009), GMM (Roodman, 2009) and Spatial Panel (Belotti, Hughes & Piano Mortari, 2017) methods. Relevant statistical tests are applied to every one of the estimations. Also, as spatial estimation exploits a complex dependency structure, the estimated parameters contain a wealth of information that can be unraveled through measures of direct, indirect, and total effects that were estimate for our model (LeSage & Pace, 2009). Total effects can be decomposed between direct and indirect effects. The direct effect is the impact of the spatial explanatory variable j on explained variable y for the state r while the total effects is the cumulative impact of the explanatory variable j of state r on explained variable of all other states. The indirect effect is the residual from total effect minus direct effect. The indirect effect is the impact of explanatory variable j of all other states on the explained variable of state r (Le Sage 2008; Le Sage, 2014; Herrera, 2015).

4.5 Descriptive statistics

The descriptive statistics of the variables used in the model are presented in Table 4.3. As can be seen, the average remuneration for employed personnel is less than the annual value added per worker (labor productivity) for all census years. However, the levels are not likely to be the same, as they are expected to evolve at similar rates. The average annual unemployment rate goes from 1.2% (Guerrero) to 5.1% (Mexico City), while manufacturing exports range from $53.3 dollars per worker (Guerrero), on average, to 106,484.2 per worker (Coahuila), on average. The greatest recipient of average manufacturing foreign direct investment (FDI) is Zacatecas ($11,940.6 per worker). This state receives manufacturing companies that support the automotive industry, but the mining and all-around companies capture the greatest FDI. Moreover, during the 2008 and the 2012-2014 periods, Zacatecas received the highest flow of the FDI. The average schooling evolved favorably throughout the entire period for Mexico City (10.6 years), the highest, but not for Chiapas (10.6 years), which is the lowest.

Table 4.3
Mexico: descriptive statistics by state, 2008, 2013 and 2018
(Values are in constant 2019 pesos)

State	Labor productivity, average ($)	Remuneration per worker, average ($)	Unemployment rate (%)	Manufacturing exports per worker, average (US $)	Manufacturing FDI per worker, average (US $)	Average schooling (years)
Aguascalientes	442,203.0	114,003.5	4.3	69,351.2	3,857.2	9.5
Baja California	245,945.0	118,280.6	3.6	102,779.4	2,855.8	9.6
Baja California	159,772.3	54,312.2	4.0	2,338.9	2,022.8	9.7
Campeche	100,664.3	43,481.5	2.7	9,969.6	1,920.9	8.9

Chiapas	278,395.1	42,238.2	2.6	7,848.6	818.0	7.0
Chihuahua	223,972.7	106,680.2	4.4	98,290.0	2,532.1	9.2
Ciudad de México	353,665.3	100,159.5	5.8	7,235.0	5,864.2	10.9
Coahuila	529,307.9	93,240.0	4.9	106,484.2	3,321.5	9.7
Colima	222,401.9	46,773.6	3.2	5,954.2	1,709.9	9.3
Durango	231,828.9	64,575.4	4.2	15,353.5	406.4	8.9
Guanajuato	346,852.8	77,075.0	4.4	35,345.2	3,757.2	8.1
Guerrero	54,636.6	11,401.1	1.4	53.3	3,337.7	7.6
Hidalgo	347,968.2	90,722.2	3.3	17,704.5	1,665.4	8.5
Jalisco	334,382.8	78,653.5	3.5	44,037.0	2,862.2	9.1
México	435,417.9	89,395.8	4.8	28,274.0	3,725.5	9.4
Michoacán	209,324.7	35,240.1	3.0	8,823.8	7,037.3	7.8
Morelos	462,095.5	92,169.0	2.8	57,212.8	4,116.6	9.2
Nayarit	155,621.4	49,476.6	4.0	4,281.2	7,999.3	8.9
Nuevo León	470,196.2	106,523.1	4.5	64,622.7	3,326.1	10.1
Oaxaca	225,990.8	50,662.0	2.0	7,370.5	5,267.4	7.3
Puebla	372,876.5	75,982.9	3.2	46,718.3	2,419.6	8.3
Querétaro	419,404.8	92,989.5	4.3	43,660.9	4,228.5	9.4
Quintana Roo	166,566.3	44,044.7	3.3	945.2	1,882.0	9.4
San Luis Potosí	543,622.4	88,647.2	3.0	60,519.9	7,471.8	8.6
Sinaloa	207,150.0	53,701.9	3.8	8,217.7	1,223.5	9.4
Sonora	448,039.4	94,118.5	4.3	78,832.8	2,485.8	9.7
Tabasco	795,479.4	117,330.2	5.7	17,220.6	2,234.1	9.0
Tamaulipas	287,941.2	119,412.8	4.8	92,484.1	3,160.1	9.4
Tlaxcala	283,319.5	55,228.3	4.8	15,347.8	1,186.2	9.1
Veracruz	666,376.0	139,151.5	3.0	30,947.4	3,474.1	8.0
Yucatán	148,546.6	43,026.4	2.3	11,021.7	1,779.3	8.6
Zacatecas	360,053.9	67,706.3	3.8	43,560.3	15,177.0	8.3

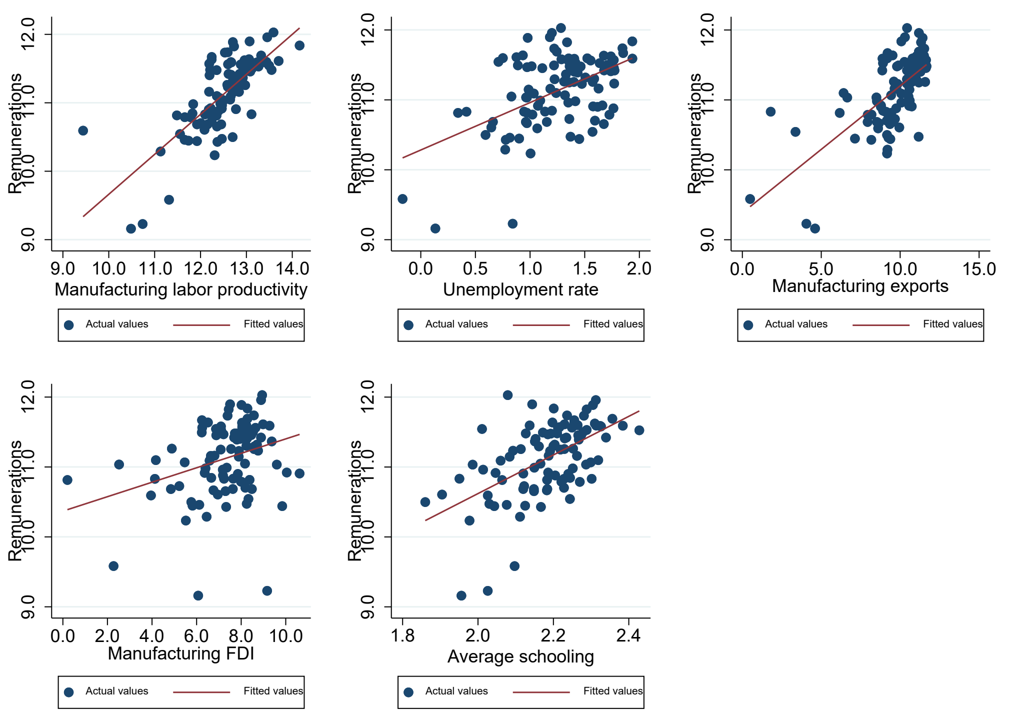
Source: Prepared by the author, based on data from the Instituto Nacional de Estadísticas y Geografía (INEGI) (2009). Censos Económicos 2009 [online], Aguascalientes, México. Retrieved from: https://www.inegi.org.mx/programas/ce/2009/; INEGI (2014). Censos Económicos 2014 [online]. Retrieved from https://www.inegi.org.mx/programas/ce/2014/). Aguascalientes, México; and INEGI (2019). Censos Económicos 2019 [online]. Retrieved from https://www.inegi.org.mx/programas/ce/2019/), Aguascalientes, México; Government of Mexico (2021). Datos abiertos. Información estadística de la Inversión Extranjera Directa [Base de datos]. Retrieved from: https://datos.gob.mx/busca/dataset/informacion-estadistica-de-la-inversion-extranjera-directa & SEP (Secretaría de Educación Pública) (2021). Report on educational indicators [Base de datos]. https://www.planeacion.sep.gob.mx/estadisticaeindicadores.aspx.
Note: All values are yearly and deflated by the Manufacturing Producer Price Index (2019=100), where appropriate.

Linear relationship between remunerations and all other variables, throughout the study period, is confirmed in figure 4.1, which shows a positive relationship between manufacturing remunerations per worker and all-other variables. However, this relationship seems to be strong between manufacturing remunerations per worker and manufacturing labor productivity.

Figure 4.1

Mexico: Manufacturing remunerations per worker and manufacturing labor productivity, unemployment rate, manufacturing exports, manufacturing FDI, and average schooling at the state level, 2008, 2013 and 2018

(*Logarithms*)



Source: Prepared by the author.

The next step was to analyze the dispersion of remuneration per worker, manufacturing labor productivity, unemployment rate, manufacturing exports per worker, manufacturing FDI per worker, and average schooling. To this end, the regionalization carried out by the Bank of Mexico in its quarterly reports is employed (Banco de México, 2022). Table 4.4 shows regions names and the states belonging to which one.

Table 4.4

Mexico: regions and states

Region	States
Norte	Baja California, Chihuahua, Coahuila, Nuevo León, Sonora, and Tamaulipas

Centro-Norte	Aguascalientes, Baja California Sur, Colima, Durango, Jalisco, Michoacán, Nayarit, San Luis Potosí, Sinaloa, and Zacatecas
Centro	Ciudad de México, Estado de México, Guanajuato, Hidalgo, Morelos, Puebla, Querétaro y Tlaxcala,
Sur	Campeche, Chiapas, Guerrero, Oaxaca, Quintana Roo, Tabasco, Veracruz, and Yucatán.

Source: Prepared by the author, based on Banco de México (2022). Reporte sobre las economías regionales Enero-Marzo 2022. https://www.banxico.org.mx.

Table 4.5 shows the regional standard deviations with respect to the national. For the entire study period, if the national standard deviation is considered as 1, the northern region averaged 29.2% less dispersion in productivity per capita, 44.4% less dispersion in remunerations, 18.4% less dispersion in unemployment rate, 46.5% less dispersion in manufacturing exports per worker, 77.2% less dispersion in manufacturing FDI and 45.7% in average schooling. In other words, the northern region has undergone a process of growth in productivity, wages, unemployment rate, exports per capita, FDI, and schooling that is more uniform than that observed at the national level. The same happens with the north central and central region. The southern region is the one with the greatest heterogeneity, displaying a variability with respect to the national, of above 1 (greatest variability). It is only lower in the cases of manufacturing exports and FDI.

Table 4.5
Mexico: Regional standard deviations with respect to the national level
(at constant 2019 pesos, proportions and percentages)

Variable	North		
	Standard deviation	Proportion with respect to the national	Percentage difference with respect to the national
Manufacturing labor productivity ($)	147,464.8	0.7	-29.2%
Remuneration per worker ($)	18,873.8	0.6	-44.4%
Unemployment rate (%)	1.1	0.8	-18.4%
Manufacturing exports per worker, average ($, dollars)	18,097.1	0.5	-46.5%
Manufacturing foreign direct investment per worker, average ($, dollars)	1,231.5	0.2	-77.2%
Average schooling (years)	0.5	0.5	-45.7%

Variable	Central North		
Manufacturing labor productivity ($)	166,653.1	0.8	-20.0%
Remuneration per worker ($)	28,848.3	0.8	-15.1%
Unemployment rate (%)	1.1	0.8	-22.1%
Manufacturing exports per worker, average ($, dollars)	26,550.4	0.8	-21.5%
Manufacturing foreign direct investment per worker, average ($, dollars)	8,718.3	1.6	61.6%
Average schooling (years)	0.7	0.8	-21.3%
Variable	Central		
Manufacturing labor productivity ($)	113,164.3	0.5	-45.7%
Remuneration per worker ($)	20,336.2	0.6	-40.1%
Unemployment rate (%)	1.3	1.0	-1.5%
Manufacturing exports per worker, average ($, dollars)	18,575.7	0.5	-45.1%
Manufacturing foreign direct investment per worker, average ($, dollars)	2,517.2	0.5	-53.4%
Average schooling (years)	1.0	1.0	1.1%
Variable	South		
Manufacturing labor productivity ($)	302,854.0	1.5	45.4%
Remuneration per worker ($)	39,840.5	1.2	17.3%
Unemployment rate (%)	1.5	1.1	11.0%
Manufacturing exports per worker, average ($, dollars)	10,354.9	0.3	-69.4%
Manufacturing foreign direct investment per worker, average ($, dollars)	3,165.7	0.6	-41.3%

Average schooling (years)	1.1	1.1	11.7%
Variable	National		
Manufacturing labor productivity ($)	208,237.7	1.0	
Remuneration per worker ($)	33,971.4	1.0	
Unemployment rate (%)	1.4	1.0	
Manufacturing exports per worker, average ($, dollars)	33,838.9	1.0	
Manufacturing foreign direct investment per worker, average ($, dollars)	5,396.1	1.0	
Average schooling (years)	0.9	1.0	

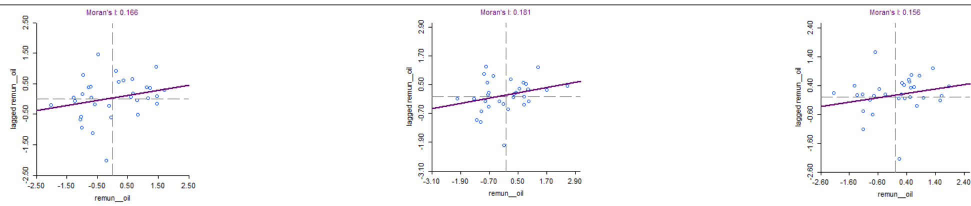
Source: Prepared by the author, based on data from the Instituto Nacional de Estadísticas y Geografía (INEGI) (2009). Censos Económicos 2009 [online], Aguascalientes, México. Retrieved from: https://www.inegi.org.mx/programas/ce/2009/; INEGI (2014). Censos Económicos 2014 [online]. Retrieved from https://www.inegi.org.mx/programas/ce/2014/). Aguascalientes, México; and INEGI (2019). Censos Económicos 2019 [online]. Retrieved from https://www.inegi.org.mx/programas/ce/2019/), Aguascalientes, México; Government of Mexico (2021). Datos abiertos. Información estadística de la Inversión Extranjera Directa [Base de datos]. Retrieved from: https://datos.gob.mx/busca/dataset/informacion-estadistica-de-la-inversion-extranjera-directa & SEP (Secretaría de Educación Pública) (2021). Report on educational indicators [Base de datos]. https://www.planeacion.sep.gob.mx/estadisticaeindicadores.aspx.
Note: All values are yearly and deflated by the Manufacturing Producer Price Index (2019=100), where appropriate.

4.6 Spatial data testing

The spatial autocorrelation test results are presented in this section. Figure 4.2 shows the dispersion diagrams of remuneration per labor versus its spatial lag for 2009, 2014, and 2019 censuses. Moran´s I global spatial autocorrelation rejects with a 95% confidence level, the null hypothesis of spatial randomness is rejected for 2014 and 2019, while in 2009 it is rejected with a 90% confidence level.

Figure 4.2
Mexico: cross-section diagnostic tests for spatial correlation in remuneration per labor, at the state level, 2009-2019
(*in Mexican pesos, 2019=100*)

2008	2013	2018



Source: Prepared by the author, based on L. Anselin, I. Syabri and Y. Kho (2006). GeoDa: An introduction to spatial data analysis, *Geographical Analysis*, 38 (1), pp. 5-22.

Table 4.6 displays Moran's I spatial tests applied to the whole set of variables in levels and cross sections for every year. Manufacturing labor productivity, manufacturing exports per worker, and average schooling are statistically significant at the 5% level for the whole period. Manufacturing remunerations per worker is statistically significant at the 5% level for the last two censuses, and is statistically significant at the 10% level. This means that overall these variables are spatially autocorrelated. This test shows a general presence of spatial specific patterns in the distribution of the variable over the whole Mexican territory, i.e., the variable does not distribute randomly.

Table 4.6

Moran's I spatial autocorrelation tests by cross sections

Variables	2008	2013	2018
Manufacturing remunerations per worker	0.164**	0.181*	0.197*
	0.112	0.110	0.111
Manufacturing labor productivity	0.175*	0.177*	0.272*
	(0.103)	0.090	0.110
Unemployment rate	0.199*	0.133	0.104
	0.111	0.111	0.107
Manufacturing exports per worker	0.233*	0.185*	0.182*
	0.109	0.111	0.112
Manufacturing foreign direct investment per worker, average	0.073	-0.032	0.111
	0.109	0.092	0.106
Average schooling	0.300*	0.311*	0.316*
	0.110	0.110	0.109

Source: Prepared by the author, based on Pisati, M. (2001). Tools for spatial data analysis. Stata Technical Bulletin, No. 60, pp. 21-37. Retrieved from: http://www.stata.com/products/stb/journals/stb60.pdf.

Notes: *Statistically significant at the 95% confidence level

** Statistically significant at the 90% confidence level

Tables 4.7 and 4.8 present the two local spatial autocorrelation tests known as Geary's C and Getis & Ord's G, respectively. The average schooling is statistically significant at the 5% level for the whole period in the Geary's C test, exhibiting spatial autocorrelation. Manufacturing remunerations per worker, unemployment rate, and manufacturing exports per worker are statistically significant at the 5% or 10% levels for at least two censuses. Manufacturing foreign direct investment per worker is statistically significant at the 10% level in 2013.

This autocorrelation test results show clustering states for some variables and census years. For example, the average schooling clusters states in the whole period. Also, Geary's C is less than 1 for average schooling, manufacturing remunerations per worker, unemployment rate, manufacturing exports per worker, and manufacturing foreign direct investment per worker. This means that there is a positive spatial autocorrelation, i.e., if one state has high average schooling then its neighbor has high average schooling too.

Table 4.7
Geary's C spatial autocorrelation tests by cross sections

Variables	**2008**	**2013**	**2018**
Manufacturing remunerations per worker	0.775**	0.827	0.687*
	(0.134)	(0.155)	(0.142)
Manufacturing labor productivity	0.840	0.658	0.750
	(0.217)	(0.296)	(0.152)
Unemployment rate	0.661*	0.749*	0.770
	(0.141)	(0.146)	(0.186)
Manufacturing exports per worker	1.157	0.613*	0.671*
	(0.186)	(0.144)	(0.136)
Manufacturing foreign direct investment per worker	0.973	1.508**	0.869
	(0.163)	(1.773)	(0.196)
Average schooling	0.595*	0.580*	0.579*
	(0.158)	(0.161)	(0.165)

Source: Prepared by the author, based on Pisati, M. (2001). Tools for spatial data analysis. Stata Technical Bulletin, No. 60, pp. 21-37. Retrieved from: http://www.stata.com/products/stb/journals/stb60.pdf.
Notes: *Statistically significant at the 95% confidence level
** Statistically significant at the 90% confidence level

The Getis and Ord's G in table 4.8 shows that manufacturing labor productivity is statistically significant at 5% or 10% level for the whole period, exhibiting spatial autocorrelation.

Manufacturing FDI per worker and average schooling are statistically significant for some census years. The table does not show the difference between Getis and Ord's G and its expected values, but, by computing both, we can see that manufacturing labor productivity displays positive spatial autocorrelation with a prevalence of high-valued clusters for the whole period. This is a first confirmation of our hypothesis.

Table 4.8
Getis and Ord's G spatial autocorrelation test by cross sections

Variable	2008	2013	2018
Manufacturing remunerations per worker	0.139	0.146	0.146
	(0.009)	(0.010)	(0.009)
Manufacturing labor productivity	0.160*	0.165**	0.170*
	(0.012)	(0.017)	(0.012)
Unemployment rate	0.136	0.131	0.131
	(0.149)	(0.005)	(0.007)
Manufacturing exports per worker	0.170	0.165	0.171
	(0.997)	(0.024)	(0.025)
Manufacturing foreign direct investment per worker	0.146	0.198*	0.166
	(0.605)	(0.026)	(0.029)
Average schooling	0.130*	0.131	0.131*
	(-2.079)	(0.002)	(0.002)

Source: Prepared by the author, based on Pisati, M. (2001). Tools for spatial data analysis. Stata Technical Bulletin, No. 60, pp. 21-37. Retrieved from: http://www.stata.com/products/stb/journals/stb60.pdf.
Notes: *Statistically significant at the 95% confidence level
** Statistically significant at the 90% confidence level

The following table shows the spatial panel autocorrelation test regression results. The LM test for spatial lag is statistically significant at the 5% level (40.280) and is also robust (347.996). In addition, Moran I´s (0.116), Geary´s C (1.035), and Getis and Ord's G (-0.485) error test are statistically significant at the 10% level. Thus, the spatial lag model is appropriate, as stated in equation 4.1.

Table 4.9
Spatial Panel Autocorrelation Tests

Spatial Error tests	Statistic
Moran I	0.116**
Geary´s C	1.035

Getis and Ord's G	-0.485**
Spatial Lagged Dependent Variable test	
LM Lag (Anselin)	40.280*
LM Lag (Robust)	347.996*

Source: Prepared by the author, based on Shehata, E.A.E. (2016). SPREGXT: Stata Module Econometric Toolkit to Estimate Spatial Panel Regression Models.
Notes: * Statistically significant at the 95% confidence level
** Statistically significant at the 90% confidence level

4.7 Results

Three estimates of the model described in the previous section were made, and the resulting parameters estimated in logarithms are shown in Table 4.10. At first glance, a panel of fixed effects is estimated, without considering the possibility of spatial correlation and using GWR results for Tabasco. This imputation is made based on the distortion caused by oil accounting producing a negative value added explained. Previous studies indicate that the exclusion or imputation of the state of Tabasco does not generate significant differences in the results (Puyana, 2009; Sanchez Juárez & Campos Benítez, 2010). This estimation shows that an increase of 1% in manufacturing labor productivity has an impact of 0.146% in remunerations and of 0.051% in the unemployment rate. In the case of manufacturing exports per worker and manufacturing FDI per worker, a positive increase of 1% would be related to an increase of 0.016% and 0.009%, respectively, of remunerations. However, for these last three variables, the parameters are not statistically significant. The average years of schooling have a positive relationship of 3.105% with earnings.

Table 4.10
Model estimation results

Parameters	Panel Fixed Effects	Generalized Method of Moments (GMM)	Spatial Panel [a/]
	(1)	(2)	(3)
Ln (Manufacturing labor productivity)	0.146*	0.369*	0.100*
	(0.032)	(0.129)	(0.027)
Ln (Unemployment rate)	0.051	0.175*	-0.003
	(0.061)	(0.073)	(0.071)
Ln (Manufacturing exports per worker)	0.016	0.080*	0.010
	(0.017)	(0.032)	(0.022)
Ln (Manufacturing FDI per worker)	0.009	-0.018	-0.007
	0.011	(0.020)	(0.013)

Ln (Average schooling)	3.105*	1.900*	2.349*
	(0.244)	(0.591)	(0.733)
Constant	2.234*	1.471	
	(0.617)	(0.932)	
WLn (Remunerations per worker)			0.017
			(0.059)
WLn (Manufacturing labor productivity)			0.047*
			(0.025)
WLn (Unemployment rate)			0.049
			(0.034)
Ln (Manufacturing exports per worker)			-0.008
			(0.010)
Ln (Manufacturing FDI per worker			0.000
			(0.008)
Ln (Average schooling)			0.012
			(0.309)
Spatial ρ			0.527
			(2.361)
Variance σ_e^2			0.006*
			(0.002)
Observations	96	96	96
R squared	0.543	0.777	0.978
Adjusted R square[b/]	0.513	0.764	0.975

Source: Prepared by the author.
Notes: *Statistically significant at the 95% confidence level
a/ In this estimation, an inverse Euclidian matrix is used.
b/ See appendix E for a graphical test of goodness of fit.

In the second column, a Generalized Method of Moments (GMM) model is presented, because of the characteristics of the model (endogeneity) and the control for persistence, with all observations at the state level. The GMM was estimated using a two-step estimation proposed by Blundell and Bond (1998). The results in (1) show that a 1% increase in productivity has an impact of 0.369% on wages, while the unemployment rate would have an impact of 0.175%. More variables were used to control for additional effects on specification. Manufacturing exports per worker have a positive impact on state wages, an increase of 1% has a positive impact of 0.080% on wages, while the impact of manufacturing FDI per worker would be -0.018%, but the latter variable is not statistically significant (that is, it is equal to zero). The years of schooling do have a positive and significant impact, as 1% in the average years of schooling of the population has an impact of 1.9% on remunerations.

Table 4.11 displays some tests conducted on GMM regression. The Arellano-Bond test for first-order serial correlation in levels is displayed in the first row. Results show that we should reject the null hypothesis of no first-order serial correlation in first differences at the 10% level. The Sargan and Hansen tests are displayed in the second and third row. Both test for validity of the instruments, at a 95% confident interval. Moreover, a graphical test for goodness of fit is displayed in Appendix E.

Table 4.11
GMM Tests: First-order autocorrelation and instrumental validity

Test	Coefficient
Arellano-Bond test forAR(1) in first differences	-1.65**
Sargan test of overidentifying restrictions	87.86*
Hansen test of overidentifying restrictions	9.51*

Source: Prepared by the author.
Notes: *Statistically significant at the 95% confidence level.
**Statistically significant at the 90% confidence level.

If the spatial structure is considered, as in equation 4.1 in the data and methodology section, and in the third specification in table 4.10, the impact obtained is a 1% increase in manufacturing labor productivity, with state remunerations growing 0.1% on average while if the average years of schooling increases by 1%, remunerations would increase by 2.34%. Both variables are statistically significant at the 5% level. Other control variables are not statistically significant.

From the estimates of the parameter Wx1, which is the spatial lag, the effect of manufacturing labor productivity (0.047%) is positive and statically significant at the 10% level. In line with the hypothesis proposed initially, an increase in the productivity of neighboring states influences remunerations.

Table 4.12
Direct, indirect, and total effects of the spatial model

Variable	Direct effects	Indirect effects	Total effects

Manufacturing remuneration per worker	0.001	0.078	0.078
	(0.003)	(0.221)	(0.222)
Manufacturing labor productivity	0.101*	0.175**	0.276*
	(0.028)	(0.101)	(0.098)
Unemployment rate	-0.004	0.187	0.183
	(0.069)	(0.139)	(0.154)
Manufacturing exports per worker	0.013	-0.024	-0.011
	(0.022)	(0.035)	(0.044)
Manufacturing FDI per worker	-0.007	-0.002	-0.009
	(0.012)	(0.033)	(0.035)
Average schooling	2.401*	0.042	2.443*
	(0.736)	(1.127)	(0.728)

Source: Prepared by the author.
Notes: [a] Statistically significant at the 95% confidence level.
[b] Statistically significant at the 90% confidence level.

The direct, indirect, and total impacts are displayed in Table 4.12. The direct effect of the manufacturing labor productivity variable on wages is positive (0.101), while the indirect effect is positive but greater (0.175). The magnitude of the total effect (0.276) indicates that the effect of manufacturing labor productivity is lesser than average schooling (2.443). This means that if state *r* increases its manufacturing labor productivity by 1%, then the manufacturing remuneration per worker in state *r* will increase on average by 0.101%, but if all-other states increase by 1% then the manufacturing remuneration per worker in state r will increase on average by 0.175%. If region *r* increases its manufacturing labor productivity by 1%, then all other states will impact manufacturing remuneration per worker by 0.276% on average.

4.8 Conclusions and policy recommendations

The different estimates of the model allow us to infer that there is a spatial structure between remunerations and manufacturing labor productivity. This is manifested both in the decrease in the magnitude of the estimator of the productivity parameter, and in that of the other estimators of the other parameters. It can be observed that the estimator of manufacturing labor productivity adopts a positive sign, in line with economic theory. It is possible to infer that a 1% increase in manufacturing labor productivity would increase wages by 0.1%, on average, in the state in question, while the spatial lag manufacturing labor productivity has an effect of 0.047% on wages. By breaking down the effects into direct and indirect, we observe that the impact of productivity on wages is positive (0.101), but the indirect impact is greater (0.175). The magnitude of the coefficient would indicate that the effect of average schooling is stronger than that of manufacturing labor productivity.

With the data for Mexico at the state level for the manufacturing industry from the Censuses published in 2009, 2014, and 2019, the relationship established by economic theory between labor productivity and remuneration is empirically confirmed. However, this result of poor wage growth in the face of productivity increases is in line with previous results for Mexico. That is, with the data series used in this work, the impact of labor productivity has a positive effect on wages, in a statistically significant way, although a slight variation is reported in the dependent variable for each unit of change in labor productivity.

This model also makes it possible to establish a significant linear relationship between the labor productivity of the country's states and local wages, as a consequence of their spatial proximity. In future research, the impact of this spatial proximity could be explored through models that allow the estimation of a non-linear relationship. Likewise, to the extent that information is available at the federal entity level or even at the municipal level, the design of models that explore the relationship between productivity and remuneration by introducing spatial variables is suggested.

The results allow us to contribute to the discussion about the positive spillover effect that labor productivity has on the territories. We see the need to develop, promote, and coordinate public policy decisions at the national and local levels that will foster labor productivity in the territories. This will have positive effects on neighboring territories in terms of income and well-being.

On the one hand, national policies could encourage the promotion of less developed territories through fiscal policies with investment incentives, support funds for Micro, Small & Medium Enterprises (MSME), purchases from and development of local suppliers, linking the most developed territories with the least developed, as well as the decentralization of functions and decision-making towards the territorial. While local public policies could promote the construction of infrastructure for greater connectivity of the territories (roads, bridges, internet, etc.), education and job training, and business networks between territories, and generate environments of cooperation, development and research that go beyond its own territory.

Chapter 5. Conclusions

These three essays show how labor productivity analysis can be enhanced by considering the spatial spillovers effects that exist between neighboring states. Spatial econometrics tools are used to estimate the convergence between states and municipalities in Mexico, analyze the decomposition of labor productivity, and, finally, examine the relationship between labor productivity and wages. In all cases, the evidence of significant spillover effects between states or municipalities is verified. Hence, spatial econometrics allow us delve into the analysis considering spillovers between geographical units.

The topics studied in this thesis are highly relevant for analyzing Mexico's recent economic development. Over the last three decades the Mexican economy has experienced modest and volatile annual growth, which is closely associated with low labor productivity growth. The importance of this dimension relies on labor productivity as the factor leading growth in some regions of Mexico. Thus, it can be seen that the manufacturing labor productivity variables converge, but territorial differences persist. Additionally, two other challenges faced by the Mexican economy are: a) high -and persistent- income inequality at the household level, and b) high -and increasing- economic and productivity gaps among Mexico's regions.

These gaps will be reduced by building infrastructure for greater territory connectivity (roads, bridges, internet, among others), linking the more developed territories with the less developed ones, as well as by decentralizing functions and decision making to the territorial level, promoting less developed territories through public and private investment, supporting funds for micro and small businesses, purchases, and local supplier development, among others. Derived from the aforementioned analysis, it can be seen that this not only has a local, but also a regional impact.

The strategy to increase labor productivity must be multidimensional since it captures the influence of many factors. Out of all the complex number of factors, the one that stood out is education. Therefore, educational levels in the most backward regions must be improved. However, there should not only be an increase in the years of education, but strengthening the strategy of quality education and job training, technical schools, promoting research networks between territories, and generating environments of cooperation, scientific development and research that go beyond politically delimited territories is recommended.

Moreover, each state has different employment, unemployment, and informal employment structures, as well as diverse labor productivities levels. In this sense, the fact that some policies work at the national level does not mean that they will also work for all regions in the same way, since structural heterogeneity exists between the different entities. For this reason, it is necessary to shape public policy adapted to the particularities of each state, taking into consideration the differences for their implementation. At the same time, regional strategies that recognize the importance of interactions between different states should be built.

Finally, we must also improve the distribution of income. During the period under study, the gap between productivity growth and wage growth was not reduced, which has contributed to maintaining or even increasing the conditions of structural inequality in Mexico. In this sense, it is not enough to generate policies to promote productivity, but it is also necessary to design and implement public policies aimed at reducing income inequality and thus contribute to overcoming the structural gaps in the region. Employment and training policies need to strengthen the relationship between labor productivity growth and remuneration. Thus, we require a better growth and an inclusive growth.

I firmly believe that studying labor productivity and its spillover effects will soon be a hot topic. Mexico has recently faced great opportunities due to geopolitical issues. Currently, the United States is relocating its production and making great investment near home, seeking to leave Asia, and China especially, and looking for diversification of the supply sources for essential inputs. Locations with high labor productivity are recipients of this new foreign direct investments (FDI). In this context, Mexico needs to understand that it has the potential to be one of the main winners in the international scenario. Hence, it is necessary to produce evidence to formulate public policy recommendations to improve Mexican labor productivity. The innovative tools we use in these essays can undoubtedly contribute to the generation of solid empirical evidence for the formulation of the necessary public policies.

APPENDIX A: Taxonomy of Spatial Econometric Models

Table A.1 Taxonomy of Spatial Econometric Models

Model	Abbreviation	Equation
Spatial Autoregressive Model	SAR	$\boldsymbol{y_{i,t} = \rho W y_{i,t} + x_{i,t}\beta + \mu_i + \varepsilon_{i,t}}$
Spatial Durbin Model	SDM	$\boldsymbol{y_{i,t} = \rho W y_{i,t} + x_{i,t}\beta + W z_{i,t} + \mu_i + \varepsilon_{i,t}}$
Spatial Autocorrelation Model	SAC	$\boldsymbol{y_{i,t} = \rho W y_{i,t} + x_{i,t}\beta + \mu_i + v_t}$ $\boldsymbol{v_t = \gamma W u_{i,t} + \varepsilon_{i,t}}$
Spatial Error Model	SEM	$\boldsymbol{y_{i,t} = x_{i,t}\beta + \mu_i + v_t}$ $\boldsymbol{v_t = \gamma W u_{i,t} + \varepsilon_{i,t}}$
Generalized Spatial Random Effects Model.	SEM	$\boldsymbol{y_{i,t} = x_{i,t}\beta + \mu_i + v_t}$ $\boldsymbol{v_t = \gamma W u_{i,t} + \varepsilon_{i,t}}$ $\boldsymbol{\mu_t = \theta W u_{i,t} + \varphi_{i,t}}$

Source: Prepared by the author, based on Belotti, Hughes & Piano (2017). Spatial panel data models using Stata, *The Stata Journal*, 17(1), pp.139.180.

Note: Where w is a spatial weight matrix. y stands for explained variables, and x and zs for explanatory variables, but $\boldsymbol{x \neq z}$. The v and epsilons are composite and idiosyncratic errors, respectively.

APPENDIX B: Castaldi's innovation-based taxonomy and Mexican codes

Table B.1

Castaldi's innovation-based taxonomy and Mexican codes in census manufacturing sector.

Type of subsector	Definition	1994 Census	1999 Census	2004 (and following) Census
Scale intensive (SI)	Includes both complex and consumer durables (food, chemicals, motor vehicles), and processed raw materials (e.g., Metal manufacturing, glass, and cement). Firms in these industries tend to be large and devote a high proportion of resources to innovation.	31. Food products, beverages, and tobacco. 35. Chemical substances, products derived from petroleum and carbon from rubber. 36. Non-metallic mineral products. Excludes petroleum and carb derivatives. * 3841. Automotive industry * 3842. Manufacture, repair and/or assembly of transportation equipment and its parts. Excludes cars and trucks.	311. Food industry. 312. Beverage and tobacco industry. 324. Manufacturing of products derived from petroleum and coal. 325. Chemical industry. 326. Plastic and rubber industry. 336. Transportation equipment manufacturing.	311. Food industry. 312. Beverage and tobacco industry. 324. Manufacture of petroleum and coal products. 325. Chemical industry. 326. Plastic and rubber industry. 336. Manufacture of transport equipment.

Supplier dominated (SD)	Industries where firms mostly produce technologically simple goods (e.g. Textiles, leather goods, pulp and paper) and have their main sources of innovation in their capital and intermediate components suppliers. For instance, firms in the textile, leather, pulp and paper industries mostly rely on innovations in the machines supplied by specialized suppliers.	32. Textiles, garments, and leather industry. 33. Paper and paper products, printing, and publishing. 34. Wood and wood products industries. Includes furniture.	313. Manufacture of textile supplies. 314. Manufacturing of textile products, except clothing. 315. Garment manufacturing. 316. Manufacturing of products of leather, fur, and substitute materials, except clothing. 321. Wood industry. 322. Paper industry. 323. Printing and related industries. 337. Manufacture of furniture and related products.	313. Manufacture of textile inputs and textile finishing. 314. Manufacture of textile products except clothing. 315. Garment manufacturing. 316. Tanning and finishing of leather and fur and manufacture of leather products, fur and substitute materials. 321. Wood industry. 322. Paper industry. 323. Printing and related industries 337. Manufacture of furniture mattresses and blinds
Science-based (SB)	Industries include electronics, drugs, bioengineering and all those industries where innovation is directly linked to advances in pure and applied sciences.	38. Metal products, machinery and equipment. Includes surgical instruments: * 3823. Manufacture and/or assembly of office machines, calculation and computer processing. * 3831. Manufacture and/or assembly of machinery, equipment and electrical accessories. Includes for the generation of electrical energy. * 3832. Manufacture and/or assembly of radio, television, communications and medical electronic	334 manufacturing of computer, communication, measurement equipment and other equipment, components, and accessories. 335. Manufacture of electrical generation equipment and appliances, and electrical accessories. 339. Other manufacturing industries.	334. Manufacturing of computer equipment. 335. Manufacture of electrical apparatus accessories and electrical power generation equipment. 339. Other manufacturing industries.

		equipment. * 3833. Manufacture and/or assembly of appliances and accessories for domestic use. Excludes electronics. * 3850. Manufacture, repair and/or assembly of precision instruments and equipment. Includes surgical instruments. Excludes electronics. * 39. Other manufacturing industries.		
Specialized suppliers (SS)	Industries include equipment building, design, and mechanical engineering (e.g. Machines and machine-tools production), where innovation typically stems from informal activities. Firms in this group tend to be small.	37. Basic metal industries. 38. Metal products, machinery and equipment. Includes surgical instruments. * 3812. Manufacture of metal structures, tanks and industrial boilers. Even blacksmithing. * 3813. Manufacture and repair of metal furniture. * 3814. Manufacture of other metallic products. Excludes machinery and equipment. * 3821. Manufacture, repair and/or assembly of machinery and equipment for specific purposes, with or without an integrated	327. Manufacture of products based on non-metallic minerals. 331. Basic metallic industries. 332. Manufacturing of metallic products. 333. Manufacture of machinery and equipment.	327. Manufacture of products based on non-metallic minerals. 331. Basic metal industries. 332. Manufacture of metal products. 333. Manufacture of machinery and equipment.

	electric motor. Includes agricultural machinery. * 3822. Manufacture, repair and/or assembly of machinery and equipment for general uses, with or without an integrated electric motor. Includes weapons.	

Source: Prepared by author, based on Castaldi, C. (2009). The relative weight of manufacturing and services in Europe: An innovation perspective. Technological Forecasting & Social Change, 76(6), pp. 709-722 and Instituto Nacional de Estadísticas y Geografía (INEGI) (2009). Censos Económicos 2009 [online], Aguascalientes, México. Retrieved from: https://www.inegi.org.mx/programas/ce/2009/; INEGI (2014). Censos Económicos 2014 [online]. Retrieved from https://www.inegi.org.mx/programas/ce/2014/). Aguascalientes, México; and INEGI (2019). Censos Económicos 2019 [online]. Retrieved from https://www.inegi.org.mx/programas/ce/2019/), Aguascalientes, México.

APPENDIX C: Results from classical shift-share analysis for the science-based, specialized supplier and supplier-dominated sector.

Figure C.1 presents results from the classical shift-share equation for the science-based sector. The science-based sector includes firms such as electronics, drugs, bioengineering and all those where innovation is directly linked to advances in pure and applied sciences (see Appendix B). In this sector, companies produce a relatively high proportion of their own inputs, innovate in their processes and technology, as well as inputs and technology for other sectors. These companies are also relatively large (Pavitt, 1984).

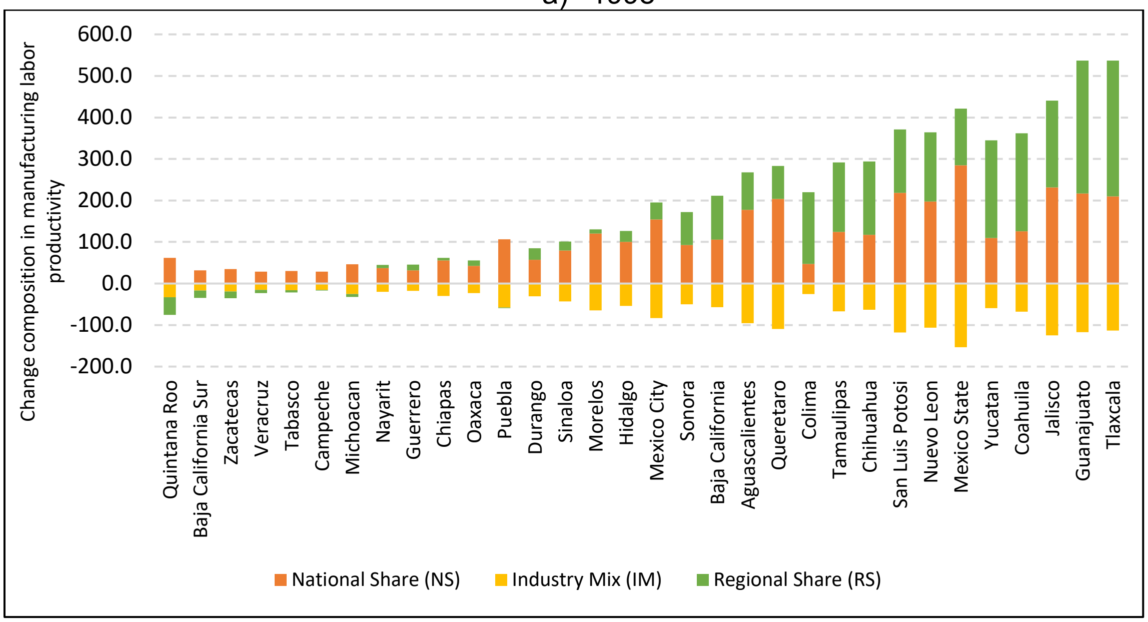
For the 1993-1998 change, Tlaxcala, Guanajuato, and Yucatan are top in the science-based sector. Valdez (2018) shows that, between 1993 and 2013, the Tlaxcala-Apizaco metropolitan area reported a positive Spatial Net Regional Effect (SNRE) and Spatial Distribution Effect (SDE), and that the Puebla-Tlaxcala corridor has a positive effect in the inputs for the chemical and petrochemical industry. Also in those years, Volkswagen, in Puebla, developed a supply chain along the Puebla-Tlaxcala corridor. The regional share is the most important component in this short period, while industry mix plays a negative role. In 2003, Durango, Baja California Sur, and San Luis Potosi were at the top of the list. Durango and San Luis Potosi belong to a region where the gross value is dominated by construction, processed foods, petroleum derivatives, and machinery and equipment (López Morales, 2019). Baja California Sur does not distinguish among manufacturers, but Navarro Alarcón, Dávila Flores and Valdés Ibarra (2019) highlight that this state has the greatest GDP index growth between 2003 and 2015. Nevertheless, Baja California Sur has the smallest contribution among all states. Regional share is the most important component, while the sectoral effect is minuscule.

By 2008, Hidalgo, Coahuila, and Mexico State came first in line. Hidalgo and Mexico State belong to the central regions, while Coahuila is near the border and belongs to the northern region. Central region has a reconversion process were Mexico City loss industrial activity in favor of states nearby and northern region. Regional share becomes the greatest part of the manufacturing productivity change, positively and negatively related. For 2013, Tlaxcala, San Luis Potosi, and Colima were at the front in this sector list. Colima, which has not yet been discussed, belongs to a region where, between 2003 and 2016, the regional manufacturing dynamics surpassed that of the country (Valdés Ibarra & Dávila Flores, 2019). In addition, the GFC recovery phase was led by the sectoral mix in this sector.

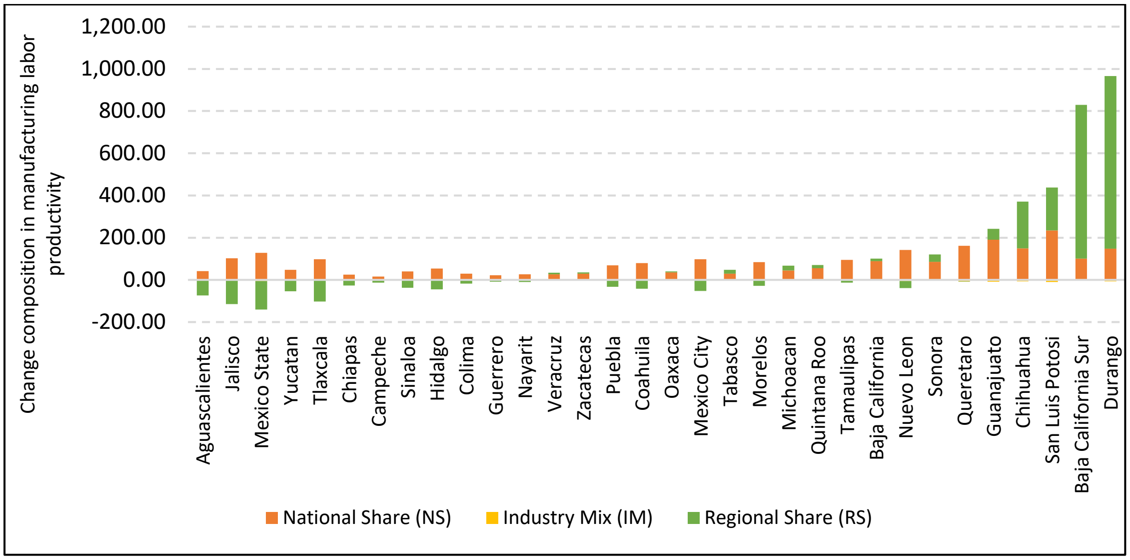
Finally, for 2008, Zacatecas, Durango, and Hidalgo led change for the manufacturing labor productivity, science-based sector. Zacatecas and Durango belong to a region where the non-oil mining, oil and coal derivatives, and wood industry sectors produce less than the national average in 2003, constituting key sectors for 2013 and so on (López Morales, 2019). Regional structure constitutes the greatest share of the change in manufacturing labor productivity.

Figure C.1
Mexico: manufacturing labor productivity performance across censuses, classical shift-share, science-based sector, 1998-2018
(in thousands of pesos of 2018)

a) 1998

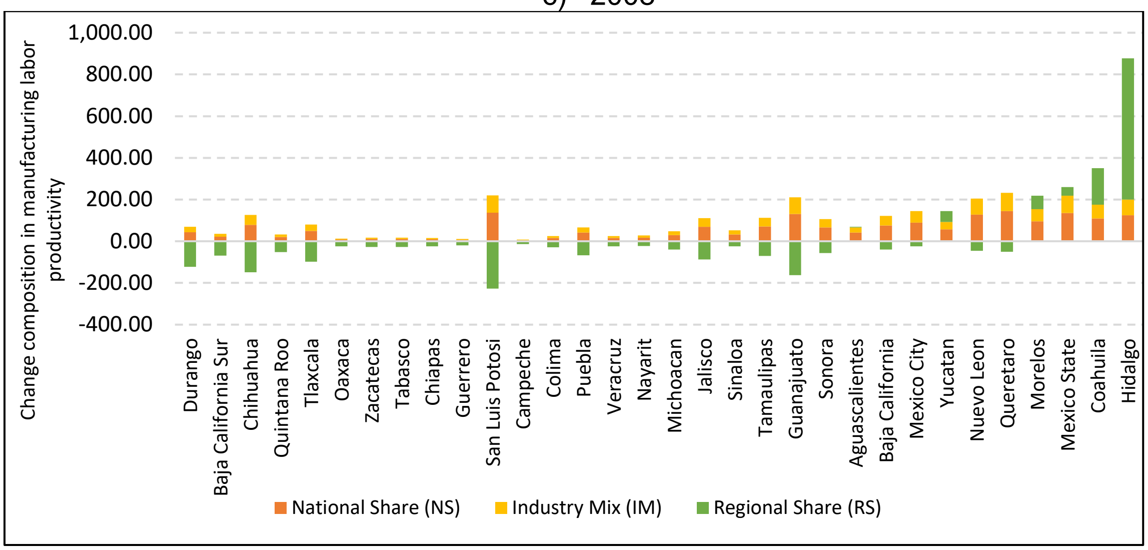


b) 2003



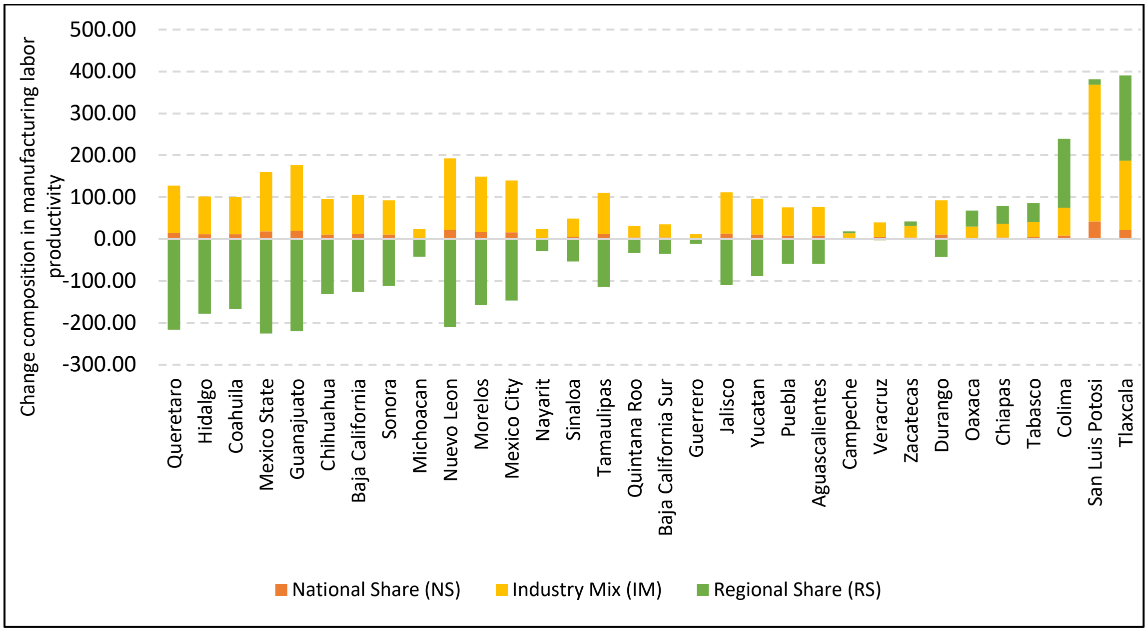
Change composition in manufacturing labor productivity
1,200.00
1,000.00
800.00
600.00
400.00
200.00
0.00
-200.00
Aguascalientes
Jalisco
Mexico State
Yucatan
Tlaxcala
Chiapas
Campeche
Sinaloa
Hidalgo
Colima
Guerrero
Nayarit
Veracruz
Zacatecas
Puebla
Coahuila
Oaxaca
Mexico City
Tabasco
Morelos
Michoacan
Quintana Roo
Tamaulipas
Baja California
Nuevo Leon
Sonora
Queretaro
Guanajuato
Chihuahua
San Luis Potosi
Baja California Sur
Durango
National Share (NS)
Industry Mix (IM)
Regional Share (RS)

c) 2008

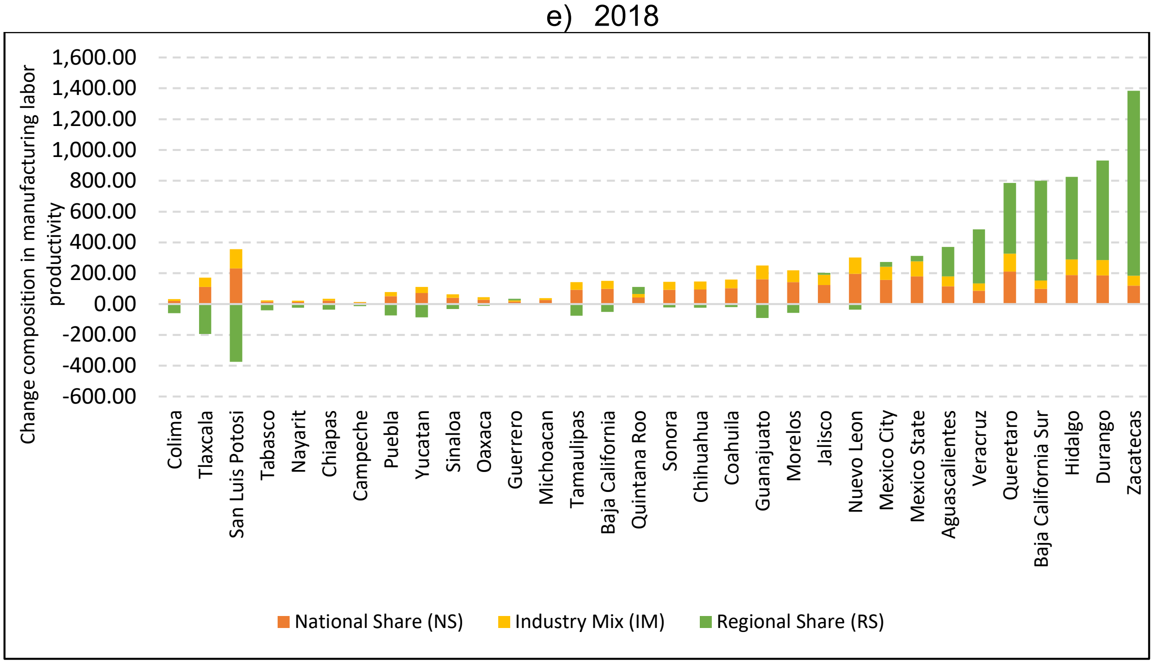


Change composition in manufacturing labor productivity
1,000.00
800.00
600.00
400.00
200.00
0.00
-200.00
-400.00
Durango
Baja California Sur
Chihuahua
Quintana Roo
Tlaxcala
Oaxaca
Zacatecas
Tabasco
Chiapas
Guerrero
San Luis Potosi
Campeche
Colima
Puebla
Veracruz
Nayarit
Michoacan
Jalisco
Sinaloa
Tamaulipas
Guanajuato
Sonora
Aguascalientes
Baja California
Mexico City
Yucatan
Nuevo Leon
Queretaro
Morelos
Mexico State
Coahuila
Hidalgo
National Share (NS)
Industry Mix (IM)
Regional Share (RS)

d) 2013



e) 2018



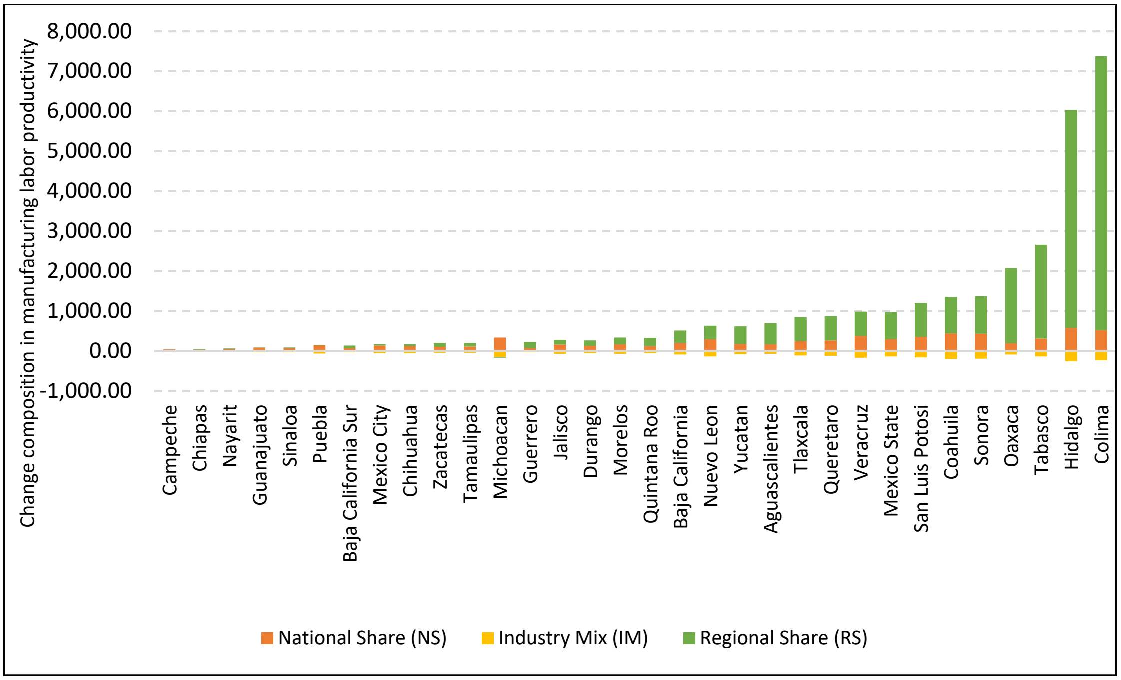
Source: Prepared by the author.

Figure C.2. depicts the manufacturing labor productivity performance using a classical shift-share analysis for the specialized supplier sectors. This sector includes firms that engage in the manufacture and design of industrial and mechanical equipment, and mechanical engineering (see Appendix B). Usually, the size of these firms is small relative to other sectors (Castaldi, 2009).

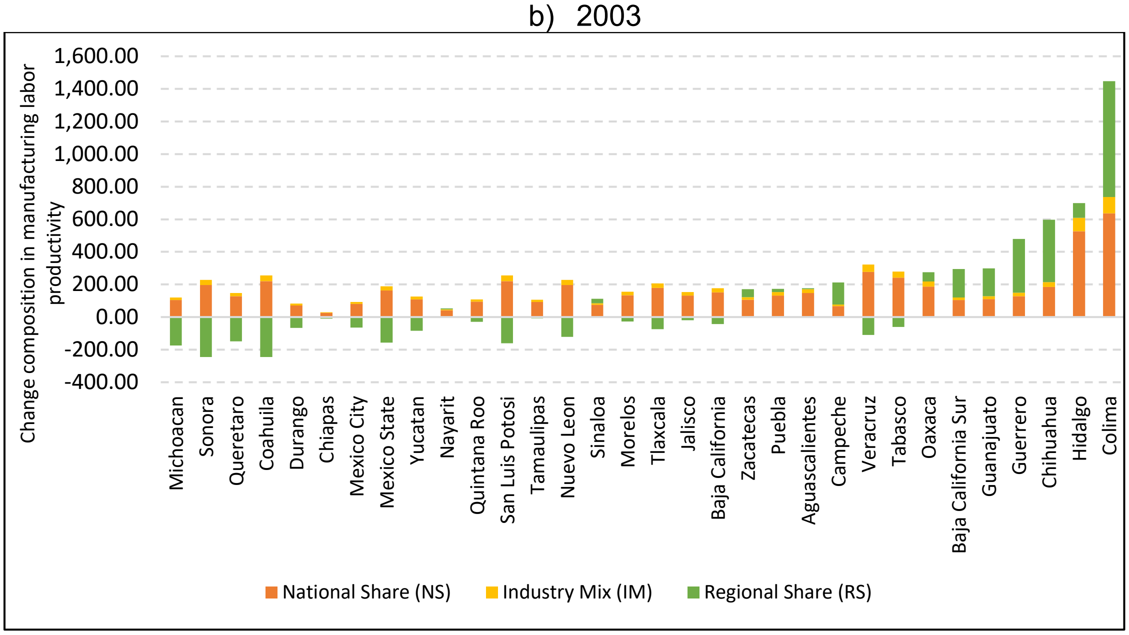
For the 1993-1998 change, Colima, Hidalgo, and Tabasco are the states with the greatest change. Díaz Bautista (2017) identifies these states as having increased their participation in national manufacturing from the 60s to 90s. Hidalgo belongs to the new industrialized periphery in the Central region, while Colima and Tabasco are newcomers. Regional shares constitute the most important component of the manufacturing labor productivity change. For the 1998 to 2003 change, Colima and Hidalgo remains on top, along with Chihuahua. The regional share becomes the principal component of the manufacturing labor productivity performance, positively or negatively related. However, industry mix is always a positive component in its performance for this period.

In 2008, Michoacan, Sonora and Veracruz are at the top of this composition change. The regional part drives the performance of the change in manufacturing labor productivity. For the 2013 snapshot, Guanajuato, Coahuila, and Yucatan are the three principal states at the top of the list of the manufacturing labor productivity change. Regional share plays a negative role in almost all the states. The industry mix leads the recovery from the GFC in this sector. Finally, in 2018, Colima, Tabasco, and Zacatecas come first on the list of the manufacturing labor productivity change. The regional share is the greatest component driving the change.

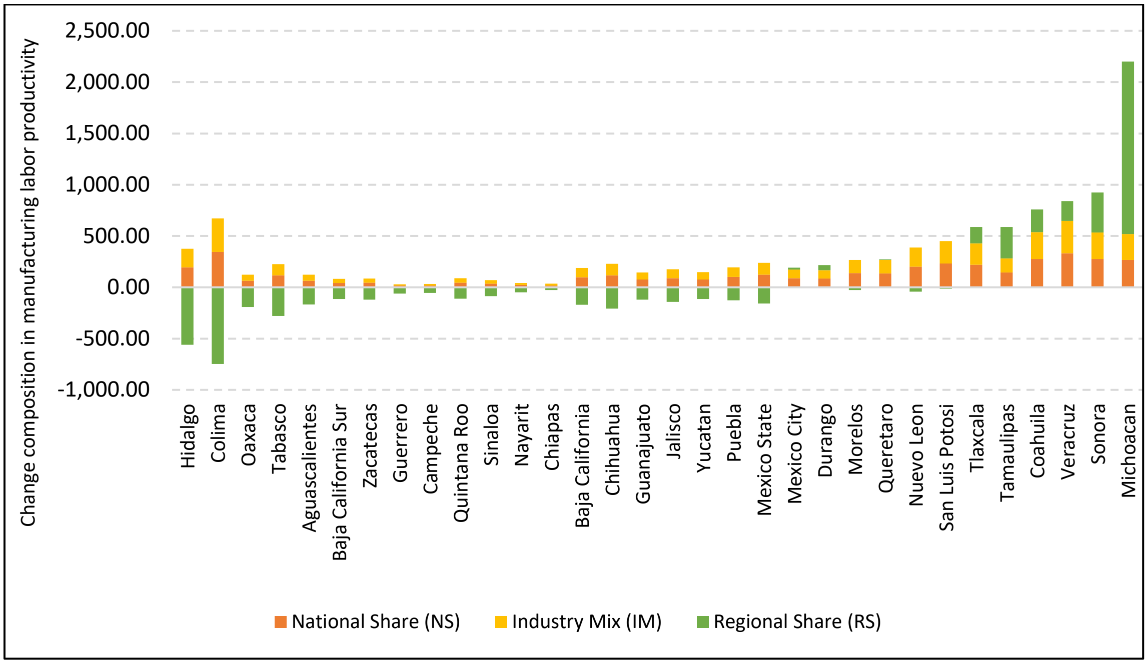
Figure C.2
Mexico: manufacturing labor productivity performance across censuses, classical shift-share, specialized supplier sector, 1998-2018
(in thousands of pesos of 2018)
a) 1998


Change composition in manufacturing labor productivity
8,000.00
7,000.00
6,000.00
5,000.00
4,000.00
3,000.00
2,000.00
1,000.00
0.00
-1,000.00
Campeche
Chiapas
Nayarit
Guanajuato
Sinaloa
Puebla
Baja California Sur
Mexico City
Chihuahua
Zacatecas
Tamaulipas
Michoacan
Guerrero
Jalisco
Durango
Morelos
Quintana Roo
Baja California
Nuevo Leon
Yucatan
Aguascalientes
Tlaxcala
Queretaro
Veracruz
Mexico State
San Luis Potosi
Coahuila
Sonora
Oaxaca
Tabasco
Hidalgo
Colima
National Share (NS)
Industry Mix (IM)
Regional Share (RS)

b) 2003

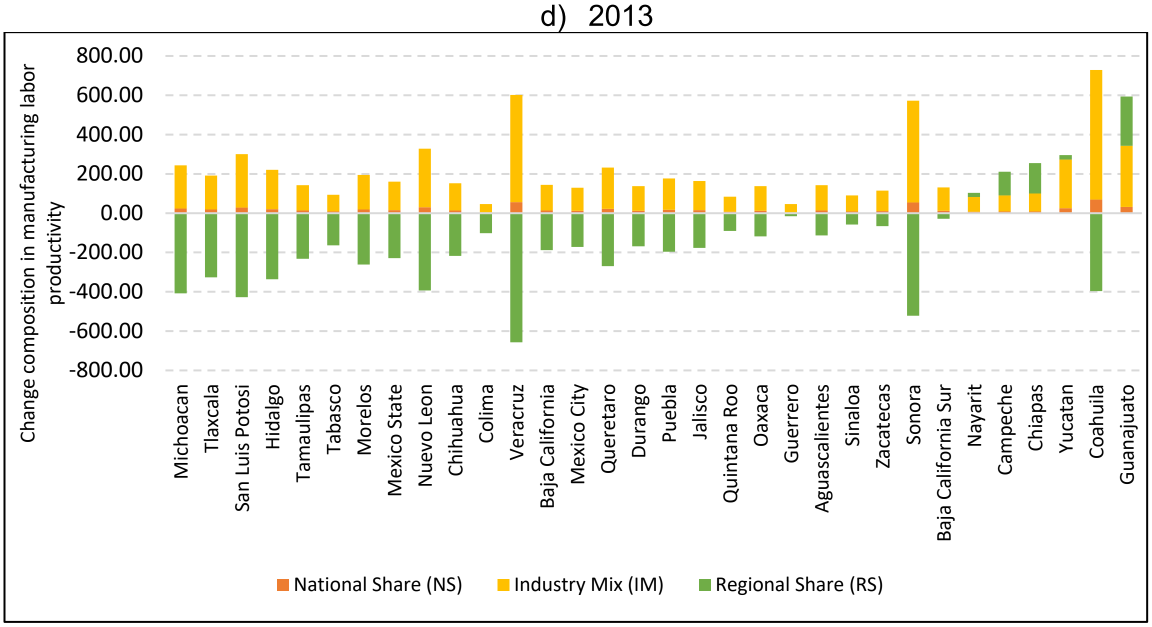

Change composition in manufacturing labor productivity
1,600.00
1,400.00
1,200.00
1,000.00
800.00
600.00
400.00
200.00
0.00
-200.00
-400.00
Michoacan
Sonora
Queretaro
Coahuila
Durango
Chiapas
Mexico City
Mexico State
Yucatan
Nayarit
Quintana Roo
San Luis Potosi
Tamaulipas
Nuevo Leon
Sinaloa
Morelos
Tlaxcala
Jalisco
Baja California
Zacatecas
Puebla
Aguascalientes
Campeche
Veracruz
Tabasco
Oaxaca
Baja California Sur
Guanajuato
Guerrero
Chihuahua
Hidalgo
Colima
National Share (NS)
Industry Mix (IM)
Regional Share (RS)

c) 2008



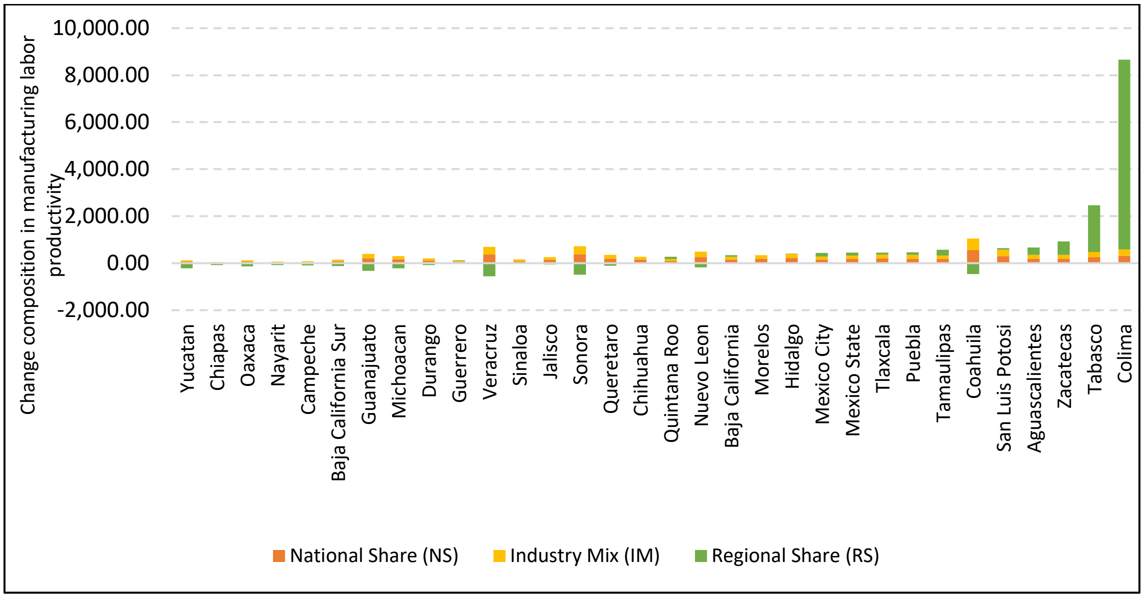
Change composition in manufacturing labor productivity
2,500.00
2,000.00
1,500.00
1,000.00
500.00
0.00
-500.00
-1,000.00
Hidalgo
Colima
Oaxaca
Tabasco
Aguascalientes
Baja California Sur
Zacatecas
Guerrero
Campeche
Quintana Roo
Sinaloa
Nayarit
Chiapas
Baja California
Chihuahua
Guanajuato
Jalisco
Yucatan
Puebla
Mexico State
Mexico City
Durango
Morelos
Queretaro
Nuevo Leon
San Luis Potosi
Tlaxcala
Tamaulipas
Coahuila
Veracruz
Sonora
Michoacan
National Share (NS)
Industry Mix (IM)
Regional Share (RS)

d) 2013



Change composition in manufacturing labor productivity
800.00
600.00
400.00
200.00
0.00
-200.00
-400.00
-600.00
-800.00
Michoacan
Tlaxcala
San Luis Potosi
Hidalgo
Tamaulipas
Tabasco
Morelos
Mexico State
Nuevo Leon
Chihuahua
Colima
Veracruz
Baja California
Mexico City
Queretaro
Durango
Puebla
Jalisco
Quintana Roo
Oaxaca
Guerrero
Aguascalientes
Sinaloa
Zacatecas
Sonora
Baja California Sur
Nayarit
Campeche
Chiapas
Yucatan
Coahuila
Guanajuato
National Share (NS)
Industry Mix (IM)
Regional Share (RS)

e) 2018



Source: Prepared by the author.

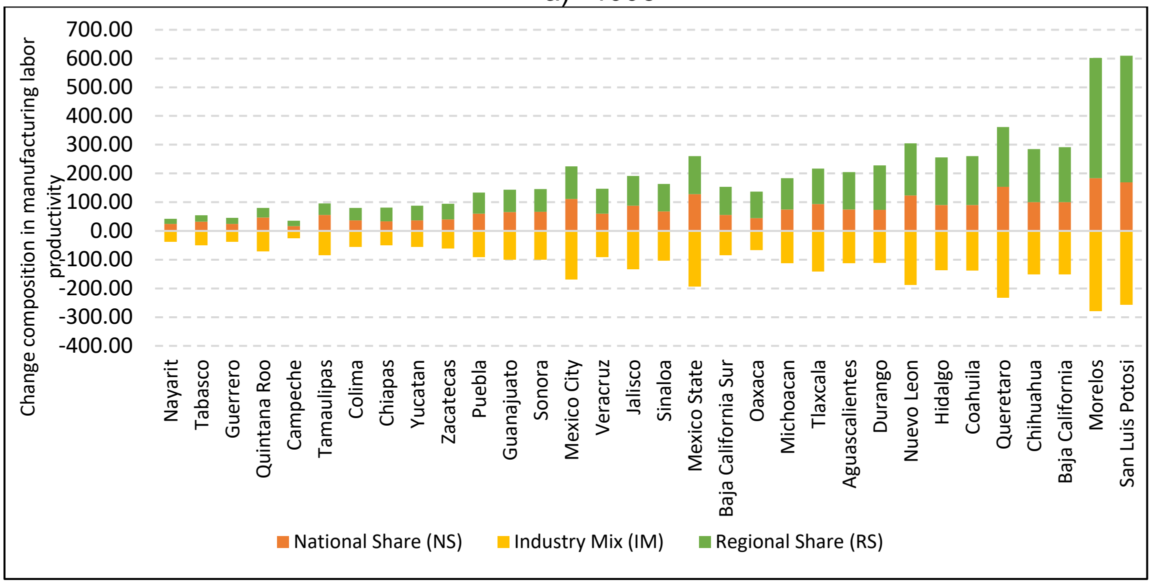
Figure C.3 shows the manufacturing labor productivity performance using a classical shift-share analysis for the supplier-dominated sector (see Appendix B). Suppliers are the innovation source in this sector. This segment includes firms in traditional sectors. These firms are relatively small and technological capabilities are the lowest compared to other sectors (Pavitt, 1984).

For the 1993-1998 change period, San Luis Potosi, Morelos, and Baja California are at the top. As stated beforehand, these states come from a period of redistribution of industrialization where Mexico City loses and the periphery and north region gain. The regional share becomes the most important part. In 2003, San Luis Potosi, Morelos, and Baja California are at the top, and the regional share is positively related to the change, but the industry mix is negative. For 2008, Mexico City, Coahuila, and Hidalgo display the greatest changes for this sector. The composition of the change is similar to the previous period: the regional share is huge and positive, the industry mix is huge and negative, but the national share becomes positive.

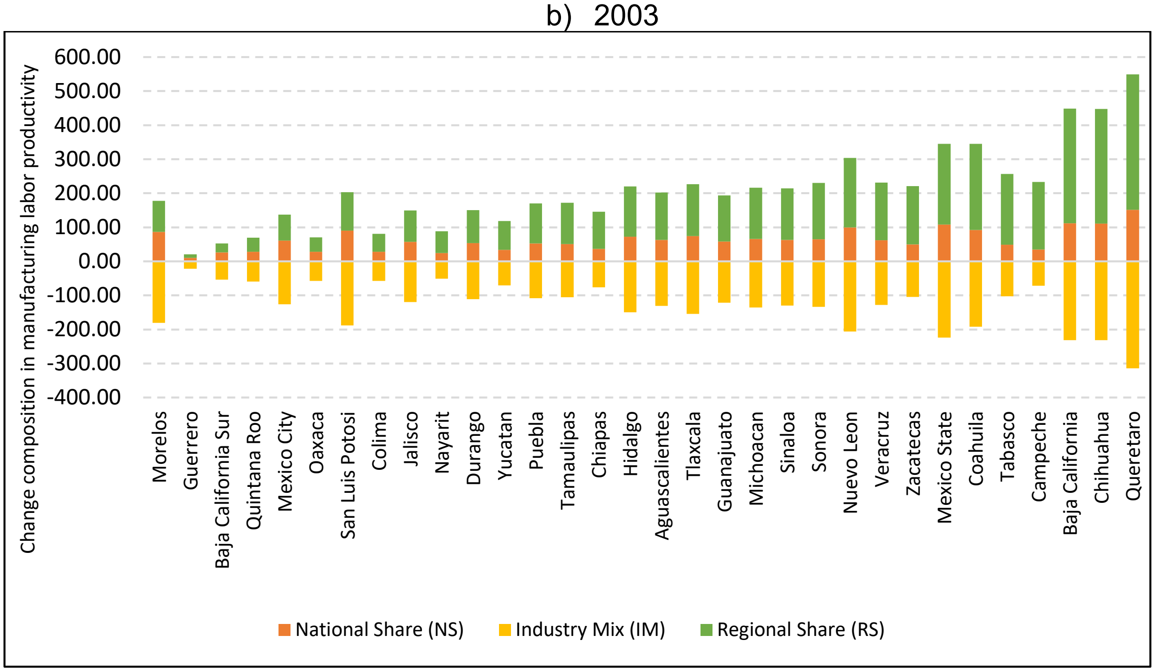
Zacatecas, Veracruz, and Queretaro are the top three in the 2008 - 2013 change. Regional share becomes the most important component and is positive for all the states. In contrast, the industry mix is negative in all cases. Finally, Baja California, Tamaulipas, and Chihuahua are at top in 2018. The change composition shows that regional share is the most important component, above industry mix, and is positive in relation to the change.

Figure C.3
Mexico: manufacturing labor productivity performance across censuses, classical shift-share, suppliers dominated sector, 1998-2018
(in thousands of pesos of 2018)

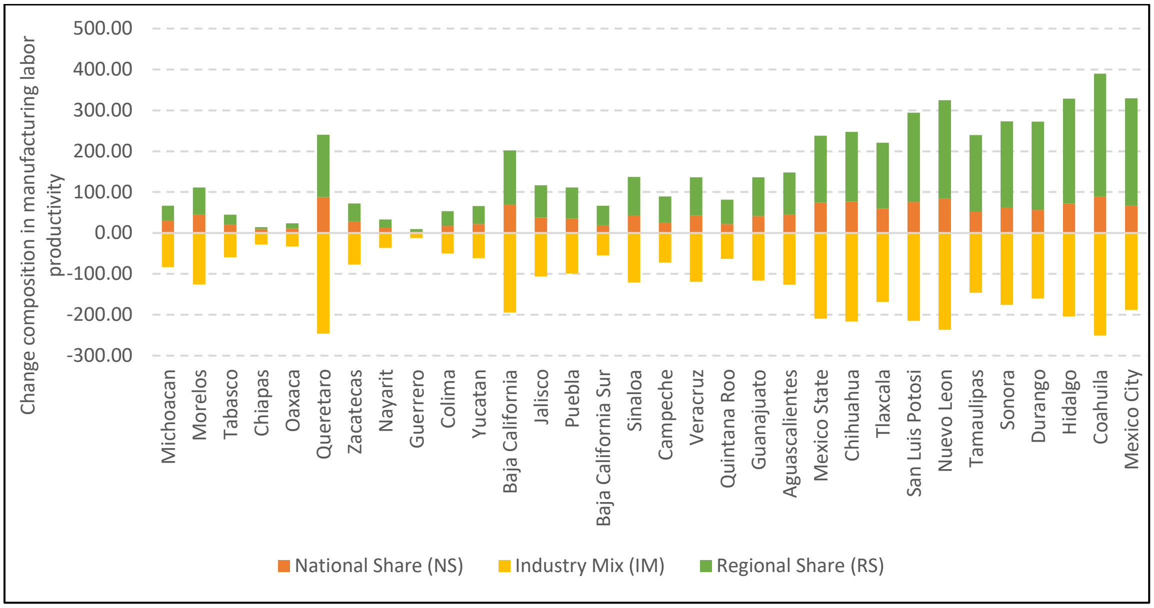
a) 1998



b) 2003

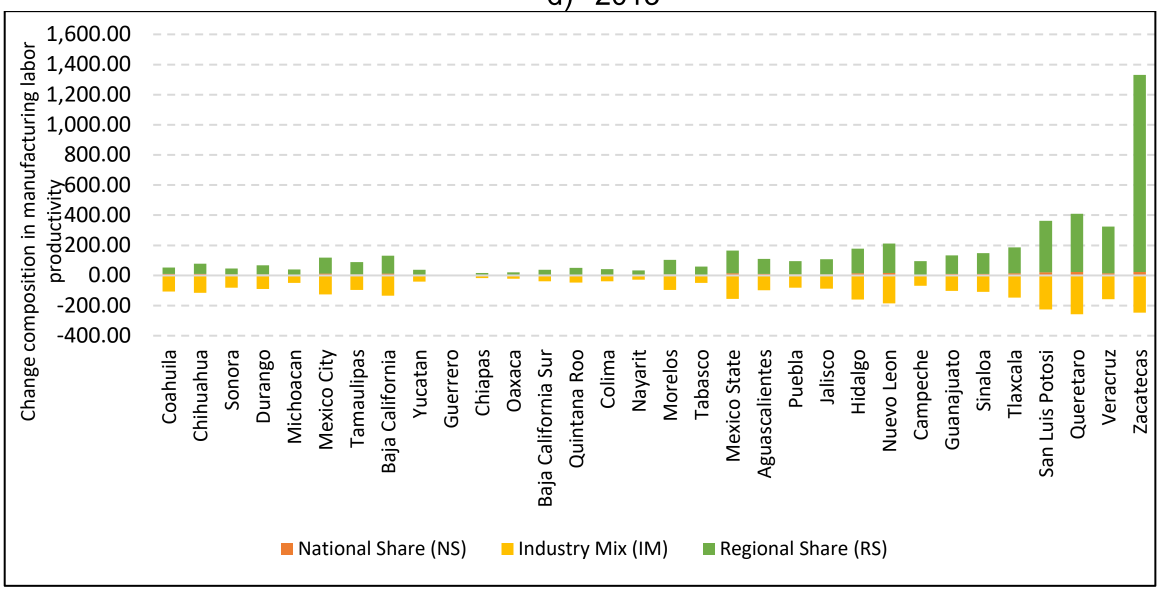


c) 2008



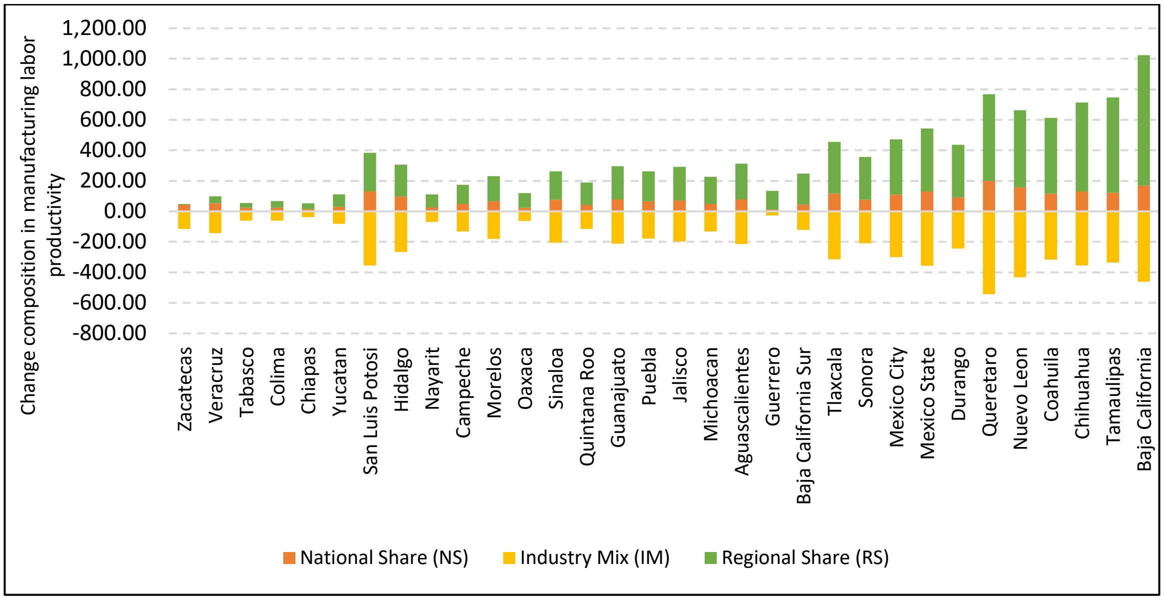
500.00
400.00
300.00
200.00
100.00
0.00
-100.00
-200.00
-300.00
Change composition in manufacturing labor productivity
Michoacan
Morelos
Tabasco
Chiapas
Oaxaca
Queretaro
Zacatecas
Nayarit
Guerrero
Colima
Yucatan
Baja California
Jalisco
Puebla
Baja California Sur
Sinaloa
Campeche
Veracruz
Quintana Roo
Guanajuato
Aguascalientes
Mexico State
Chihuahua
Tlaxcala
San Luis Potosi
Nuevo Leon
Tamaulipas
Sonora
Durango
Hidalgo
Coahuila
Mexico City
National Share (NS)
Industry Mix (IM)
Regional Share (RS)

d) 2013



1,600.00
1,400.00
1,200.00
1,000.00
800.00
600.00
400.00
200.00
0.00
-200.00
-400.00
Change composition in manufacturing labor productivity
Coahuila
Chihuahua
Sonora
Durango
Michoacan
Mexico City
Tamaulipas
Baja California
Yucatan
Guerrero
Chiapas
Oaxaca
Baja California Sur
Quintana Roo
Colima
Nayarit
Morelos
Tabasco
Mexico State
Aguascalientes
Puebla
Jalisco
Hidalgo
Nuevo Leon
Campeche
Guanajuato
Sinaloa
Tlaxcala
San Luis Potosi
Queretaro
Veracruz
Zacatecas
National Share (NS)
Industry Mix (IM)
Regional Share (RS)

e) 2018



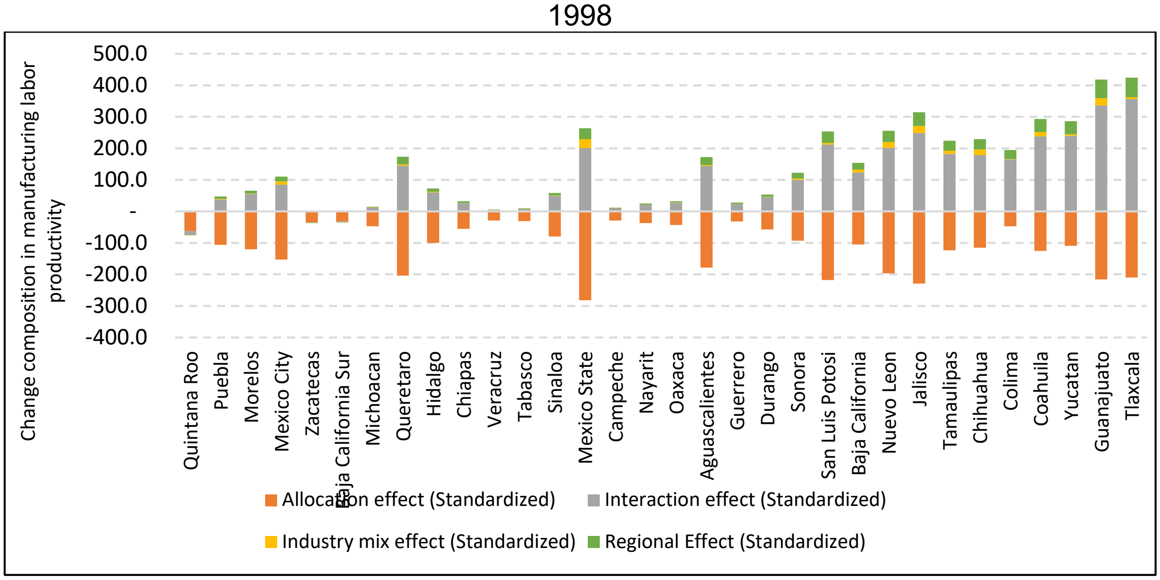
Source: Prepared by author.

APPENDIX D: Results from the multifactor partitioning shift-share analysis for the science-based, specialized supplier and supplier-dominated sector.

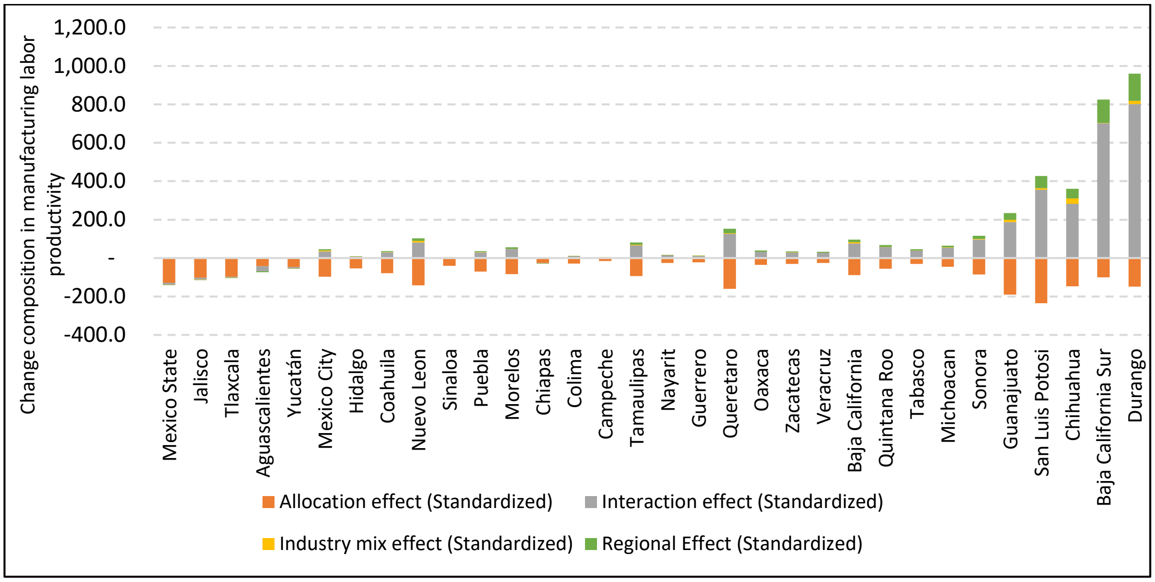
Figure D.1 shows the multifactor partitioning for the science-based sector. In the change period 1994-1998, the allocation effect was greater than regional effect. This effect indicates that manufacturing labor productivity growth is due to specialization. This seems to occur in all periods, except for 2013, when regional becomes negative for some states and appears to be more volatile than in other years.

Importantly, throughout the periods shown here: when the business cycle is positive, states located in the central, central north, and northern regions perform better. This is the case in 1998, 2003, and 2018. But, when crises or recovery periods are depicted, states located in the south or even in central regions perform better, such as in 2008 and 2013. A cofounding factor would be that this sector linked these states to international markets.

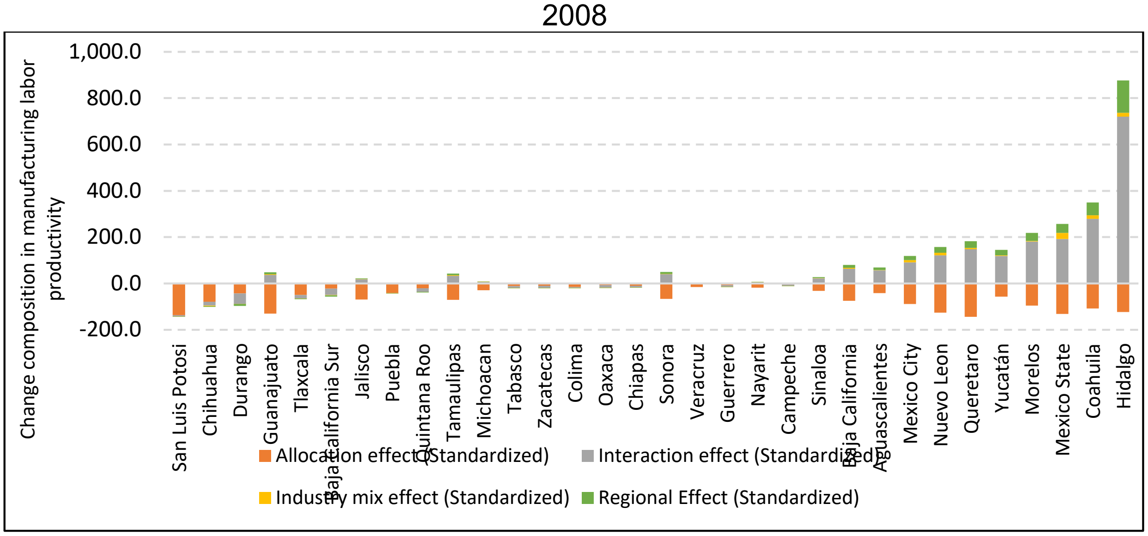
Figure D.1
Mexico: manufacturing labor productivity performance across censuses, multifactor partitioning, science-based sector, 1998-2018
(in thousands of pesos of 2018)
1998



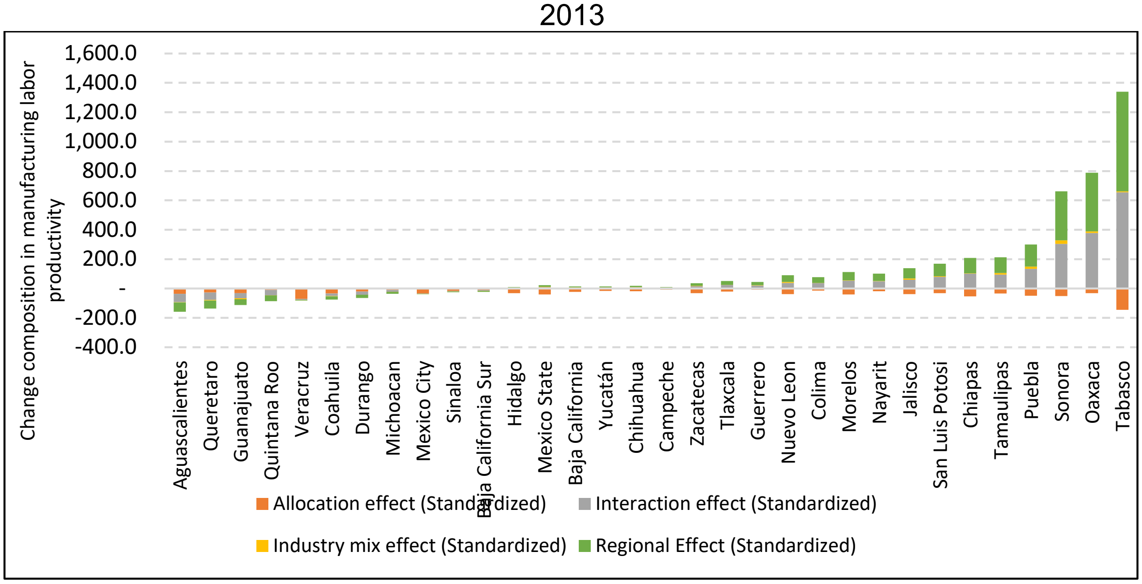
2003



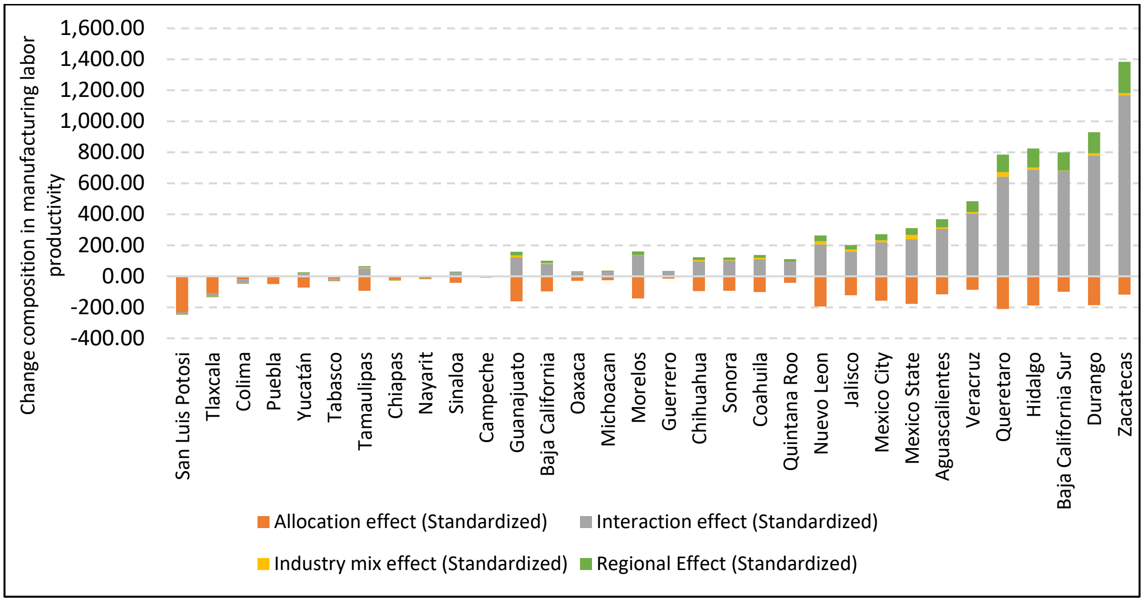
2008



2013



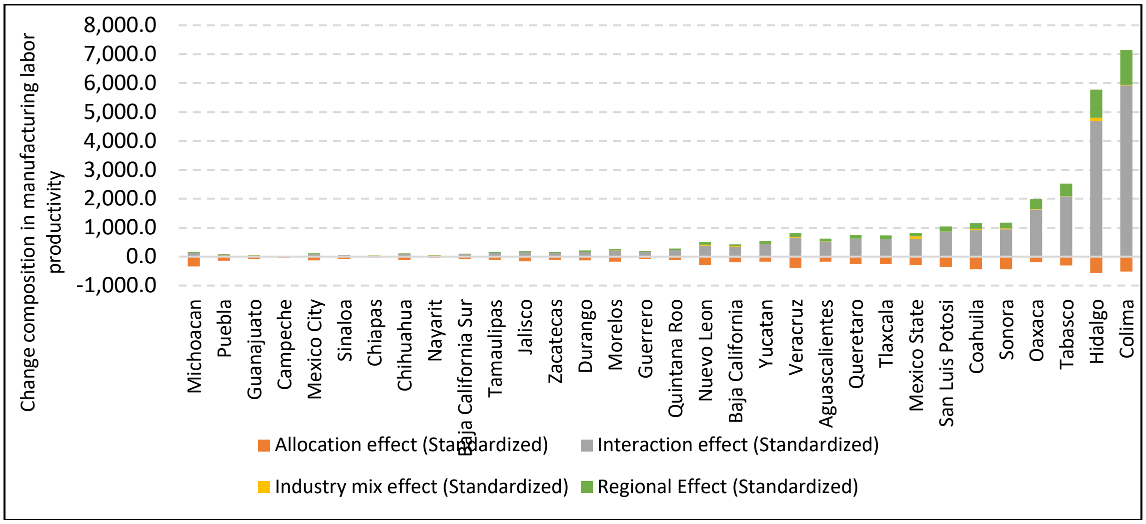
2018



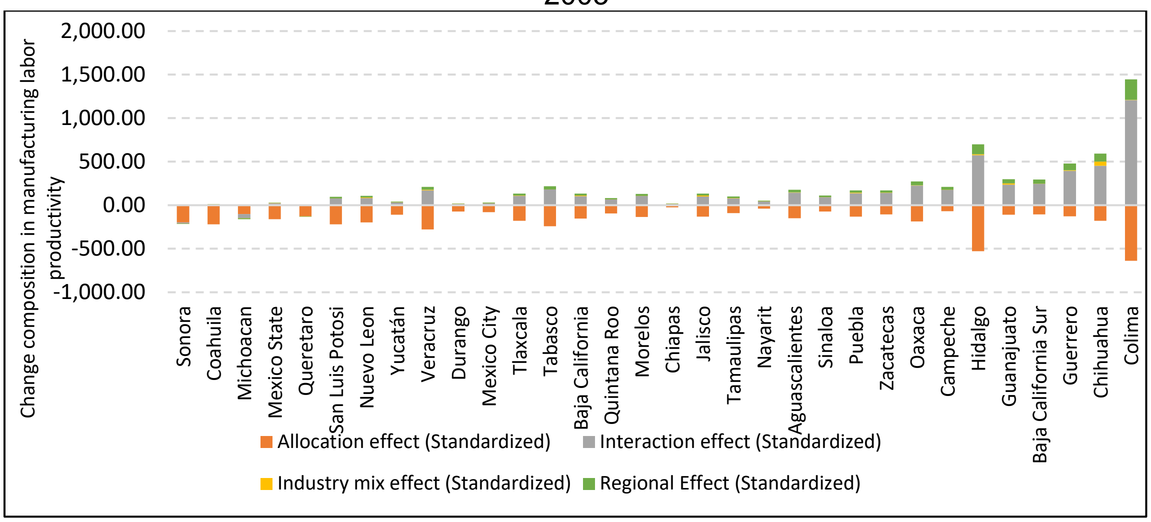
Source: Prepared by author.

Figure D.2 shows the multifactor shift-share for the most traditional sector: specialized suppliers. The allocation effect appears to be the same size as the regional effect in 1998, 2013 and 2018, but greater in 2003 and 2008. The regional and sectoral effects diminish over time. If we compare this decomposition analysis with the classical one, the regional effects play a minor role in manufacturing labor productivity.

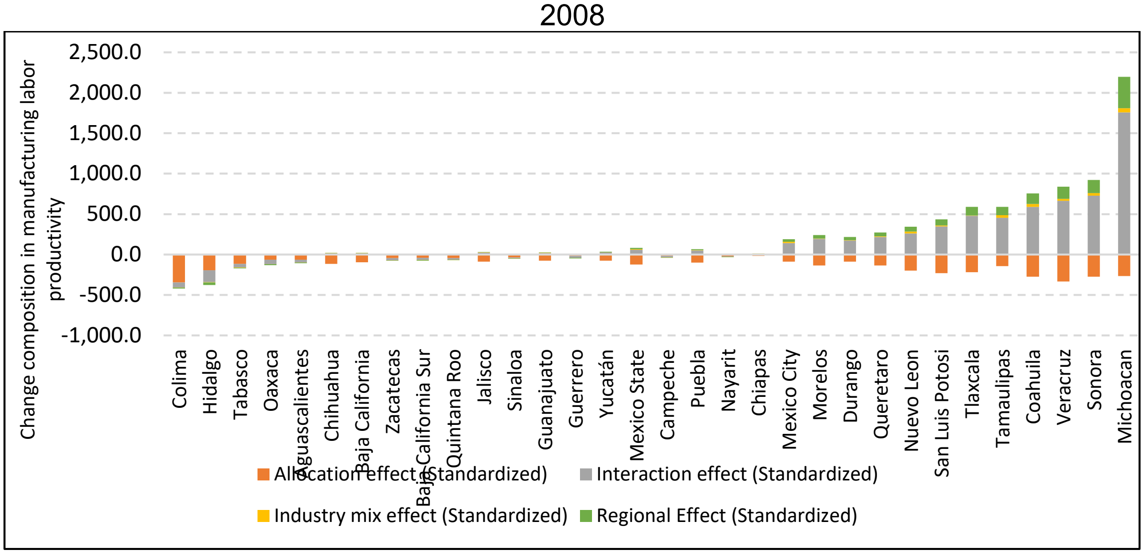
Figure D.2
Mexico: manufacturing labor productivity performance across censuses, multifactor partitioning, specialized supplier sector, 1998-2018
(in thousands of pesos of 2018)
1998



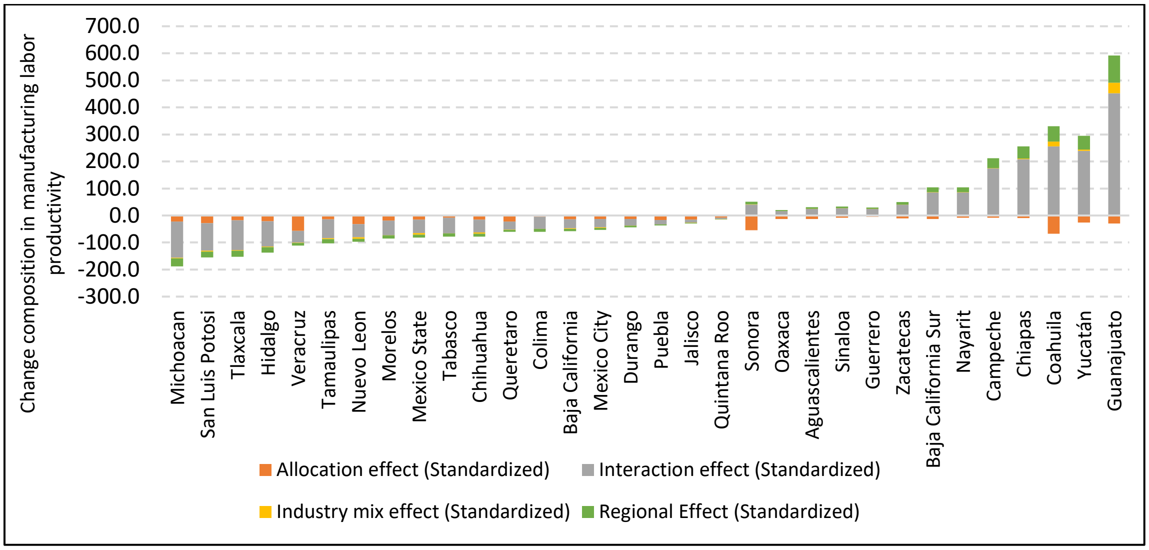
2003



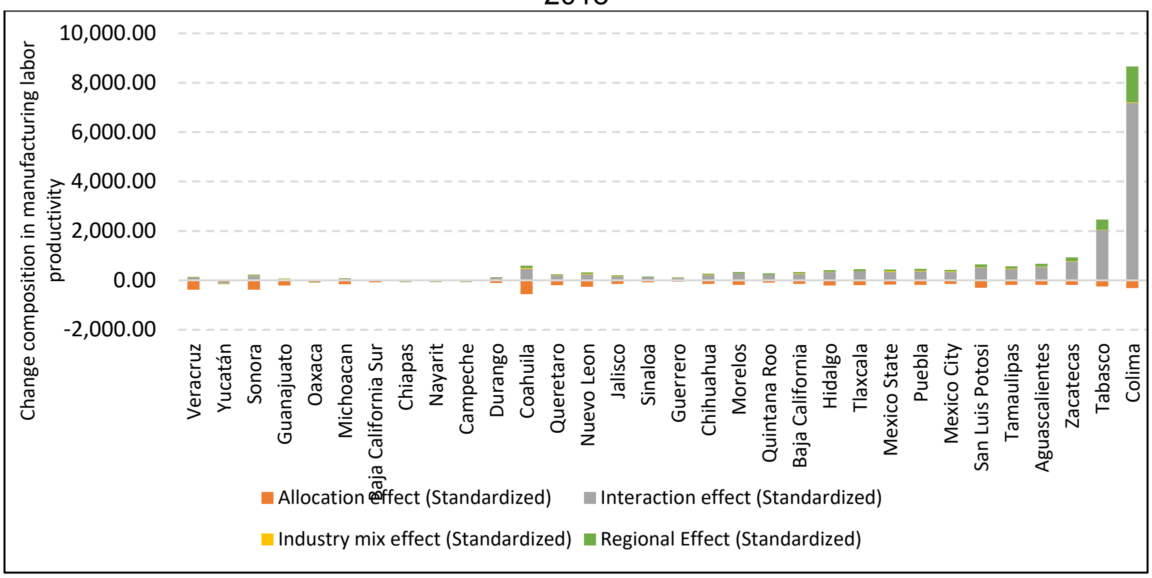
2008



2013



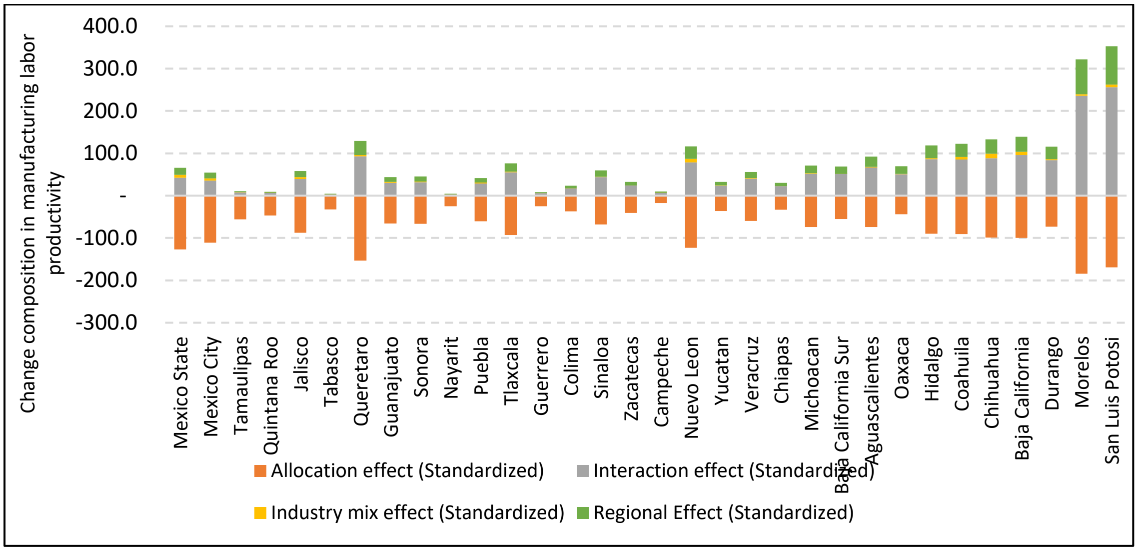
2018



Source: Prepared by author.

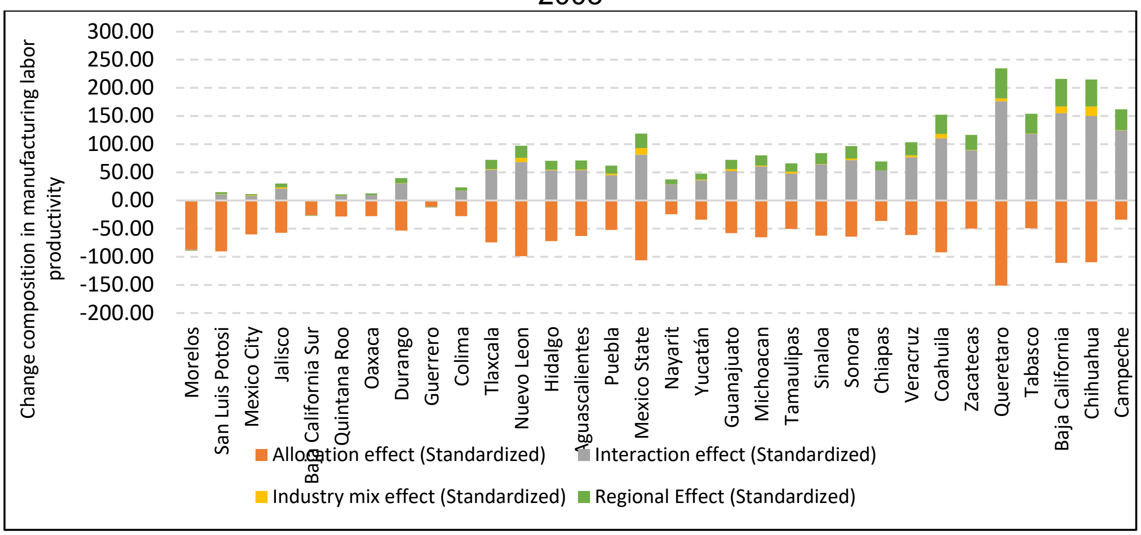
Figure D.3 shows the multifactor shift-share for the supplier-dominated sector. The allocation effect is greater than regional effects, in magnitude. The regional and sectoral effects are diminishing over time, except in 2013. If we compare this decomposition analysis with the classical analysis, here the regional effects play a minor role in manufacturing labor productivity.

Figure D.3
Mexico: manufacturing labor productivity performance across censuses, multifactor partitioning, suppliers dominated sector, 1998-2018
(in thousands of pesos of 2018)
1998



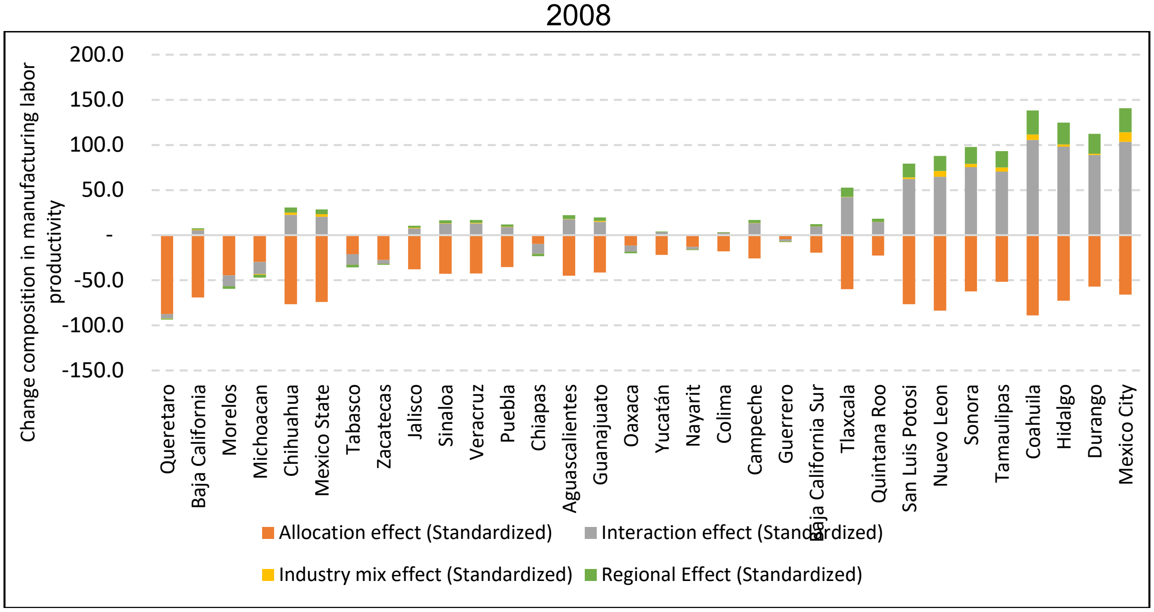
Change composition in manufacturing labor productivity
400.0
300.0
200.0
100.0
-
-100.0
-200.0
-300.0
Mexico State
Mexico City
Tamaulipas
Quintana Roo
Jalisco
Tabasco
Queretaro
Guanajuato
Sonora
Nayarit
Puebla
Tlaxcala
Guerrero
Colima
Sinaloa
Zacatecas
Campeche
Nuevo Leon
Yucatan
Veracruz
Chiapas
Michoacan
Baja California Sur
Aguascalientes
Oaxaca
Hidalgo
Coahuila
Chihuahua
Baja California
Durango
Morelos
San Luis Potosi
Allocation effect (Standardized)
Interaction effect (Standardized)
Industry mix effect (Standardized)
Regional Effect (Standardized)

2003



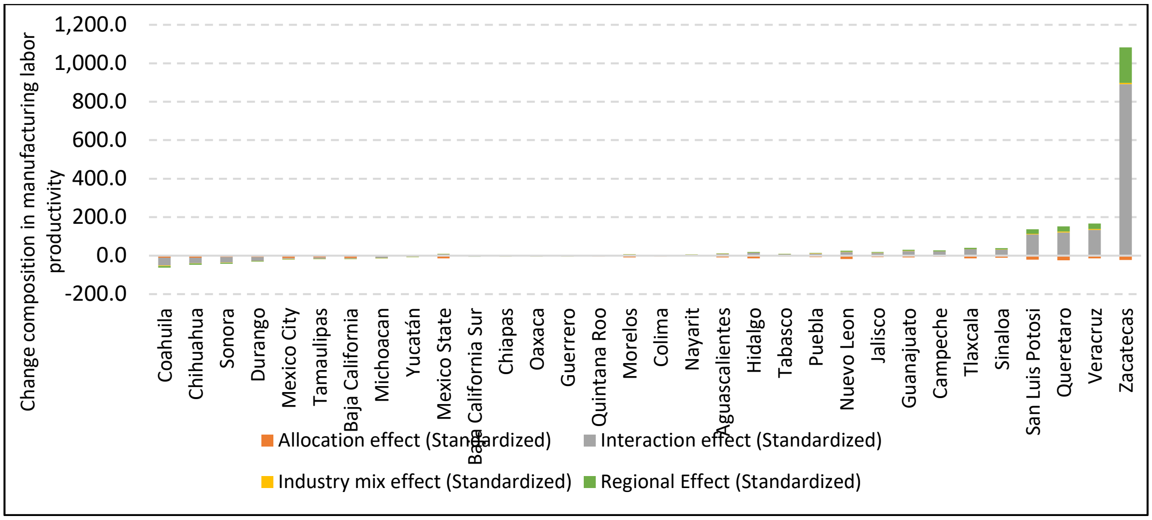
Change composition in manufacturing labor productivity
300.00
250.00
200.00
150.00
100.00
50.00
0.00
-50.00
-100.00
-150.00
-200.00
Morelos
San Luis Potosi
Mexico City
Jalisco
Baja California Sur
Quintana Roo
Oaxaca
Durango
Guerrero
Colima
Tlaxcala
Nuevo Leon
Hidalgo
Aguascalientes
Puebla
Mexico State
Nayarit
Yucatán
Guanajuato
Michoacan
Tamaulipas
Sinaloa
Sonora
Chiapas
Veracruz
Coahuila
Zacatecas
Queretaro
Tabasco
Baja California
Chihuahua
Campeche
Allocation effect (Standardized)
Interaction effect (Standardized)
Industry mix effect (Standardized)
Regional Effect (Standardized)

2008

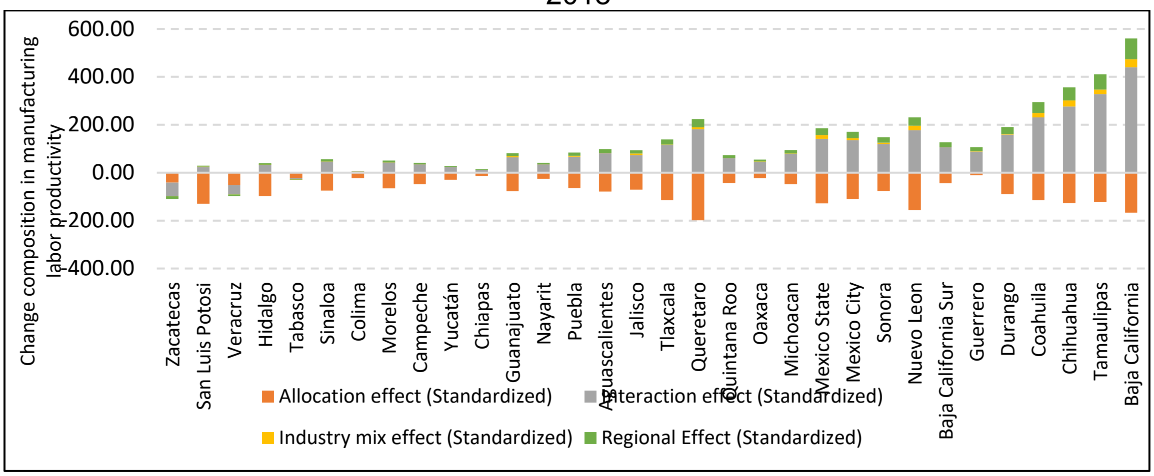


Change composition in manufacturing labor productivity
200.0
150.0
100.0
50.0
-
-50.0
-100.0
-150.0
Queretaro
Baja California
Morelos
Michoacan
Chihuahua
Mexico State
Tabasco
Zacatecas
Jalisco
Sinaloa
Veracruz
Puebla
Chiapas
Aguascalientes
Guanajuato
Oaxaca
Yucatán
Nayarit
Colima
Campeche
Guerrero
Baja California Sur
Tlaxcala
Quintana Roo
San Luis Potosi
Nuevo Leon
Sonora
Tamaulipas
Coahuila
Hidalgo
Durango
Mexico City
Allocation effect (Standardized)
Interaction effect (Standardized)
Industry mix effect (Standardized)
Regional Effect (Standardized)

2013


Change composition in manufacturing labor productivity
1,200.0
1,000.0
800.0
600.0
400.0
200.0
0.0
-200.0
Coahuila
Chihuahua
Sonora
Durango
Mexico City
Tamaulipas
Baja California
Michoacan
Yucatán
Mexico State
Baja California Sur
Chiapas
Oaxaca
Guerrero
Quintana Roo
Morelos
Colima
Nayarit
Aguascalientes
Hidalgo
Tabasco
Puebla
Nuevo Leon
Jalisco
Guanajuato
Campeche
Tlaxcala
Sinaloa
San Luis Potosi
Queretaro
Veracruz
Zacatecas
Allocation effect (Standardized)
Interaction effect (Standardized)
Industry mix effect (Standardized)
Regional Effect (Standardized)

2018

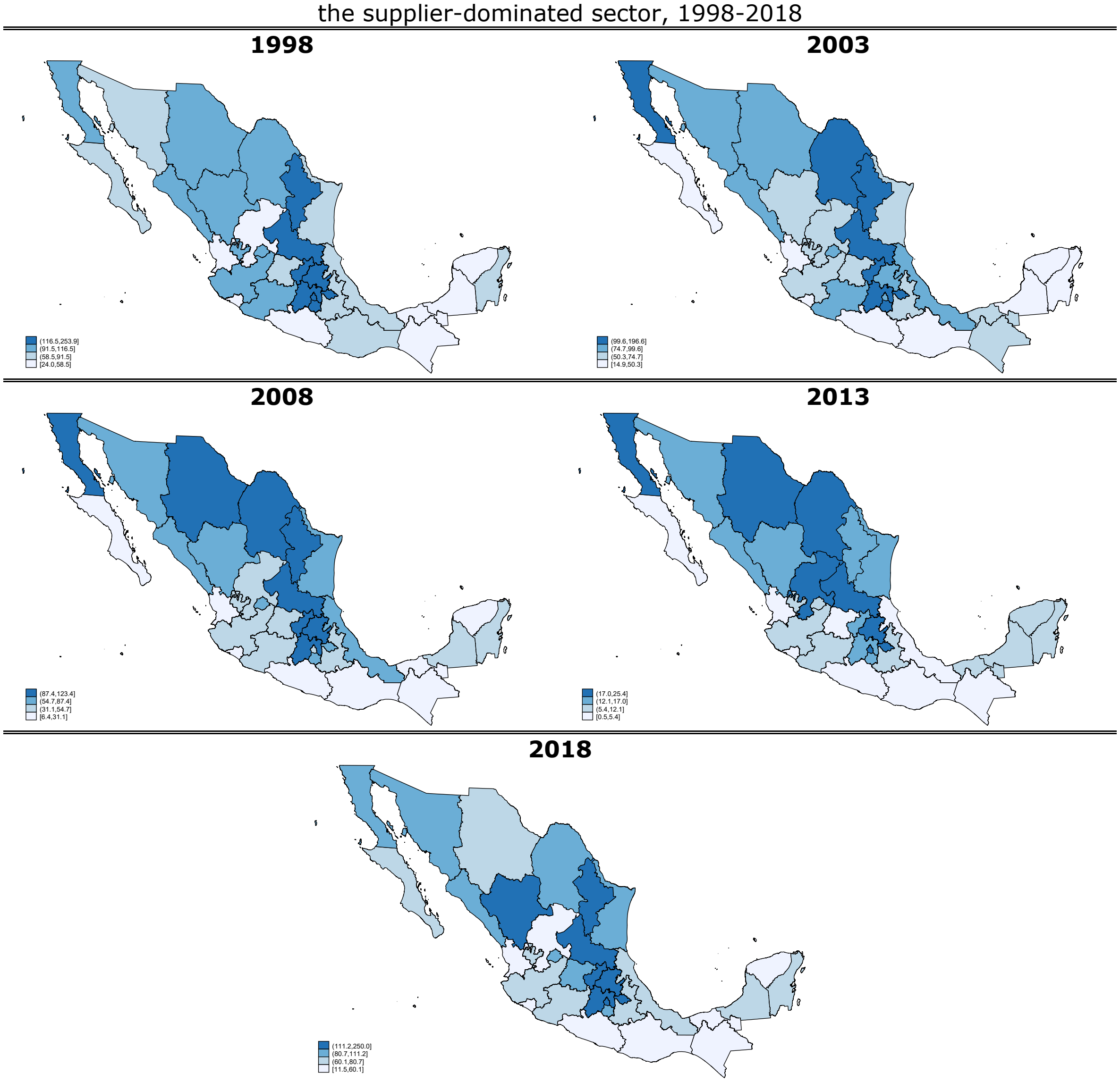

Change composition in manufacturing labor productivity
600.00
400.00
200.00
0.00
-200.00
-400.00
Zacatecas
San Luis Potosi
Veracruz
Hidalgo
Tabasco
Sinaloa
Colima
Morelos
Campeche
Yucatán
Chiapas
Guanajuato
Nayarit
Puebla
Aguascalientes
Jalisco
Tlaxcala
Queretaro
Quintana Roo
Oaxaca
Michoacan
Mexico State
Mexico City
Sonora
Nuevo Leon
Baja California Sur
Guerrero
Durango
Coahuila
Chihuahua
Tamaulipas
Baja California
Allocation effect (Standardized)
Interaction effect (Standardized)
Industry mix effect (Standardized)
Regional Effect (Standardized)

APPENDIX E: Result from spatial regression analysis.

The maps displayed in E.1 show the fitted values for the supplier dominated sector. This sector clearly had the highest weight in Mexico's central region in 1998 but it decreased over the years. Sectoral manufacturing productivity gains weight in the central north and northern regions. As time passes by, the highest quartile is located near to the border. For 2018, the central region became the winner in differential productivity. We need to remember that around those years there was a slowdown in economic activity in the United States. There also appears to be spatial correlation between states in this sector.

Maps E.1

Mexico: Fitted values for the differential total growth of the manufacturing labor productivity in the supplier-dominated sector, 1998-2018



Source: Prepared by author.

The maps displayed in E.2 graph manufacturing labor productivity growth rate differentials for the science-based sector. Gains in productivity for this sector go to the northern, central north, and central regions. Guanajuato, Nuevo Leon, and Queretaro are always among the winners for all periods. Jalisco and San Luis Potosi lose weight for one period, but recover suddenly. Over the years, the structure displayed became solid and sound.

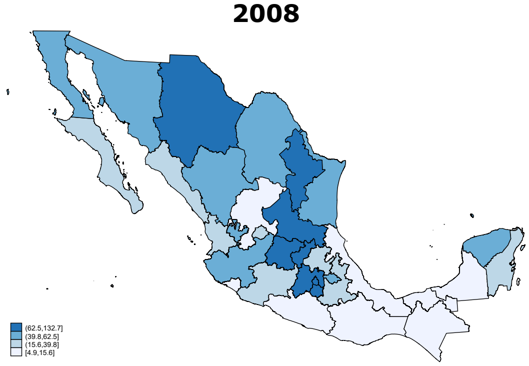
Maps E.2

Mexico: Fitted values for the differential total growth of manufacturing labor productivity in the science-based sector, 1993-2018

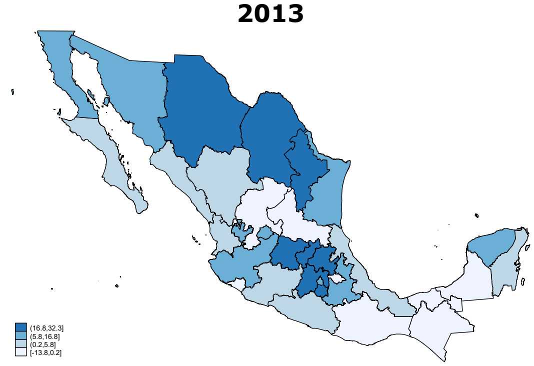
1998

2003

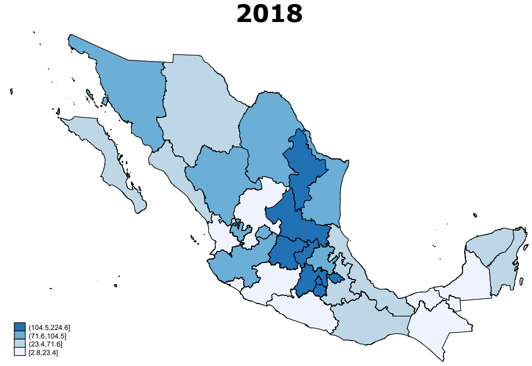
2008



2013



2018



Source: Prepared by author.

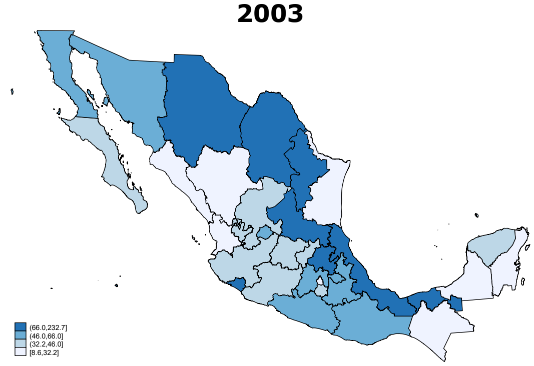
Finally, Maps E.3 displays manufacturing labor productivity growth rate differentials for the specialized supplier sector. In this sector, businesses are related to machinery and equipment, and are usually small-sized operations. Through the census years, Coahuila, and Veracruz are in the top quartile, and it became important for Nuevo Leon and Sonora. States located in the central region lose weight, to remain in the second quartile. Southern states show a heterogeneous behavior, resulting in random patterns.

Maps E.3

Mexico: Fitted values for the differential total growth of the manufacturing labor productivity in the specialized supplier sector, 1993-2018

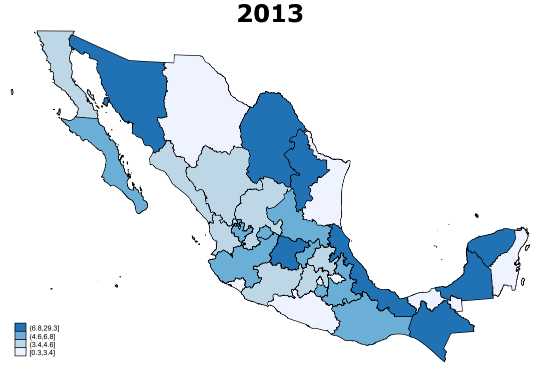
1998

2003

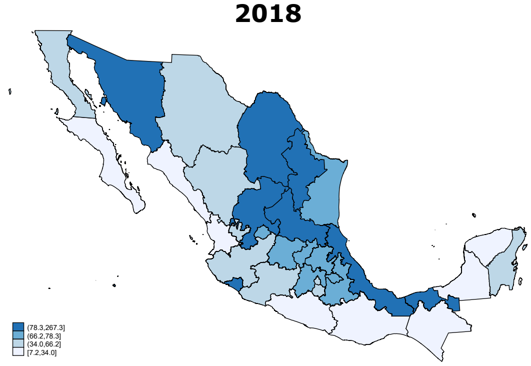


2008

2013



2018



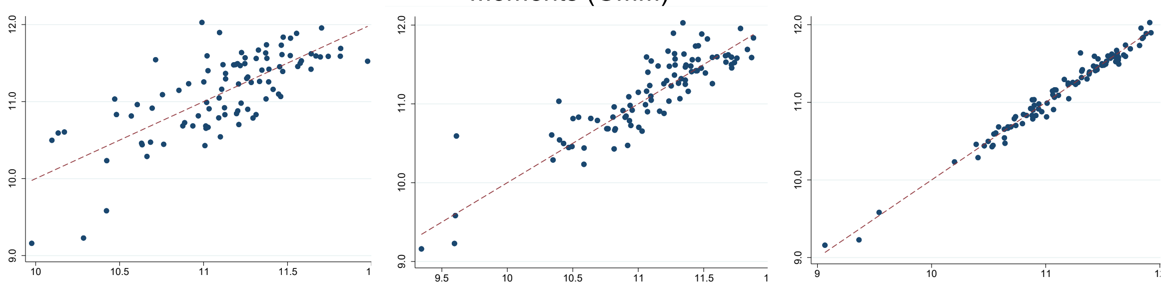
Source: Prepared by the author.

APPENDIX F: Graphical test of goodness of fit

Figure F.1

Model estimation results: Graphical test of goodness of fit

Fixed Effects Panel | Generalized Method of Moments (GMM) | Spatial Panel



Source: Prepared by the author.

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Curriculum Vitae

Jesús Antonio López Cabrera was born in Minatitlán, Veracruz, on March 22, 1977. He earned a Bachelor's degree in Economics from Universidad Nacional Autonóma de México (UNAM) in May 2001, and a Master of Science in Agricultural Economics from Texas A&M University in December 2012. He was accepted into the Finance PhD graduate program in 2018.

This document was typed using Microsoft Word by Jesús Antonio López Cabrera