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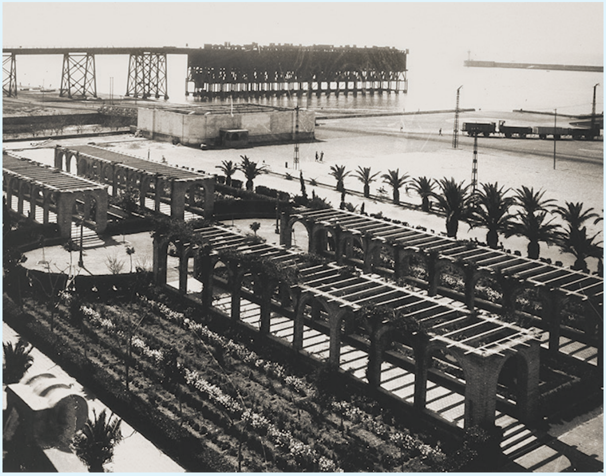

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I. Artículos

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Regional labor productivity in the Mexican manufacturing sector, 2007-2016

Productividad laboral regional en el sector manufacturero de Mexico, 2007-2016

Jorge Eduardo Mendoza Cota
Colegio de la Frontera Norte (COLEF)

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PALABRAS CLAVE: Productividad laboral, Mexico, Manufacturas, Educación, Análisis espacial, Inversión extranjera directa.

JEL Codes: C21, R12, J01.

ABSTRACT:

The paper analyzes the labor productivity of the Mexican manufacturing sector during the period 2007-2016. Manufacturing labor productivity has grown slowly, but slightly faster than the national average. The Northern border states have shown a decline in the rate of growth of labor productivity, whereas states of the central region have accelerated their rate of growth. Labor productivity at the regional level showed positive spatial correlation; therefore, a spatial Durbin panel model was estimated. The results showed that foreign direct investment and gross capital formation had important effects on the rate of growth of labor productivity. In addition, technical schooling and labor training positively impacted productivity growth.

RESUMEN:

La productividad laboral del sector manufacturero es analizada para el periodo 2007-2016. La productividad laboral del trabajo de la economía mexicana ha crecido lentamente. El sector manufacturero ha crecido a un ritmo ligeramente superior que la productividad laboral al nivel nacional. Los estados de la frontera norte mostraron una caída de la tasa de crecimiento de la productividad laboral mientras que los estados centrales incrementaron su crecimiento. Se estimó un modelo Durbin espacial. Los resultados mostraron que la inversión extranjera directa, la capacitación de trabajadores y la formación bruta de capital fijo tuvieron efectos positivos en la productividad laboral.

1. INTRODUCTION

One of the main obstacles for Mexico's economic development is the sluggish growth in labor productivity both at the sectorial and regional level (Krozer, Moreno Brid y Rubio, 2015). The long run impact of labor productivity is related to its role in generating higher wages and capital gains. As a result, growth in labor productivity raises consumption and investment, increasing the welfare of the economy (Sprague, 2014).

Since the decade of the eighties, the Mexican growth economy has adopted a strategy of opening its economy. One of the arguments to implement this strategy of economic liberalization has to do with the importance of foreign direct investment (FDI). It has been maintained that FDI encourages a better allocation of resources and a greater productivity in the economy.

After the establishment of the North American Free Trade Agreement (NAFTA), the Mexican economy significantly expanded its export sector, predominantly in the manufacturing sector. However, the trade dynamics have not been able to encourage the rapid growth of labor productivity in the manufacturing sector. Therefore, Mexico continues to be characterized as an economy with low labor productivity and low wages. The trend of Mexican labor productivity indicates that, at the sectorial and regional level, growth has been rather slow and heterogeneous. Multiple factors have been considered as likely determinants of this stagnant behavior, such as low levels of schooling, and a lack of capital.

At the theoretical level, the effects of trade liberalization on efficiency and labor productivity have been discussed extensively. The arguments are, among others, that trade and better investment decisions encourage efficiency in production and consumption, greater competitiveness and the use of internal and external economies of scale. However, it has been claimed that trade increases could have negative effects on economic growth and productivity by reducing the enterprises innovation activities, since they can acquire inputs and technology from external markets (López-Córdova, Esquivel y Monge, 2003). Regarding FDI, the presence of large multinational enterprises could increase productivity by expanding the economies of scale and encouraging the adoption of more efficient technologies. Nevertheless, there are constraints for that process that are related to the level of education of the workforce. Also, it has been argued that FDI could have an economic efficiency spillover effect by supplementing the lack of financial resources for local firms and adapting new technologies (Topalova y Khandelwal, 2011). From the theoretical point of view Decreuse and Maarek (2015) established a model to address the impact of FDI on labor productivity in developing countries. This theoretical approach analyzes productive heterogeneity between firms, in a frictional labor market. According to the authors, FDI has two opposite effects. One the one hand, it increases productivity, due to technological developments, and, on the other hand, encourages labor market competition between firms. Clegg and Wang (2004) studied the multinational firm's effects on the Chinese economy using cross-section data for the year 1995. The results found the existence of technological and labor productivity spillovers in the high-tech foreign firms, which contributed to the upgrading of the Chinese manufacturing sector.

Regarding the role of education on the expansion of labor productivity Lucas (1998) and Romer (1990) pointed out the importance of human capital for the sustained expansion of economic growth. From this point of view, the Mexican economy has exhibited a relatively low level of schooling and labor skills, which have limited the impacts of FDI on labor productivity.

With respect to the effect of exports on labor productivity, several papers have indicated that exports and trade could encourage the transference of ideas and knowledge (Grossmand and Helpman, 1991) and Feeney (1999) who indicated that trade promotes specialization and therefore allows for learning by doing and faster productivity growth.

The empirical research on labor productivity have produced mixed results. Blomström and Wol (1994) analyzed the Mexican manufacturing sector with data from 1970 and encountered that the output per worker was two times higher in the multinational corporations than in domestic plants, although total factor productivity was lower due to the effect of higher intensity of capital in the multinational enterprises. Aravena and Fuentes (2013) estimated the total factor productivity and extended it to include human capital. They found that in the Mexican case, productivity growth was explained by the intensity of capital. Also, the result showed that the labor quality of workers, measured as the weighted average of schooling, was a relevant factor for explaining the evolution of labor productivity.

An important determinant for labor productivity expansion has to do with labor skills. Both schooling and training increase the productivity of labor, promoting economic growth and income of the factors of production. Mendoza and Pereyra (2014) studied the impact of high skilled workers on total worker income for the period 2001-2009. They used a mix panel model applied to the manufacturing subsectors of Mexico located in the urban areas of the northern border states of Mexico. The results indicated that the productivity of workers with more years of schooling grew at rate of 4.6% in the period considered, thus suggesting that labor productivity increases faster in the presence of positive capital flows and FDI. In spite of these results, the authors indicated that the largest share of the employed population showed a low level of education, at the elementary and high school levels.

In addition, the productive specialization and FDI positively impacted the wages of urban workers with higher levels of education. The outcome suggests that urban and economic infrastructure generates positive externalities that multiply the positive effects of technological innovation created by the FDI and the greater productivity of workers with higher levels of schooling in the manufacturing sector. The results agreed with the findings of Joordan (2008) that suggests positive externalities and backwards chain-links.

Ramirez (2002) analyzed the impact of public infrastructure investment on economic growth and labor productivity for the period 1954-1994 in Mexico. By estimating a cointegration model, they presented a dynamic labor productivity function, including as explanatory variables the stock of public and private capital and the economically active population. The findings indicated that a drastic reduction of public investment could be a factor in decreasing labor productivity. In addition, Castro (2006) and Machuca and Mendoza (2017) estimated econometric models which produced evidence that labor productivity is not improving wages in the manufacturing sector.

Brown and Dominguez (1999a) estimated total factor productivity indices in the manufacturing sector. They pointed out that, since 1994, the Mexican economy experienced an increase in labor productivity; however, there was a significant heterogeneity in the manufacturing subsectors. In a second paper, Brown and Dominguez (1999b) estimated an econometric model to estimate the impact of microeconomic variables (technology, advertisement, etc.) and macroeconomic variables (GDP, imports and exports). The results suggest that there are heterogeneous impacts of the explanatory variables, depending on the intensity of capital and the location of the manufacturing industries.

The characteristics of productivity growth were studied by De Leon (1995). According to the author's estimations, until the first half of the decade of the nineties the large urban areas of Mexico were leading the productivity increases, while the northern border of Mexico exhibited lower growth rates than the national average. This result changed after the decade of the nineties and the northern border region started to experience more rapid rates of productivity growth. Mendoza (2004), pointed out that in the in-bond assembly plants (maquiladoras) there are different levels of technological endowments, size of plants, and labor training, creating diverse levels of labor productivity both at the national level and in the northern border states. Appling a growth model with panel data in the maquiladora industry for the period 1991-1999, he found that the central states of Mexico experienced higher labor productivity than those of the northern border states. The subsectors that showed higher labor productivity were metallic products, machinery and equipment, chemical products and rubber and plastics industries. Therefore, both theoretical and empirical studies on labor productivity have considered that capital, schooling and labor training are important determinant for encouraging labor productivity.

Within this context, the present paper seeks to analyze labor productivity growth in the manufacturing sector and its determinants at the regional level. The analysis considers information for the period 2007-2016 in order to capture recent historic developments in labor productivity in Mexico. The variables used are FDI, manufacturing exports, technical schooling, labor training, and gross capital formation at the state level.

In order to assess the determinants of labor productivity in Mexico, a spatial econometric model was developed. The estimations indicated that FDI and fixed capital formation and labor training positively impacted labor productivity. Also, the results exhibited evidence of spatial spillovers that underline the importance of regional manufacturing interconnections at the state level.

The document is structured as follows: the first section is the introduction, which includes a review of the theoretical empirical findings on the contributing factors of labor productivity; the second section analyses the structure and trends of labor productivity in the manufacturing sector at the regional level; the third section describes the methodological strategy and data bases; in section four the results of the spatial econometric model are discussed, and section five presents the conclusions of the paper.

2. TRENDS OF LABOR PRODUCTIVITY IN MEXICO

2.1 Labor productivity in the Mexican economy

There are several causes of the lack of dynamism of labor productivity in Mexico. Hanson (2010) pointed out that the high proportion of the labor force employed in the informal sector partially explained the slow growth of labor productivity. The author argues that the low profitability of labor experience in the informal markets and the government social programs have constrained the incentives for human capital accumulation. Another aspect is related to the poor success of the Mexican education system, which are reflected in the PISA (Programme for International Student Assessment) test results, that has negatively impacted the economic growth (Arias, 2010).

According to information from the National Institute of Statistics and Geography (INEGI), the global labor index of the Mexican economy, measured as the ratio of occupied population to GDP, showed limited growth during the period 2005-2017, where it increased from 97.6 the first quarter of 2005 to 106.6 in the third quarter of 2017, representing a quarterly average growth rate of 0.2%.[1]. In addition, the labor productivity performance of the Mexican economy exhibited irregular growth. From 2006 to 2009, the average annual rate of growth was -1.32%; this negative variation was the result of the negative impact on productivity generated by the recession of 2008 and 2009. The period also exhibited a great volatility, given the positive productivity growth of 2006 and 2007 (Table 1).

During the period 2010-2014, faster growth in the total productivity of the economy was experienced. The average percentage growth of 1.41% and the standard deviation was 1.53%. This productivity growth was related to the recovery from the recession and the continuous economic activity in that period. Finally, in the third period, from 2014 to 2017, the economic activity of the Mexican economy experienced moderate growth, that translated into a decreasing percentage growth of the productivity of the Mexican economy. In 2014, the annual productivity growth was 2.26%; since then a decrease in the percentage growth occurred. As a result, the average percentage change declined and the volatility of the period increased.

1 Own estimations based on the Global index of labor productivity in Mexico published by the National Institute of Statistics, Geography and informatics (INEGI).

The estimations of the total factor productivity according to the Annual Survey of the Manufacturing Sector, which is constructed with labor income and the value of fixed capital formation in constant pesos, indicated that total factor productivity increased at an average rate of 1.2% between 2009 and 2017. The contribution of the factors of production were relatively stable with capital accounting for an average of 86% of the total factor productivity growth and labor with 12.5%.[2]

2.2. Labor productivity in the Mexican manufacturing sector

The Mexican manufacturing labor market exhibited three characteristics with respect to labor productivity and the share of wages to value added in that sector. The first aspect is that between 2004 and 2014 the average labor productivity, measured the manufacturing sector value added divided by the number of hours worked, showed a slightly higher growth than the national level with 2.8% and 2.1% between 2004 and 2014, respectively (Table 2). It is important to underline that this average wage is higher than that presented in the last section because it is denominated in dollars and, therefore, captures the competitive effect of the Mexican peso depreciation.

The second characteristic of the manufacturing labor market is that wages rose at a lower rate than labor productivity in the manufacturing sector, and wages of the overall economy grew at a lower rate with average rates of 1.5% and 1.6%, respectively. As a result, the share of wages in the total value added decreased from 24.8% to 23.3% in the period studied.

Finally, within the manufacturing subsectors there is a great heterogeneity. The fastest rates of growth of labor productivity were experienced in the basic metallic industry and the food industry, and petroleum and coal, among others. In contrast, the paper, electric equipment and the plastic and rubber industries exhibited moderate rates of growth. In fact, some manufacturing industries experienced negative rates of growth, such as the publishing industry, the communications and computer industry and the textile industry.

2 Total factor productivity was measured based on this formula: PTF = (Yt/Yt-1) /[a(Kt/Kt-1) + b(Lt/Lt-1)], where Y is total production, *K* is capital, *L* labor and *Q* is total production and *a* and *b* are weight coefficients for the factors of production.

2.3 Regional characteristics of labor productivity growth

Besides the heterogeneity of labor productivity growth experienced within the manufacturing sector, there also was a high heterogeneity at the regional level. This diverse rhythm of labor productivity growth of the Mexican states, which was related to the re-localization of manufacturing production process that expanded the exporting industries with higher technology and better labor procedures (Mendoza, 2004).

The state of the analysis of labor productivity in Mexico illustrates that, the majority of the states where manufacturing activities are important presented a range level of labor productivity. Between 2007 and 2016 Jalisco, Aguascalientes, Guanajuato and Puebla showed both the fastest growth of annual average growth and the higher labor productivity index, in the manufacturing sector. The determinant of this relatively fastest growth could be related to the FDI in the automobile industry in those states. They were followed by the states of Chihuahua, Campeche, Tabasco, Queretaro and Baja California, which are characterized by producing petroleum in the case of Tabasco and Campeche or the in-bond assembly plants (maquiladoras) in the case of Chihuahua and Baja California. (Table 3). Therefore, the central states are exhibiting higher labor productivity than the border region of Mexico, probably because of a higher level of technology and capital endowments in the plants localized in that region.

3. SPATIAL ANALYSIS OF LABOR PRODUCTIVITY IN MEXICO

3.1 Spatial panel strategy estimation

The theoretical and empirical studies discussed have yielded important results about the factors that determine labor productivity growth. However, the empirical studies at the regional level have not taken into consideration the problems that arise from estimating an econometric model in a cross section or panel data. The estimation of the determinants of labor productivity at the regional level require an econometric model that considers the spatial effects arising from spatial dependence or spatial heterogeneity, in particular the effects of location and distance (Anselin, 1988).

Initially, the strategy for studying the regional effects on labor productivity consisted of applying a Moran's index to the data base by states. The estimation showed a positive correlation for the productivity variable, suggesting important effects of neighboring states on labor productivity. Subsequently, a spatial econometric model was developed, which consisted of obtaining information from the space and location of the variables by establishing three spatial models. These spatial econometric models are very useful for regional economic analysis because spatial spillovers can be measured and their significance tested, and therefore regional determinants can be taken into account in the analysis of labor productivity.

The first model estimated is an autoregressive method (SAR) applied to the regional analysis. The autoregressive process is a suitable method for analyzing regional interactions of the variables when there is dependency among observations and locations (Lesage and Pace, 2009). The SAR model is based on the function:

$$y = \rho Wy + X\beta + \varepsilon,$$

where: *y* is the dependent variable, *X* is the explanatory variable, ε is the error term and *W* is a matrix of spatial weights linked to the spatial lag effect on the dependent variable ρ.

The second model spatial econometric model is a spatial error model (SEM) that estimates a model with a spatial correlated term. This model applies an autoregressive technique by considering all spatial dependencies as unobserved errors. Therefore, this model assumes that there are several factors influencing labor productivity and some are not taken into consideration, therefore their dependencies are reflected in the residual errors helping to correct the estimates of the model. The methodology of estimation consists of a model with a spatially lagged error, expressed as:

$$Y= X\beta + u,$$

where $u = \lambda Wu + \varepsilon$.

The third spatial model was developed by Anselin (1998) and it includes both a spatially lagged dependent variable and spatially lagged independent variables called the Spatial Durbin Model (SDM) which is formally expressed as:

$$Y = \rho WY + \beta 0 + X\beta 1 + WX\beta 2 + u,$$

where $u = \lambda Wu + \varepsilon$.

The dependent and independent variable are linked to the weights matrix (Elhorst, 2010). Therefore, the SDM is a generalization of the SAR model because it also includes spatially weighted independent variables as the explanatory variables of the model. Another advantage of this methodology is that the direct and indirect effects associated with each explanatory variable are estimated and, therefore, the analysis can be disaggregated into spatial direct and indirect effects of the explanatory variables (Lesage, 2014). As a result, the analysis of the determinants of labor productivity could be extended to include the regional direct and indirect effects impacting that variable.

The strategy for estimating labor productivity used in the paper relies on a panel data model. The cross section spatial regressions do not consider the spatial and temporal heterogeneity. Both space-specific and time-invariant variables affect the dependent variable and could produce biased estimations (Elhorst, 2014). A panel data model requires a dependent variable with endogenous interactions but also interaction among the explanatory variables and the error terms. It is assumed that the panel is balanced with a matrix constant over time. Therefore, in order to solve for this possibility a bias in the outcome spatial panel model is established as follows:

$$P_{t,i} = \rho WP_{t,i} + \alpha\iota_N + X_{t,i}\beta + WX_{t,i}\theta + \mu + \xi\iota_N + \nu_t \ldots \tag{1}$$

$$\nu_t = \lambda W\nu_t + \varepsilon_t \ldots \tag{2}$$

where P is the dependent variable, labor productivity, β and θ are vectors of unknown parameters to be estimated based on the number of independent and explanatory variables K used in the model: labor productivity, technical schooling, gross capital formation, IED, exports and training, in time t at the state level, I; W is a nonnegative spatial weight symmetric matrix of order $p=1$, with only first-order contiguity neighbors; WP represents the endogenous interaction effects among the dependent variable in this case labor productivity; WX the exogenous effects among the independent variables; $W\nu$ indicates the interaction effects among the disturbance terms; ρ is called the spatial autoregressive coefficient and λ the spatial autocorrelation coefficient. With this model fixed and random effects for spatial and time-specific effects can be estimated considering μ and ξ as random variables, independent and identically distributed (Helhorst, 2014).

The panel data set consists of 10 observations over time (2007-2016) and for the 31 states of Mexico plus Mexico City. The productivity of labor was calculated as the total value added of the manufacturing sector divided by the total work hours used in that sector. The data was obtained from the Monthly Industrial Survey of Mexico (EMIM). The state gross fixed capital formation, state exports and foreign direct investment were obtained from the National Institute of Geography and Statistics (INEGI); the technical training and the enrolment technical high school data were found in the Interactive System of Education Statistics.[3]

4. ESTIMATION RESULTS

The panel model on the determinants of labor productivity was estimated using three spatial models: a spatial autoregressive model (SAR), a spatial Durbin model (SDM) which is a generalization of the SAR model and the spatial error model (SEM), which is focused on spatial auto-correlation in the error term. All the three models were estimated with fixed and random effects. The method of estimation used is based on Quasi-Maximum Likelihood estimators (Belloti, Hughes and Piano, 2016).

For the estimations of the direct, indirect and marginal effects in the SDM and SAR models, a Hausman statistic is estimated. The null hypothesis assumes a no systematic diference between the two panel estimations. However, a problem with spatial panel data models is that the Hausman specification test sometimes does not meet its asymptotic assumptions. In order to solve this issue, a robust Hausman test was estimated. The procedure considers the covariance of the diference between the fixed- and random-efects estimates. In addition, the *estat ic* test was calculated. It

3 The technological baccalaureate is suitable for students with a technical or engineering profile; it is not related to humanities, letters or social sciences.
Technical training for work is a service through which people are prepared to engage in productive activity; it has as its background primary education. It is given in courses of between 100 and 450 hours of duration, for a period of three to five months in subjects such as industrial, agricultural, commercial and service techniques

uses two information criteria for comparing the fit of different models. The first criterion computed is the Akaike Information Criterion (AIC), and the second information criterion computed is the Bayesian Information Criterion (BIC). Both criteria provide information about the models estimated. In particular, it compares the best combination of the model's complexity and explanatory power.

4.1 The results of the spatial models

Initially the database was tested for autocorrelation applying the Global Moran's index p and z values. The results exhibited spatial (at the state level) clustering with both higher values grouped close to each other, as well as lower values. The global Moran index was positive for all the years estimated, which were 2007, 2010, 2013 and 2106 with values of 0.43, 0.40. 0.33 and 0.49 (Table 4). Therefore, we can consider that the data set for labor productivity presents a clustering in both higher and lower values.

In addition, the null hypothesis states that the data set values are randomly distributed, which was rejected by the *p*-value and was statistically significant at a 1% level of confidence. In addition, the *z*-value is positive and above 1.96 which indicates that the null hypothesis that assumes the existence of positive spatial correlation was accepted at a confidence level of 95%. Therefore, a spatial econometric technique seems to be appropriate for estimating the regional determinants of labor productivity in Mexico. In particular, the cluster map provides information about the states with statistically significant results (with *p* values from 0.05 to 0.001).

The cluster map for labor productivity in 2007 shows that the northern states of Baja California and Chihuahua exhibited significant clusters of low labor productivity, whereas the states of Mexico, Hidalgo, Tamaulipas and Tabasco presented higher labor productivity clusters (Map 1). In 2016, the cluster map showed that Baja California and Chihuahua continued to exhibit clusters of low labor productivity and the states of Hidalgo and Tabasco presented clusters with a higher level of productivity. Finally, the states of Puebla, Campeche and Quintana Roo presented high to low productivity clusters. The graphical representation of regional labor productivity suggests the existence of clusters and spatial effects in the dataset analyzed.

In order to estimate the effect of the explanatory variable's change in both the independent and dependent variables, spatial econometric models were applied using direct, indirect and total marginal effects. The model selection is based on the empirical methodology proposed by Lasage and Pace (2009) and Elhorst (2010), which consists of first considering the SDM model as a general specification and then proceeds to estimate and test alternative models. Table 5 shows the estimations of the SDM, SAR and SEM panel models with both fixed and random effects.

Different tests were applied to the estimations in order to decide which model adjusted better to the data set and if they corresponded to a fixed effects or random effects model. In order to define the choice between fixed and random effects, a robust Hausman test was estimated for the three different spatial models, in order to avoid the impossibility to meet the asymptotical differences of the Hausman test. The estimation of a robust Hausman test for the three spatial models indicated that the SDM model displayed a lower chi^2 value, which shows that the results of the test have a more significant *p* statistic in this model (Table 5). Therefore, the fixed model is more appropriate to estimate the panel model.

In addition, tests for model selection were established by using the Test and Testn1 (Belloti, Hughes and Piano, 2017) and the Akaike's information criterion and Bayesian information criterion (BIC), which are used for estimating the likelihood of the models as parameters are incorporated to the models. The lower value chi^2 of the two first models corroborated the use of the SDM model (Table 6). Regarding the Akaike's information criterion the statics showed that the lowest value of the SEM indicated better goodness of fit. Also, the Bayesian information criterion was applied to estimate the problem of adding parameters introducing a penalty term for the number of parameters in the model. The lower value of the BIC estimation was for the SDM model (Table 6). Finally, the test and testn1 indicated that the SDM is the best model compared with the alternative models. After the estimation of the coefficient pf the fixed effects model SDM, the test were carried out and the results supported the previous tests.

As in all spatial models, the SDM uses the dependence of the structure of the variables to estimate the effects of the independent variables on the dependent variable of the model, in the presence of spatial dependence. Therefore, the estimated SDM model presents a set of main effects of the variables on the dependent variable, the spatial vector (ρ) includes the spatial coefficients, which are important because the shows the spillover effects

$$SM_{2001-11} = Pob\ Censo_{2011} - Pob\ Censo_{2001} - \left(Nacimientos_{2001-11} - Muertes_{2001-11}\right)$$

of neighboring spatial units in the specific spatial units. The results showed in Table 7 indicated that the SDM model with fixed effects presents spatial effects given by the *z* of *rho* which at a 1% level of confidence. In addition, there was evidence of direct effects of technical training of the labor force as main effect for labor productivity and the spatial effect of gross capital formation at the state level (Table 7). The estimations also confirmed that technical schooling and public investment in infrastructure at the regional level are important determinants of changes in the productivity of labor at the regional level.

In addition, in order to take advantage of the spatially correlated units, estimations to differentiate between direct, indirect and marginal effects were calculated. The results of the direct, indirect and total effects are obtained by computing a dynamic fixed effects SDM model including a lag. The dynamic characteristics of this model are expressed in both short-run and long run direct, indirect and total effects.

The results of the estimations exhibited an R-square within 0.31 and an overall R-square of 0.913 (Table 8). Also, the spatial coefficient was statistically significant, implying an important degree of spatial dependence between units considered in the model. Therefore, the SDM model is suitable for estimating both direct effects and the indirect spatial spillover effects of the variables included at the regional level.

The dynamic SDM model, calculated with Quasi-Maximum Likelihood (QML) estimators. It divides the effects into both a short-term and long-term perspective. The short-term direct effects indicated by the coefficients estimated suggest that both FDI and gross capital formation, at the state level, play an important role in the level of productivity at the regional level. Both coefficients were positive and statistically significant. However, the exports coefficient showed a negative and statistically significant sign, implying negative effects of exports on labor productivity. Regarding the long-term indirect effects, besides the FDI and gross capital formation, the labor training presented a positive sign which was statistically significant. This finding supports the assumption of the positive effects of education and labor training as spatial spillover effects. Finally, the total effects coefficients in the short-term corroborate that the most important variables were gross capital formation and FDI.

The direct and total effects in the short term corroborate the positive effects of FDI, which is considered to be a mechanism for spreading technology innovations and, therefore, improves the production process and the productivity of labor. Also, the gross capital formation at the state level played an important role in encouraging productivity, according to both the short-run and total effects indicated by positive coefficients. In addition, worker training was an important variable for encouraging labor productivity.

Finally, the long-term direct effects also showed that again that the coefficient of FDI indicated that this variable is an important factor for increasing labor productivity. However, exports again exhibited a negative coefficient in the long run. The probable explanation could be that an important part of exports are manufactured goods, which are based on low-labor skills. However, some multinational firms have developed improvements in the process of production, although product design has been marginally developed. The long-run indirect effects presented positive impacts of labor training and FDI, but only FDI was statistically significant. Finally, the coefficients of the long-run total effects indicated the existence of positive and statistically significant effects of gross capital formation and labor training, although the coefficient of FDI was positive, it was not statistically significant at 1% or 5%. Therefore, it can be concluded that both in the short and the long run, training, FDI and gross capital formation have been factors that have positively impacted labor productivity in Mexico at the regional level. In addition, there is evidence of spatial dependence between the states in terms of labor productivity, which suggests that there are geographical spillovers provided by the spatial coefficient which was positive and statistically significant.

5. CONCLUSIONS

The moderate growth of labor productivity in Mexico has been an obstacle for its rapid economic growth and for wage increases. During the period studied both labor income and labor productivity in the manufacturing sector experienced a rather slow growth.

Three important characteristics of labor productivity in the manufacturing sector stand out. Labor productivity in the manufacturing sector increased at a slightly faster rate than the national average. Second, labor productivity grew faster than wages, probably determined by institutional factors constraining wages expansion. A third aspect has to do with the heterogeneity of the speed of growth of the manufacturing sector both at the sectoral and state level. At the sectoral level, the subsector of metallic industries exhibited higher labor productivity whereas light industries like food and beverages exhibited lower labor productivity. At the regional level, labor productivity was lower in the northern Border States, which reflect the low labor skills required in the maquiladora industry; whereas central states such as Guanajuato and Queretaro have seen important increases in productivity.

In order to assess the determinants of labor productivity in Mexico, a spatial econometric model was developed. The estimations of the model support the statements that indicate that FDI is a mechanism for diffusing technological innovations in the process of production, which can result in higher levels of productivity and economic growth both in the short and the long-run. The results support previous papers that have estimated the effect of FDI on the firms output and have pointed out that FDI plays an important role in increasing labor productivity, production and exports to foreign markets (Helpman, et al, 2004). In addition, the gross fixed capital formation coefficients in the long log run were also positive and statistically significant, which corroborate the importance of capital endowment in order to promote labor productivity.

The labor training coefficient also was positive and statistically significant for the short and long-run indirect effects and total effect coefficients, indicating that workers training is an important factor, that together with capital formation and FDI encourage labor productivity. However, the variables of exports and technical schooling did not present positive and statistically significant coefficients for either the short and the long-run. The probable explanation of the results is related to the low level of value added of Mexican manufacturing exports. A large share of manufacturing exports is concentrated in low-skill manufactures that do not require high-skilled labor or a rapid growth of labor productivity and value added and therefore, the requirement of technical education is less important for determining the level of labor productivity. Finally, it is important to point out that the estimations of the spatial model indicated the existence of spatial spillovers, which indicates that the positive effects of the variables mentioned was related not only to the states that increased labor productivity but also to neighboring states. From the regional point of view, the labor productivity spillovers among states suggests that the increasing manufacturing activity in states that are geographically close together, such as the northern border states and central states of Mexico, have positively impacted labor productivity.

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TABLE 1

GLOBAL INDEX OF LABOR PRODUCTIVITY IN MEXICO. QUARTERLY AND ANNUAL PERCENTAGE CHANGE

2006/01	2.40	2010/01	2.47	2014/01	0.93
2006/02	0.42	2010/02	3.30	2014/02	2.11
2006/03	1.51	2010/03	3.25	2014/03	2.48
2006/04	0.75	2010/04	5.24	2014/04	3.53
2006	1.27	2010	3.57	2014	2.26
2007/01	0.11	2011/01	2.55	2015/01	1.96
2007/02	0.03	2011/02	2.11	2015/02	0.77
2007/03	1.25	2011/03	2.17	2015/03	1.17
2007/04	-0.04	2011/04	-1.08	2015/04	-1.03
2007	0.34	2011	1.44	2015	0.72
2008/01	-1.38	2012/01	1.08	2016/01	0.86
2008/02	-0.29	2012/02	-0.39	2016/02	0.92
2008/03	-0.83	2012/03	-1.25	2016/03	-0.71
2008/04	0.24	2012/04	2.11	2016/04	2.06
2008	-0.56	2012	0.39	2016	0.78
2009/01	-5.52	2013/01	-0.66	2017/01	0.92
2009/02	-8.24	2013/02	1.49	2017/02	0.18
2009/03	-6.48	2013/03	1.30	2017/03	0.71
2009/04	-4.96	2013/04	-1.13	2017/04	0.01
2009	-6.30	2013	0.25	2017	0.46
Mean	-1.32	Mean	1.41	Mean	1.05
SD	3.41	SD	1.53	SD	0.82

Source: Own elaboration with data from INEGI, National Accounting System of Mexico.

TABLE 2

LABOR PRODUCTIVITY AND WAGES IN THE MANUFACTURING SECTOR OF MEXICO (DOLLARS)

	2004		2009		2014		2004	2009	2014	2004-2014	2004-2015
Economic activity	Productivity	Hourly wages	Productivity	Hourly wages	Productivity	Hourly wages	Percentage of total wages to value added per worker			Productivity growth	Wage growth
National	7.22	1.79	8.30	1.76	8.91	2.08	24.8%	21.2%	23.3%	2.1%	1.5%
31 - 33 Manufacturing sector	8.47	2.59	10.44	2.59	11.16	3.04	30.6%	24.8%	27.2%	2.8%	1.6%
311 food industry	5.92	1.64	8.13	1.44	11.22	1.84	27.7%	17.7%	16.4%	6.4%	1.1%
312 beverages and tobacco industry	16.89	3.15	20.73	2.67	21.58	2.55	18.7%	12.9%	11.8%	2.5%	-2.1%
313 textiles inputs	5.01	2.17	5.48	2.10	4.64	2.18	43.3%	38.2%	46.9%	-0.8%	0.0%
315 Apparel industry	3.12	1.41	3.54	1.44	3.45	1.85	45.3%	40.6%	53.6%	1.0%	2.7%
316 Leather industries	3.08	1.56	3.32	1.56	4.25	1.91	50.6%	47.1%	44.9%	3.2%	2.0%
321 Lumber industry	2.70	1.00	2.32	1.03	2.65	1.34	36.9%	44.5%	50.6%	-0.2%	3.0%
322 Paper industry	9.63	2.74	11.18	2.96	11.09	3.46	28.4%	26.5%	31.2%	1.4%	2.3%
324 Petroleum and coal derivatives	35.05	10.25	24.13	12.22	58.49	23.09	29.2%	50.6%	39.5%	5.1%	8.1%
325 Chemical industry	25.43	6.00	36.28	5.95	28.86	6.25	23.6%	16.4%	21.7%	1.3%	0.4%
326 Plastic and rubber industry	6.90	2.46	7.70	2.36	5.78	2.62	35.6%	30.7%	45.3%	-1.8%	0.6%
327 Minerals non-metallic	12.59	2.30	3.38	1.53	7.09	2.04	18.3%	45.3%	28.7%	-5.7%	-1.2%
331 Basic metal industries	14.77	3.87	41.25	4.14	38.04	4.71	26.2%	10.0%	12.4%	9.5%	2.0%
332 Metallic products industry	5.17	1.94	6.09	2.02	6.11	2.44	37.5%	33.2%	39.9%	1.7%	2.3%
333 Machinery and equipment	8.25	3.30	12.25	3.66	10.83	4.44	40.0%	29.9%	41.0%	2.7%	3.0%
334 Communication and computer industry	7.04	3.25	6.17	3.43	5.03	3.71	46.1%	55.6%	73.7%	-3.4%	1.3%
335 Electric equipment	8.45	3.33	9.79	3.26	9.23	3.55	39.5%	33.3%	38.4%	0.9%	0.6%
336 Transportation equipment	13.06	3.89	14.19	3.90	16.12	3.75	29.8%	27.5%	23.3%	2.1%	-0.4%
337 Furniture industry	3.35	1.43	3.38	1.53	3.79	2.02	42.8%	45.3%	53.1%	1.3%	3.4%

Source: Own elaboration with data from the Mexican Economic Census 2004, 2009 y 2014, INEGI.

TABLE 3
LABOR PRODUCTIVITY INDEX[1] IN THE MAIN MANUFACTURING STATES OF MEXICO, 2007-2016

Period	2007	2016	TCPA
Jalisco	105.675	148.525	3.4%
Aguascalientes	103.55	135.175	2.7%
Yucatan	99.6	134.05	3.0%
Guanajuato	101.6	125.475	2.1%
Puebla	93.425	123.425	2.8%
Chihuahua	97.85	122.8	2.3%
Campeche	101.45	120.225	1.7%
Tabasco	103.75	116.9	1.2%
Queretaro	103.975	113.3	0.9%
Baja California	101.9	110.775	0.8%
Nuevo Leon	105.575	108.775	0.3%
Mexico	98.575	107.675	0.9%
San Luis Potosi	99.025	107.375	0.8%
Ciudad de Mexico	100.9	107.15	0.6%
Quintana Roo	91.1	101.05	1.0%

Source: Own elaboration with data from the Bank of Economic Information of INEGI. AARG= annual average rate of growth. 1. Value added per hours worked.

TABLE 4
LOCAL MORAN INDEX FOR LABOR PRODUCTIVITY AT THE STATE LEVEL IN MEXICO

	z-value	p-value	Moran ‘s I
2007	3.84	0.001	0.427
2010	3.89	0.006	0.403
2013	3.35	0.006	0.332
2016	4.35	0.002	0.493

Source: Own elaboration.

TABLE 5
ROBUST HAUSMAN TEST FOR THE SEM, SAR AND SAR MODELS

SEM	Ho:	chi(6)	Prob>=chi2
	difference in coeffs not systematic	10.81	0.094
SDM			
	difference in coeffs not systematic	31.6	0.0009
SAR			
	difference in coeffs not systematic	12.31	0.0554

Source: Own estimations.

TABLE 6
AKAIKE'S INFORMATION CRITERION AND BAYESIAN INFORMATION CRITERION

Model	Obs	ll(null)	DF	AIC	BIC
SDM	320	117.01	12	-210.018	-164.799
SAR	320	104.927	7	-195.854	-169.506
SEM	320	103.442	7	-192.885	-169.507

Source: Own estimations. Lower the number the better, model complexity and explanatory power variables overfit the model

TABLE 7
MEXICAN MANUFACTURING LABOR PRODUCTIVITY DETERMINANTS: A SPATIAL PANEL APPROACH, 2007-2016

		Fixed effects			Random effects		
		SEM	SDM	SAR	SEM	SDM	SAR
	R-square	0.049	0.143	0.066	0.0485	0.142	0.065
	between	0.22	0.089	0.232	0.2218	0.125	0.233
	overall	0.2	0.085	0.212	0.2026	0.116	0.214
	Mean of fixed-effects	2.184		1.206			
	Log-likelihood	103.443	117.01	104.927	-7.239	4.876	-5.86
Main effect							
	fbkf	0.053	0.018	0.063	0.0579	0.023	0.068
	Z	-2.05	-0.74	-2.74	-2.13	-0.89	-2.8

TABLE 7
MEXICAN MANUFACTURING LABOR PRODUCTIVITY DETERMINANTS: A SPATIAL PANEL APPROACH, 2007-2016

		Fixed effects			Random effects		
		SEM	SDM	SAR	SEM	SDM	SAR
	exp	-0.02	-0.009	-0.021	-0.0175	-0.009	-0.02
	Z	(-0.67)	(-0.30)	(-0.74)	(-0.59)	(-0.3100)	(-0.68)
	cap	-0.008	-0.001	-0.009	-0.0092	-0.003	-0.011
	Z	(-0.21)	(-0.03)	(-0.25)	(-0.23)	(-0.08)	(-0.29)
	bt	0.124	0.131*	0.128	0.1413	0.148*	0.144
	Z	-1.97	-2.15	-2.05	-2.16	-2.32	-2.21
	fdi	0.005	0.032	0.006	0.0049	0.029	0.005
	Z	-0.69	-1.25	-0.87	-0.61	1.06	-0.8
	cons				1.9247	0.524	1.028
	Z				-2.68	-0.3	-1.43
Spatial effect							
Sigma2_e				0.220*			0.205*
z				-3.45			-3.23
rho			0.139*			0.129	
z			-2.07			-1.93	
Lambda		0.209*			0.2042*		
z		-2.99			-2.77		
Wx effect	fbkf		0.179*			0.180*	
	Z		-4.8			-4.58	
	exp		-0.055			-0.048	
	Z		(-1.01)			-0.89	
	cap		-0.333			-0.003	
	Z		(-0.57)			(-0.43)	
	bt		-0.08			-0.049	
	Z		(-0.48)			-0.28	
	fdi		-0.003			-0.001	
	Z		(-0.11)			(-0.5)	

TABLE 7
MEXICAN MANUFACTURING LABOR PRODUCTIVITY DETERMINANTS: A SPATIAL PANEL APPROACH, 2007-2016 (CONCLUSIÓN)

		Fixed effects			Random effects	
	SEM	SDM	SAR	SEM	SDM	SAR
Variance						
lgt_theta		0.139	0.03		-2.921	-2.878
Z		-2.07	-12.59		-20.88	(-20.57)
sigma2_e		0.028	2.877		0.031	0.033
Z		-12.62	(-20.97)		-11.96	-11.93

Source: Own estimations. fbkf= state gross capital formation, exp= state exports, bt = technological high school, cap= state workers training, fdi = state foreign direct investment. *1 % confidence level.

TABLE 8
LABOR PRODUCTIVITY IN MEXICO: DYNAMIC SPATIAL DURBIN MODEL, 2007-2016

Number of obs = 288				
Number of groups = 32, Panel length = 9				
R-sq: within = 0.3124, between = 0.9325, overall = 0.9135				
Mean of fixed-effects = 0.6233				
Log-likelihood = 143.8058				
pd	Coef.	Std. Err.	z	P>|z|
Main				
pd				
L1.	0.69	0.06	11.90	0.00
Wpd				
L1.	-0.35	0.02	1.46	0.14
fbkf	0.03	0.02	1.46	0.14
exp	-0.08	0.03	-3.15	0.00
Cap	-0.01	0.03	-0.38	0.70
bt	0.06	0.05	1.18	0.24
fdi	0.11	0.03	4.03	0.00
Wx				
fbkf	0.08	0.04	2.14	0.03

TABLE 8
LABOR PRODUCTIVITY IN MEXICO: DYNAMIC SPATIAL DURBIN MODEL, 2007-2016

exp	-0.03	0.05	-0.62	0.54
cap	0.09	0.05	1.76	0.08
bt	0.07	0.15	0.48	0.63
fdi	-0.09	0.03	-3.21	0.00
Spatial				
rho	0.30	0.06	4.66	0.00
Variance				
sigma2_e	0.02	0.00	13.19	0.00
SR_Direct				
fbkf	0.04	0.02	2.02	0.04
exp	-0.09	0.03	-3.41	0.00
cap	0.00	0.03	-0.14	0.89
bt	0.06	0.06	1.08	0.28
fdi	0.10	0.03	3.89	0.00
SR_Indirect				
fbkf	0.12	0.05	2.55	0.01
exp	-0.07	0.07	-1.02	0.31
cap	0.12	0.07	1.84	0.07
bt	0.08	0.20	0.40	0.69
fdi	0.08	0.03	2.72	0.01
SR_Total				
fbkf	0.17	0.05	3.04	0.00
exp	-0.16	0.08	-2.05	0.04
cap	0.00	0.03	-0.14	0.89
bt	0.02	0.23	0.08	0.94
fdi	0.02	0.07	1.95	0.05
LR_Direct				
fbkf	0.10	0.07	1.42	0.16
exp	-0.27	0.09	-3.13	0.00
cap	-0.06	0.11	-0.52	0.61
bt	0.23	0.18	1.27	0.21
fdi	0.36	0.10	3.75	0.00
LR_Indirect				
fbkf	0.22	0.11	1.95	0.05
exp	-0.04	0.17	-0.25	0.81
cap	0.29	0.16	1.85	0.06

TABLE 8

LABOR PRODUCTIVITY IN MEXICO: DYNAMIC SPATIAL DURBIN MODEL, 2007-2016

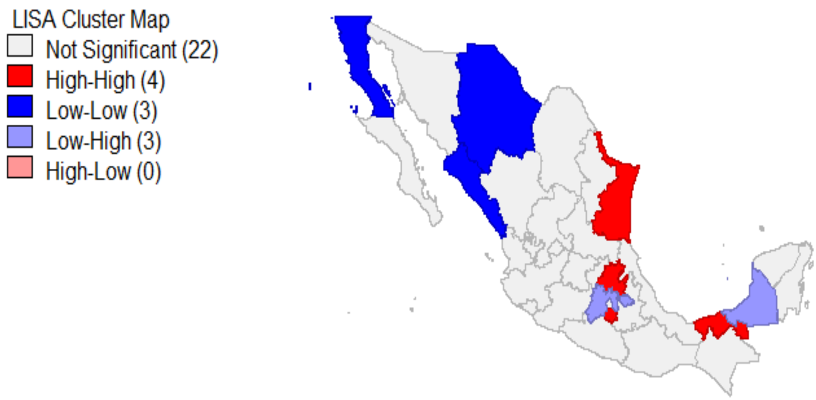
(CONCLUSIÓN)

bt	-0.27	0.44	-0.60	0.55
fdi	0.31	0.10	3.16	0.00
LR_Total				
fbkf	0.32	0.11	2.92	0.00
exp	-0.32	0.16	-1.95	0.05
cap	0.23	0.16	1.88	0.04
bt	-0.03	0.45	-0.08	0.94
fdi	0.05	0.03	1.50	0.13

Source: Own estimations. fbkf= state gross capital formation, exp= state exports, bt = technological high school, cap= state workers training, fdi = state foreign direct investment. *1 % confidence level. fbkf= state gross capital formation, exp= state exports, bt = technological high school, cap= state workers training, fdi = state foreign direct investment. *1 % confidence level.

MAP 1

LABOR PRODUCTIVITY CLUSTER MAP 2007



Source: Own elaboration.

MAP 2
LABOR PRODUCTIVITY CLUSTER MAP 2016

Source: Own elaboration.