Banco de México

Documentos de Investigación

Banco de México

Working Papers

N° 2007-09

Multifactor Productivity and its Determinants: An Empirical Analysis for Mexican Manufacturing

Héctor Salgado Banda
Banco de México

Lorenzo E. Bernal Verdugo
Banco de México

May 2007

Documento de Investigación
2007-09

Working Paper
2007-09

Multifactor Productivity and its Determinants: An Empirical Analysis for Mexican Manufacturing*

Héctor Salgado Banda†
Banco de México

Lorenzo E. Bernal Verdugo‡
Banco de México

Abstract

We use data from the Annual Industrial Survey for 1996-2003. First, we estimate production functions by means of growth accounting exercises and panel data econometrics for the whole sector and for 14 comprehensive groups. Various measures of Multifactor Productivity (MFP) are constructed, as we consider diverse combinations of inputs with capital, labour, electricity and transport. This allows us to compare MFP growth rates between groups. Second, we analyse econometrically some of the determinants of MFP and Labour Productivity (LP) growth. We find that, on the one hand, there is some evidence of a positive relationship between market concentration and technology adoption; on the other hand, both technology adoption and human capital seem to be promoting productivity, whilst market concentration is exerting a negative influence on it. In sum, our results suggest that, once controlling for the effect on technology adoption, more concentration (conversely, less competition) has a negative impact on productivity.

Keywords: Panel data, Productivity, Manufacturing, Competition.
JEL Classification: C33, D24, L11

Resumen

Se usan datos de la Encuesta Industrial Anual de 1996 a 2003. Primero, se estiman funciones de producción con contabilidad de crecimiento y econometría de datos de panel para el sector y para 14 grupos. Se construyen varias medidas de Productividad Multifactorial (PMF) al considerar diversas combinaciones de insumos con capital, trabajo, electricidad y transporte. Esto permite comparar tasas de crecimiento de la PMF entre los distintos grupos. Segundo, se analizan econométricamente algunos de los determinantes de la PMF y de la Productividad Laboral (PL). Se encuentra que, por una parte, existe evidencia de una relación positiva entre concentración de mercado y adopción tecnológica; por otra parte, tanto adopción tecnológica como capital humano parecen estar promoviendo la productividad, mientras que la concentración de mercado tiene una influencia negativa sobre ella. En suma, los resultados parecen sugerir que, una vez que se controla por el efecto sobre la adopción tecnológica, una mayor concentración (inversamente, menor competencia) tiene un impacto negativo sobre la productividad.

Palabras Clave: Panel de datos, Productividad, Manufacturas, Competencia.

---

*D. Flores provided outstanding research assistance. We are very grateful to D. Chiquiar for his guidance in this study. We also thank C. Capistrán, A. Díaz de León, A. Gaytán, E. Martínez and seminar participants at Banco de México and 2006 LACEA-LAMES for helpful comments. G. Leyva, A. Durán and O. Soto were of great help answering our doubts about the data. Any errors are the sole responsibility of the authors.

† Dirección General de Investigación Económica. Corresponding author.
Email: hsalgado@banxico.org.mx.

‡ Dirección General de Investigación Económica. Email: lbeverdugo@banxico.org.mx.

1 Introduction

Data on output and employment in the Mexican manufacturing industry suggest an increase in Labour Productivity (LP) over the 1988-2006 period, see Figure 1. Despite this, much has been said about how this industry has been losing competitiveness due to the lack of structural reforms (i.e. the need of a more flexible labour market and more competitive input markets). This, combined with the increasing presence of other emerging economies in international markets, has put this industry in particular, under additional pressure. To fully understand the dynamics behind Mexican manufacturing, which represented an average share of 18.8% of GDP during the 1996-2006 period, it is crucial to know its main characteristics.

Figure 1: Output and Employment in Manufacturing as a Percentage of Total, 1988-2006

This paper tries to achieve this objective by analysing the Mexican manufacturing industry, studying its recent development, LP and factors related to it, and by estimating production functions in which several input combinations are considered in order to obtain a number of Multifactor Productivity (MFP) measures and thus determine its behaviour and performance, both at a disaggregated level and as a whole. Moreover, it aims to determine econometrically some of the factors that tend to influence MFP and LP growth. Taking advantage of the disaggregation and availability of the data at the activity class level, this paper also performs a direct comparison between sectors in dimensions such as output share composition, export orientation, concentration, human capital intensity and technology adoption, on the one hand, and in their MFP and LP evolution, on the other.

Several variables have been evaluated in previous studies as possible determinants of MFP (see Section 2 for further references). The present study goes a step beyond the estimation of the parameters of production functions in Mexican manufacturing, as it considers a number of variables in its attempt to assess their effects on both MFP and LP performance. Amongst the variables used in this analysis are: *i*) input use intensity (capital, electricity and transport), *ii*) technology adoption, *iii*) concentration, *iv*) human capital intensity, and *v*) exports.

The use of the system generalised method of moments (system GMM) estimators have proven (see, for instance, Blundell and Bond (2000)) to be the most adequate econometric method to be applied with data showing the characteristics like those of the panel under consideration. This is an important contribution of this paper to the shortcomings regarding econometric methods used in the existing literature. With

the purpose of adding robustness to the results, as well as comparability with other studies, additional estimations with methods other than the system GMM are undertaken. However, the results are not as appealing and strong as those found under the GMM methodology.

The results regarding the effects of technology adoption and concentration on MFP performance are in line with those previously reported in similar studies (see, for instance, Calderon and Voicu (2004), Nickell (1996) and Okada (2005)), whilst some newly explored variables such as human capital and input use intensities are found to play an important role in explaining differences in MFP across manufacturing industries. For completeness, the same relationships are studied for the case of LP, which are found to be similar to those for MFP.

Since technology adoption turns out to be one of the determinants of productivity performance, this study also attempts to identify some of the factors influencing the adoption of technology in the industry. The results point out that manufacturing establishments operating in more concentrated markets (that is, with fewer producers) are more likely to invest in technology. Since technology adoption, in turn, positively affects both MFP and LP, it would be natural to think that concentration implicitly favours MFP and LP. However, it is important to note that, when this variable is included in the productivity estimations, our results suggest that concentration exerts a negative impact on both MFP and LP growth. In fact, the net effect is negative, that is, those sectors where there is more concentration (less competition) would tend to have a lower productivity growth.

The remainder of the paper is organised as follows. Section 2 briefly revises the related literature, emphasising on studies on Mexican manufacturing. Section 3 describes the data and the construction of the variables used. In Section 4, a general diagnosis of the Mexican manufacturing is presented, mainly based on its output share composition, export orientation, concentration, technology adoption, LP and human capital intensity. Section 5 explains, on the one hand, the methodology used to: *i*) obtain the MFP measures for the different manufacturing groups and for the whole sector using growth accounting exercises and econometric estimations, and *ii*) identify some of the factors that may help to explain the productivity measures; and, on the other hand, presents the respective results. Finally, Section 6 summarises.

2 Related Literature

On the attempt to estimate and measure MFP levels and growth rates, the estimation of the parameters of any given functional form for production is crucial. One of the most novel approaches to the estimation of such parameters is found in Blundell and Bond (2000), who consider a panel data for US manufacturing companies to show that the instruments available for the Cobb-Douglas production function estimation in first differences GMM are weak, a problem that may be present in studies like those of Mairesse and Hall (1996) and Nickell (1996). They propose the use of additional instruments by means of a system GMM estimator, which can be both valid and informative in the context of highly persistent series and with a panel of a small temporal dimension. They find coefficient estimates of 0.23 and 0.77 for capital and labour, respectively.

The literature considers a wide variety of factors that may help explain the MFP performance of manufacturing establishments and industries. One of the most commonly studied relationships is that

between MFP and Research and Development (R&D). For example, Mairesse and Hall (1996), using two panel data sets with information at the plant level in the manufacturing sectors of the US and France for 1978-1989, estimate the parameters of a Cobb-Douglas production function for each country by means of a difference GMM, in which labour, capital and "knowledge" (proxied for by investment in R&D) are considered as inputs. They find that the effect of R&D on productivity growth during the 1980s is nearly zero in both countries.

Competition is also one of the key factors associated with MFP performance in related studies. Nickell (1996) applies a difference GMM estimation for a panel data of around 700 British manufacturing establishments during 1972-1986. He finds that competition, lower levels of rents or more competitors in the industry have a significative positive effect on the growth rate of MFP. In a similar paper applied to the Japanese manufacturing, Okada (2005) uses a panel data of around ten thousand firms for the period 1994-2000 to study the impact that product market competition has on establishments' productivity. Following Nickell (1996), the difference GMM is used to estimate an output equation in which price-cost margins are used as the main proxy of the competition faced by the firm. Coefficient estimates equal to 0.72 and 0.33 for the labour and capital inputs, respectively, are encountered. As Nickell (1996), Okada (2005) reaches similar conclusions on the effect of competition on firms' performance.

Another factor that is taken into account as a variable explaining differences in MFP performance is domestic vs foreign ownership. Griffith (1999) uses a panel of data of manufacturing establishments in the automotive industry in the United Kingdom during 1980-1992 to analyse whether there are differences in productivity between domestic- and foreign-owned firms. A Cobb-Douglas production function is estimated by means of different econometric methods, including a system GMM, obtaining, for this particular case, coefficients of 0.08, 0.38 and 0.50 for capital, labour and intermediate materials, respectively. At the establishment level, MFP is calculated as the residual of these regressions. It is found that foreign-owned establishments have a higher MFP than their domestic counterparts.

Finally, other studies use structural changes in the economy as variables determining changes in productivity trends. For example, Pavcnik's (2002) results (obtained by means of semiparametric methods) suggest that liberalised trade enhanced plant productivity in the Chilean manufacturing industry during 1979-1986. In a similar fashion, Eslava *et al.* (2004) conclude, based on Ordinary Least Squares and Instrumental Variables methods, that the market flexibility gained after the reforms in Colombia becomes an important factor in explaining the productivity gains in its manufacturing industry during 1982-1998.

2.1 Studies on Mexican Manufacturing

With regards to studies for Mexican manufacturing, there are few contributions that focus on the estimation of production functions and calculation of MFP. In line with some of the previously described studies, some observers have tried to assess the extent to which MFP trends in Mexican manufacturing can be explained by factors that are not inherent to plant behaviour. For instance, Lopez-Cordova (2002) studies MFP at the plant level and its evolution in the face of trade and investment liberalisation under the North American Free Trade Agreement (NAFTA), from 1993 to 1999. This analysis estimates eight production functions (one for each manufacturing subsector except Other Manufacturing) and obtains coefficient estimates in the ranges of 0.04-0.19 for unskilled labour, 0.06-0.14 for skilled labour, 0.70-0.80 for

materials and 0.05-0.11 for capital. The main finding is that liberalisation has improved manufacturing productivity.

Lopez-Cordova and Mesquita (2003) study the role that integration plays on productivity performance by looking at the experience of Mexico and Brazil. They find that, for both economies, trade liberalisation has been an important productivity enhancing factor.

Other studies on Mexican manufacturing investigate the relationship between MFP performance and variables that depend to a greater extent on decisions taken at the firm or establishment level. For example, with regards to R&D, technology adoption, international integration and output reallocation, Calderon and Voicu (2004) compare plants' productivity growth and patterns of job creation and destruction across their relative degree of integration into foreign product markets, their access to technology, and behaviour with respect to R&D (measured as the amount spent on R&D and technology acquisitions as percentage of sales). Their findings suggest that the degree of integration in international markets is a strong determinant of firm performance, that is, firms that use larger shares of imported inputs show a stronger productivity growth; in fact, better access to imported inputs is found to be the most significant vehicle for the productivity enhancing effects of trade openness. Regarding the effect of technology on productivity, they find that firms that invest in R&D are more productive and display faster productivity growth than firms that do not invest in R&D. In a related study, Calderon and Voicu (2005) conclude that the observed gains in aggregate productivity can be mostly explained by reallocation of output to more productive plants, which is enhanced by a greater openness of the Mexican economy.

Foreign Direct Investment (FDI) and foreign ownership are also studied as possible determinants of MFP performance. Perez-Gonzalez (2004) studies the effect of these two variables on the productivity of Mexican manufacturing. Using data on output, employment and investment at the establishment level from the Annual Industrial Survey (AIS) for the period 1984-1993, and from the FDI database from Banco de Mexico to identify the ownership of the establishment, the study attempts to assess the change in plant performance after the FDI reforms were implemented in 1989 once foreign ownership reaches the majority threshold, that is, once foreign share holders acquire control of the establishment. The measure of performance used is plant MFP, which is obtained as the residual of standard log-linear Cobb-Douglas production functions, for each two-digit industry. The main findings are that FDI and MFP are positively correlated at the establishment level but the impact of FDI on productivity is mainly concentrated in establishments where multinational corporations acquire majority control.

As mentioned throughout the previous pages, the existing literature presents some issues that this paper attempts to analyse. The first of them consists in the exploration of variables whose impact on MFP and LP had not been previously studied. This is the case of human and physical capital intensities, variables that are found to have significant positive and negative effects, respectively, on both MFP and LP. Additionally, driven by its importance as a factor favouring MFP and LP performance, this paper also aims to identify the factors influencing technology adoption, finding that a higher expenditure on patents, trademarks and R&D is more likely to occur in establishments facing a lower degree of competition, although less competition (or more concentration, to put it in terms of the remainder of the paper) is found to exert, in net terms, a negative impact on productivity growth. A second important contribution of this paper is with regards to the econometric methodology used in the estimation of production function and calculation of MFP, as well as in the estimation of the variables affecting it. On

this respect, this paper makes an important contribution as it considers a recent technique specifically suited for data sets with the characteristics as the one under consideration. The system GMM yields unbiased and efficient estimators of the production function paramaters, which in turn allow for a more correct measurement of MFP, a virtue that also applies to the estimation of the determinants of MFP and LP.

3 Data and Variables

We use, mainly, the AIS from INEGI, which provides information on manufacturing regarding the following aspects: output, employment, investment, electricity consumption, and transport expenditure.[1] The AIS has been published since 1963. At first, it considered only 29 activity classes, but was extended in 1993, taking advantage of the Industrial Census (IC), considering as the population all the manufacturing establishments existing at that time. Thus, this new sample included, in 2003, over 5,400 establishments grouped into 205 activity classes corresponding to the 9 subsectors of the Mexican Activity and Product Classification (CMAP is its acronym in Spanish).[2] The surveyed establishments produce nearly 85% of total manufacturing output and employ about 65% of the sector's labour force. We consider a panel data for the sample period 1996-2003.[3] The most recent AIS is for 2004. However, it suffered considerable changes that do not allow us to consider it in this study (for example, there is no data on number of hours worked anymore).

The present document studies the 205 activity classes included in the AIS as a whole (i.e. total sector). However, to analyse in more detail specific subsectors, particularly the Machinery & Equipment subsector, we classify the 205 activity classes into 14 comprehensive groups, based on the North American Industry Classification System (NAICS).

The description and correspondence between both classifications are detailed in Table 1, which presents: *i*) the 9 CMAP subsectors, *ii*) the 14 NAICS groups, and *iii*) how the 9 CMAP subsectors have been reorganised into the 14 NAICS groups. For instance, subsector 3, Lumber & Wood, contains five activity classes (the numbers in parentheses in Table 1); these same five activity classes are reclassified into two NAICS groups, G3 Lumber & Wood and G14 Miscellaneous, with three activity classes going to G3 and the two remaining ones going to G14. Information on the main activities and products in each group can be found in the Appendix.

The variables considered in this study are[4]

Output

Gross Value Added (VA). The proxy for this variable is the difference between the value of finished products (Y) and the expenditure in intermediate materials (M). The series are deflated to be expressed

[1] The construction of the variables followed OECD (2001).

[2] It is important to note that despite the number of establishments, the AIS sample is somehow biased towards relatively large establishments: more than a hundred employees, with a few exceptions.

[3] We do not consider the crisis period 1994-1995 as this could bias our results.

[4] Similar results, unreported, are reached when other variables and methodologies for employment, capital and output (i.e. number of workers, value of finished products, etc.) are considered. The decision to focus on the ones described in this section is to facilitate comparisons with related studies.

in 1993 prices using a specific price index for each activity class elaborated by INEGI, based on information obtained from both the AIS and the Monthly Industrial Survey (MIS).[5]

Table 1: Correspondence: Subsectors (CMAP) and Groups (NAICS)

Subsector		Group		
S1	(38)	G1	(38)	Food, Beverage & Tobacco
S2	(32)	G2	(32)	Textile, Apparel, Fur, Leather & Footwear
S3	(5)	G3	(3)	Lumber & Wood
		G14	(2)	Miscellaneous
S4	(9)	G4	(9)	Paper, Printing, Publishing & Reproduction
S5	(38)	G2	(1)	Textile, Apparel, Fur, Leather & Footwear
		G5	(2)	Petroleum & Coal
		G6	(32)	Chemicals
		G13	(1)	Computer & Electronic Products
		G14	(2)	Miscellaneous
S6	(16)	G7	(16)	Non-metallic & Glass
S7	(7)	G8	(7)	Primary & Fabricated Metal
S8	(57)	G8	(12)	Primary & Fabricated Metal
		G9	(11)	Machinery
		G10	(10)	Electrical Equipment, Appliances & Components
		G11	(7)	Automobiles
		G12	(4)	Other Transportation Equipment
		G13	(12)	Computer & Electronic Products
		G14	(1)	Miscellaneous
S9	(3)	G14	(3)	Miscellaneous

Number of Activity Classes in parentheses

Value of Finished Products (Y). It is the market value of the output of each activity class, using for its calculation an average wholesale price. This variable includes what is produced with the inputs used in a given year, regardless whether the products are sold or not. Therefore, the use of this variable considers the variation in the establishments' inventories. Its value is deflated with price indices specific to each activity class elaborated by INEGI.

Total raw and intermediate materials (M). Expenditure in materials and inputs consumed in the production process. This concept includes: *i*) domestic raw materials, parts and components, *ii*) imported raw materials, parts and components, *iii*) packages, and *iv*) fuels and lubricants.

[5] Mairesse and Hall (1996) conclude that their results are very similar when using either value-added or sales as the dependent variable. Basu and Fernald (1995) state that using value-added in production function estimations may yield incorrect results in the presence of imperfect competition and increasing returns to scale. In unreported results, this study considered both variables; certainly, the conclusions do not change drastically.

Capital

Capital stock (K). The series are constructed following the perpetual inventory methodology which consists in the period-to-period update of an initial capital stock using investment in fixed assets for every period.[6] That is, with the initial capital stock, a depreciation rate, and investment flows, it is possible to calculate each period's capital stock. In short, capital cumulates according to the law of motion

$$K_{ijt+1} = (1 - \delta_{ij})K_{ijt} + I_{ijt}, \tag{1}$$

where K represents capital stocks, δ is a depreciation rate, I stands for investment flows, i is an activity class, j is a type of capital good, and t is a year.

The initial capital stock is obtained from the IC of 1993, where the fixed assets valuation is made as of December 31 1993, taking into account the depreciation and changes in their value caused by the variation in prices and in the exchange rate. Given that the IC includes the totality of the existing manufacturing establishments in each activity class, it is necessary to adjust the initial value of the capital stock to make it compatible with the sample size of the AIS. Thus, based on the fact that the sample represents 85% of total manufacturing output and 65% of employment, it is assumed that the initial capital stock, for each activity class, is 75% of the reported value in the IC of 1993.[7]

The investment flows for each period are calculated using the AIS, where purchases and sales of fixed assets in each period are reported. The investment series are deflated using specific price indices for capital goods (each asset type in each manufacturing branch has its own price index) elaborated by Banco de Mexico. This means that different price dynamics for different types of capital goods are being taken into account.

The depreciation rate, specific for each of five asset types[8] in each activity class, is the amount by which assets depreciate due to use or obsolescence during the year as a proportion of the value of the capital stock at the end of the year. Information available in the IC from 1998 is used.[9] The depreciation rates are assumed to remain constant over time. For each year, the total capital stock is the sum of the stocks for each asset type.[10]

Employment

Worked hours (L). Includes the occupied personnel (both white- and blue-collar workers). This variable has been analysed in similar studies, see for example Disney *et al.* (2003), Eslava *et al.* (2004), Klette (1999), Lopez-Cordova (2002) and Perez-Gonzalez (2004).

[6] As usually explained in studies that use data on capital stocks, the construction of such series is rather challenging due to the many assumptions made given the absence of more precise and periodical measures of this variable.

[7] The results hold to alternative capital stock series when different initial levels are assumed (either 65% or 85% of the value reported in the IC of 1993).

[8] Namely: *i*) machinery and production equipment, *ii*) buildings, constructions and fixed installations/facilities, *iii*) land, *iv*) transportation equipment, and *v*) other fixed assets.

[9] In the IC of 1998, the establishments report fixed asset valuation at the end of 1998 as well as its depreciation during 1998 due to use or obsolescence. This information allows the calculation of asset type's specific depreciation rates for each activity class.

[10] The results remain qualitatively the same when using: *i*) a single, homogeneous depreciation rates for all asset types and activity classes, and *ii*) an implicit price index for fixed capital formation to deflate the investment flows on capital goods.

Worked hours adjusted by quality (L_{adj}). Total amount of hours worked by the occupied personnel (L) multiplied by the wage per hour in the activity class as ratio of the wage per hour in total manufacturing.[11]

Energy

Electricity (E). Value of the electricity consumed by manufacturing establishments in the production process reported for each activity class in the AIS. To deflate the series, an electric energy specific index is constructed as a weighted average of the specific price indices from the Producer Price Index (PPI) of industrial electric energy elaborated by Banco de Mexico. The inclusion of energy consumption as an input of production has been explored in several studies, see for instance Casacuberta *et al.* (2004), Eslava *et al.* (2004) and Klette (1999).[12]

Transport

Transport (T). Expenditure on transportation of manufactured products reported in the AIS is used. The series are deflated using a transportation specific price index, which is calculated as a weighted average of different transportation indices elaborated by Banco de Mexico from PPI. These indices are aggregated using the generic goods' weights in the PPI.[13]

3.1 Some Considerations

As most micro-empirical studies, this document faces some limitations, which are commented next.

First, we do not have establishments, firms or companies as a unit of study. Instead, each data point corresponds to an "activity class", that conglomerates a number of manufacturing establishments into it. Implicitly, this is assuming that every establishment in each activity class is somehow alike in terms of its manufacturing processes, technology, etc.

Second, the time horizon considered in this study is relatively short (8 years, from 1996 to 2003), which may impede to observe a complete economic cycle and thus bias our productivity estimates. For example, it is worth mentioning the sharp fall in the Automobile sector's output in some of the years of the sample, an issue that, in this study, would imply a decrease in productivity.

Third, the construction of variables may suffer from the typical problems in measurement and construction of variables (i.e. simple models of depreciation, lack of data, use of proxies for variables, deflated variables with 'general' price indices, etc.). For example: *i*) the variable of capital aggregates different types of investment in different years using simple models of depreciation. This is a common practice in similar studies and it may yield biases, and *ii*) VA is deflated by specific price indices for each activity class; however, the majority of the establishments manufacture more than a single and homogeneous product, that is, one price index is considered for different establishments with different product ranges in the same activity class.

[11] Group's wages per hour are calculated as the weighted average of wages per hour in the activity classes corresponding to each group, using worked hours as weights. The same procedure is followed for the calculation of wages per hour in the whole sector.

[12] Consumption (thousands of Kw/h) could have been used as well. However, there are many zeroes reported in 1998 and 2003.

[13] The generics used for the calculation of this specific index are: *i*) railroad cargo transportation, *ii*) general automotive cargo transportation, *iii*) sea cargo transportation, and *iv*) air cargo transportation.

Fifth, more precise calculations and estimates could be obtained if additional information were available, particularly about: *i*) the composition of worked hours (schooling and training levels, productive process incidence, etc.), *ii*) the capital stock (asset lifetime, energy efficiency, technological level, training required for its operation, etc.), *iii*) the use of and expenditure in telecommunications, and *iv*) the main type of transportation used (by air, rail, road or sea) and destination (distance) of their products.

Finally, on the econometric side, due to the few observations available in some manufacturing subsectors/groups, one must be cautious with the obtained production function estimates.

4 Characteristics of Mexican Manufacturing: 1996-2003

This section is divided into two parts. First, we briefly analyse different dimensions such as output share composition, export orientation, concentration and technology adoption of the Mexican manufacturing industry. Second, we focus on LP, human capital intensity and labour mobility.

4.1 Some Characteristics

Composition

Regarding the composition of output amongst the different groups in Mexican manufacturing, in 2003 the groups with a large share in total output were G11 Automobiles (15.8%), G6 Chemicals (15.5%) and G8 Primary & Fabricated Metal (11.0%), whilst the lowest shares were for G3 Lumber & Wood (0.3%), G5 Petroleum & Coal (0.6%) and G14 Miscellaneous (1.0%), see Table A1 in the Appendix.[14]

Also, the change in composition, between 1996 and 2003, is shown for each group. In this regard, it is observed that G13 Computer & Electronic Products is the only group that has considerably increased its share, by moving from 3.7% in 1996 to 8.6% in 2003 (4.9 p.p.). Contrasting with this case, the three groups that presented the greatest decreases are G2 Textile, Apparel, Fur, Leather & Footwear (-1.5 p.p.), G6 Chemicals (-1.5 p.p.) and G8 Primary & Fabricated Metal (-1.3 p.p.).

Export Orientation

With respect to export orientation, the 14 groups in Mexican manufacturing show some differing patterns, see Table A2 in the Appendix. This measure is equal to the ratio of exports to total sales. In 2003, this ratio was between 2.4% for G5 Petroleum & Coal and 79% for G13 Computer & Electronic Products. It is noteworthy that only 3 out of 14 groups have shown an increase in their export orientation: G13 Computer & Electronic Products (+7.1 p.p.), G10 Electrical Equipment, Appliances & Components (+6.5 p.p.) and G9 Machinery (+3.6 p.p.). The whole sector has shown a decrease of 1.8 p.p. in this measure by moving from 29.4% in 1996 to 27.6% in 2003. Effectively, and in spite of the period under consideration, G11 Automobiles and G13 Computer & Electronic Products are clear exporting groups.

Concentration

The market structure of Mexican manufacturing is studied based on Herfindahl-Hirschman (HH) concentration indices calculated for each of the 14 groups.[15] In general, concentration has increased between 1996 and 2003 amongst the diverse groups of the sector, see Table A3 in the Appendix. Concentration

[14] Table A1 also includes the share based on worked hours.

[15] The index is calculated as the sum of the squares of the market share held by the establishments pertaining to each group.

went up in 10 out of 14 groups, except in G13 Computer & Electronic Products, G9 Machinery, G8 Primary & Fabricated Metal and G4 Paper, Printing, Publishing & Reproduction.[16] When considering the concentration indices obtained for the activity classes corresponding to each group, it is observed that between 1996 and 2003 the minimum value of the HH index increased in 12 of the 14 groups. Concentration increased in 149 out of 205 activity classes between 1996 and 2003; moreover, in 1996 there were 72 activity classes highly concentrated (i.e. HH>1,800), in 2003 the number increased to 90 activity classes.

Technology Adoption

Measured as the expenditure in technology transfers and royalties as a proportion of VA. The variable includes concepts such as patents and trademarks, technical consulting, basic engineering, services in administrative technology and business operation.[17] This measure can be understood as a proxy for by innovation and technology related activities. For simplicity, henceforth we will refer to it as 'technology adoption'.

The groups in the top three positions of the ranking are G13 Computer & Electronic Products, G6 Chemicals and G10 Electrical Equipment, Appliances & Components. The groups in the last three positions are G12 Other Transportation Equipment, G8 Primary & Fabricated Metal and G3 Lumber & Wood, see Table A4 in the Appendix.

4.2 Labour Productivity, Human Capital Intensity and Labour Mobility

Labour Productivity (LP) is defined as VA per worked hour. Table 2 shows the levels of this variable in 1996, 1999 and 2003, as well as its annual average growth rate during 1996-2003. G13 Computer & Electronic Products and G5 Petroleum & Coal are the groups presenting the highest average growth rates, whilst G9 Machinery and G12 Other Transportation Equipment the lowest ones.

To proxy for by the quality and the skill level of labour hired by the different manufacturing groups, we construct the variable Human Capital Intensity. It is equal to labour remunerations per worked hour paid in each manufacturing group divided by the weighted average labour remunerations paid in the whole sector (i.e. relative wage).[18] G5 Petroleum & Coal shows the greatest intensity in human capital, followed by G6 Chemicals, G11 Automobiles, and G13 Computer & Electronic Products. At the bottom of the ranking are G3 Lumber & Wood, G2 Textiles and G14 Miscellaneous, see Table A5 in the Appendix. This could be reflecting differences in the quality of human capital required by each group, as well as the possibility that some unions obtain additional benefits due to their bargaining power (rent extraction).

Its value ranges between 0 and 10,000, the latter being the case of monopoly. The index is given by $HH_{jt} = \sum_{i=1}^{J} (MS_{ijt})^2$ with $MS_{ijt} = Y_{ijt} / \sum_{i=1}^{J} Y_{ijt}$, where MS is market share (in percent, from 0 to 100); and i is an establishment in group j at time t. HH indices are reported for activity classes as well, see Table A3 in the Appendix. The HH indices are calculated according to the shares in the value of finished products.

[16] It is important to note that the indices are calculated on the basis of the establishments considered in the AIS sample, that is, other issues such as imports competing with domestically produced goods or the competition faced by domestic firms in international markets, are not explicitly taken into account in the construction of the index.

[17] It does not include purchase of patents and trademarks.

[18] Differences in Human Capital Intensity might be related to the observed differentials in LP amongst manufacturing groups.

Table 2: VA per Worked Hour: Levels and Average Annual Growth Rate (1996-2003)

		Levels			Average Change
		1996	1999	2003	1996-2003
G13	Computer & Electronic Products	63.9	80.0	124.4	10.0 %
G5	Petroleum & Coal	75.6	100.6	127.9	7.8 %
G3	Lumber & Wood	20.3	24.8	32.0	6.7 %
G10	Electrical Equipment, Appliances & Components	42.0	49.9	59.4	5.1 %
G1	Food, Beverage & Tobacco	56.7	65.4	73.7	3.8 %
G8	Primary & Fabricated Metal	66.8	73.9	85.7	3.6 %
G14	Miscellaneous	24.5	26.7	31.3	3.5 %
G2	Textile, Apparel, Fur, Leather & Footwear	24.5	25.1	30.2	3.0 %
G7	Non-metallic & Glass	77.5	86.0	95.4	3.0 %
G11	Automobiles	86.0	90.9	104.4	2.8 %
G4	Paper, Printing, Publishing & Reproduction	48.0	56.3	58.2	2.8 %
G6	Chemicals	71.0	75.8	80.2	1.7 %
G12	Other Transportation Equipment	19.1	28.1	20.4	1.0 %
G9	Machinery	40.7	37.6	43.1	0.8 %
G15	Total Manufacturing	55.3	61.7	69.8	3.4 %

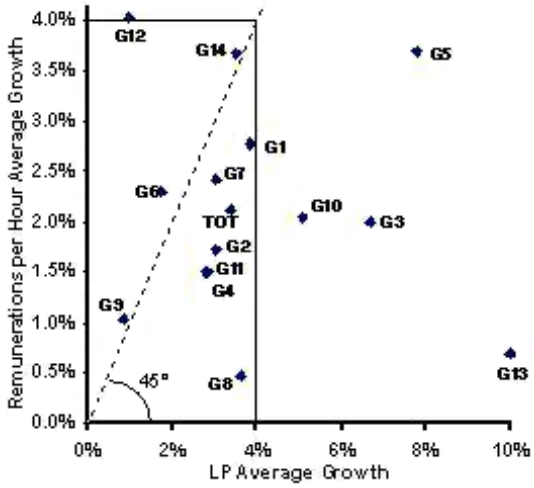
Groups ranked with respect to average LP growth rate

Additionally, the change in LP can be related to the observed change in real remunerations per worked hour in each group. It is found that the manufacturing groups showing highest increases in LP are not necessarily those with the highest increases in real remunerations per hour, see Table A5 in the Appendix. The groups presenting highest increases in real remunerations are G12 Other Transportation Equipment, G5 Petroleum & Coal and G14 Miscellaneous; whilst the groups with the lower increases are G8 Primary & Fabricated Metal, G13 Computer & Electronic Products and G9 Machinery.

In order to analyse in more detail both LP and real wage, Figure 2 plots the annual average growth rate of real remunerations against the annual average growth rate of LP. The 45° line represents the points at which both rates are equal. Therefore, above this line are the groups whose increase in real remunerations per worked hour is greater than their increase in LP, whilst for the groups located below the line the opposite applies. The groups located above the line are G9 Machinery, G12 Other Transportation Equipment, G6 Chemicals and G14 Miscellaneous. It is noteworthy that these groups are also those with very low LP growth: ranked in positions 14, 13, 12 and 7, respectively. Moreover, it is important to highlight the situation of G13 Computer & Electronic Products which, despite being the group with the highest average growth in LP (10.0%), is the group with the second lowest increase in real remunerations (0.7%); this might be due to the exposure of this particular group to global competition (i.e. it is the top exporter).

Finally, to understand the importance that labour mobility has on the sector's LP growth, an exercise is made, consisting of a more detailed assessment of the role played by: *i*) the reallocation of the labour input amongst groups, and *ii*) the LP growth rate per group. Following the approach outlined in Cameron

Figure 2: Average Increase in Remunerations per Worked Hour and LP, 1996-2003



et al. (1997), Table 3 presents a decomposition of the net gains in LP into two effects: *i*) the intragroup effect, derived from the gains in LP in each manufacturing group, and *ii*) the intergroup effect, derived from labour reallocation between groups. Such decomposition is based on the fact that LP in the whole sector can be expressed as the weighted average of LP in each group

$$\frac{VA}{L} = \sum_{j=1}^{14} \left(\frac{Y_j}{L_j} \right) \omega_j, \tag{2}$$

where VA is value added, j denotes a group and

$$\omega_j = \frac{L_j}{L}.$$

Taking first differences of equation (2), the change in LP can be calculated as

$$\Delta \frac{VA}{L} = \sum_{j=1}^{14} \left(\Delta \frac{VA_j}{L_j} \right) \omega_{j,t-1} + \sum_{j=1}^{14} (\Delta \omega_j) \frac{VA_{j,t-1}}{L_{j,t-1}}. \tag{3}$$

The first term of the right hand side of equation (3) is the intragroup effect, whereas the second term is the intergroup effect. Intuitively, equation (3) shows that, regarding the intragroup effect, groups with faster LP growth will have larger contributions to aggregate LP growth. With regards to the intergroup effect, it will be the case that groups with a declining share in total employment will contribute negatively, whereas the groups increasing their shares will have a positive contribution. Still, the magnitude of the contribution will depend on each group's level of LP.

It is found that labour reallocation between groups has not been an important source for aggregate LP growth, that is, reallocation of the labour input between groups with differing productivity levels has played a minor role in explaining the aggregate increase in LP (5.3%). However, the positive contribution of the intergroup effect is an indication that the groups with relatively higher levels of LP have obtained net gains in labour shares, which more than offset the net losses obtained by the relatively less productive

groups. In turn, the intragroup effect explains 94.7% of the observed change in LP in the whole manufacturing sector, effect that is greatly reinforced by the fact that all groups present positive LP growth rates. For example, in Table 3 it is observed that G1 Food, Beverage & Tobacco is the group that makes the greatest contributions to both intragroup and intergroup effects, which is expected since this group, in addition to being the largest in terms of employment, obtained the greatest increase in labour share, and a LP growth rate of 3.8% (higher than the average of 3.4% for the whole sector). In sum, this might be reflecting the existence of some rigidities related to labour mobility between groups.[19]

Table 3: Decomposition of LP Growth in Total Manufacturing (Percent)

	Group	Intra	Inter	Total
G1	Food, Beverage & Tobacco	29.1	10.1	39.3
G13	Computer & Electronic Products	8.8	-0.7	8.1
G11	Automobiles	11.1	1.2	12.3
G8	Primary & Fabricated Metal	10.8	-2.5	8.3
G10	Electrical Equipment, Appliances & Components	6.4	-0.1	6.3
G6	Chemicals	9.3	-0.2	9.1
G4	Paper, Printing, Publishing & Reproduction	4.4	2.1	6.5
G7	Non-metallic & Glass	6.5	-0.5	6.0
G14	Miscellaneous	1.3	0.3	1.6
G9	Machinery	0.4	-0.2	0.2
G5	Petroleum & Coal	1.3	-0.5	0.9
G12	Other Transportation Equipment	0.0	0.1	0.1
G3	Lumber & Wood	0.6	-0.6	-0.1
G2	Textile, Apparel, Fur, Leather & Footwear	4.7	-3.2	1.5
G15	Total Manufacturing	94.7	5.3	100.0

Similar results are encountered when data disaggregation is set at the activity class level for the calculation of the intra and intergroup effects. First, the reallocation of the labour input from less to more productive activity classes plays a minor role in explaining the growth rate of LP for the whole sector, accounting for only 2.3% of the net change in LP. Second, the bulk of the growth rate of LP is explained by the intragroup effect which, with a contribution even greater than that at the group level, accounts for 97.7% of the change in LP. However, at the activity class level, the exercise allows for the identification of activity classes, in groups other than G1 Food, Beverage & Tobacco (which includes 4 out of the 10 activity classes with the greatest contributions), that make important contributions to aggregate LP growth; for example: *i*) production, assembly and repair of computers, and *ii*) production and assembly of automobiles and trucks, which contribute with 8.2% and 5.6%, respectively, to the LP growth rate in the whole sector.

[19] As a matter of fact, this is not the mobility that was expected from the implementation of NAFTA. See, for instance, Harrison and Hanson (1999).

5 Methodology and Results

This section explains both the methodological approach undertaken to estimate the production functions and to analyse some of the determinants of productivity, and presents the corresponding results.

5.1 Production Function

A Cobb-Douglas production function-type is assumed

$$Y_{it} = A_{it} K_{it}^{\alpha_i} L_{it}^{\beta_i}; \quad i = 1, \ldots, N; \quad t = 1, \ldots, T, \tag{4}$$

where Y is a measure of output (VA in our case), A is a productivity parameter, K is capital and L is labour, α and β are the output elasticities with respect to their corresponding factor, i is an activity class and t is time.

In addition to the traditional calculation of α and β, other factor elasticities are calculated and estimated, that is, different production functions, with electricity (E) and transport (T), are considered. Hence, the more general production function is given by

$$Y_{it} = A_{it} K_{it}^{\alpha_i} L_{it}^{\beta_i} E_{it}^{\gamma_i} T_{it}^{\lambda_i}. \tag{5}$$

This approach is applied for the whole manufacturing sector and for the 14 groups.

5.1.1 Growth Accounting

To obtain the level of MFP, from (4) or the more general production function (5), we solve for A, which can be calculated for each year

$$A_{it} = \frac{Y_{it}}{K_{it}^{\alpha_i} L_{it}^{\beta_i}}.$$

The output elasticities of factors are approximated by the share of the input in the total cost assuming constant returns to scale (CRS) and perfect competition. Therefore, the considered shares are specific for each combination of inputs. The weighted average of the input shares is obtained for every activity class corresponding to each group in the period 1996-2003.

A complementary approach consists on the calculation and comparison of growth rates. Besides the changes in MFP, changes in the utilisation of inputs also explain the observed output growth. Specifically, the contribution of each input to the average growth rate of output is equal to the average growth rate of each input times its elasticity, that is

$$\triangle \%Y_{it} = \triangle \%A_{it} + \alpha_i \triangle \%K_{it} + \beta_i \triangle \%L_{it}.$$

Results

Total Sector

Table 4 presents the MFP growth rates, the factor shares and their respective contributions to the observed average growth rate of value added for the whole sector. The output elasticity of capital is between 0.28 (with $KLET$) and 0.34 (with KL), whilst the elasticity of labour is between 0.56 (with

$KLET$) and 0.66 (with KL). These parameters are in line with those used by others studies on MFP in the Mexican economy, assigning to capital an elasticity between 0.30 and 0.33, and for labour between 0.67 and 0.70 (see, for instance, Faal 2005 and Bergoeing *et al.* 2002). Regarding the other factors, electricity's values are between 0.06 and 0.07 and for transport between 0.10 and 0.11.

Table 4: Growth Accounting: Total Manufacturing, 1996-2003

Factor Shares				Contribution to Avg. Growth				Avg. MFP	
K	L	E	T	K	L	E	T	Level	Growth
0.34	0.66			1.26%	-0.08%			16.1	2.06%
0.31	0.62	0.07		1.15%	-0.07%	-0.08%		17.3	2.24%
0.30	0.59		0.11	1.12%	-0.07%		0.31%	17.1	1.88%
0.28	0.56	0.06	0.10	1.03%	-0.07%	-0.07%	0.29%	18.1	2.06%

It is worth mentioning the fact that the change in MFP (Solow residual measure) is the main explanatory component of the observed changes in growth rates, both for output and LP. In the case of output, its growth is explained between 58% and 69% by MFP, depending on the combination of inputs considered; whilst, as will be seen in Table 8, LP growth is explained in 61.8% by MFP.[20]

The crucial point to note is that the average growth rate of MFP in 1996-2003 increases when E is included into the production function, whilst diminishes when T is added to the input's list. This could shed some light that E (T) is contributing, negatively (positively), to the traditional Solow-residual measure (MFP with K and L), see Table 5.

Table 5: Changes in MFP Average Growth Rates, 1996-2003

KL to KLE	KL to KLT	KLE to KLET	KLT to KLET
+	-	-	+

The finding that transport is contributing positively to the MFP measure does not mean that this sector has been presenting remarkable developments. In fact, the actual infrastructure in Mexico is incipient and compared to other economies is ranked amongst the lowest positions, see for example, IMCO (2004a, 2004b), World Bank (2006) and World Economic Forum (2006).

To understand a bit more the result that electricity is contributing negatively to the traditional Solow-residual measure, it is relevant to emphasise that Mexico is lagging behind the rest of the countries, both in terms of prices and capacity, see for example: IMCO (2004a, 2005, 2007), International Energy Agency and Organisation for Economic Co-operation and Development (2005), World Bank (2006) and World Economic Forum (2006).

[20] This is related to Bergoeing *et al.* (2002), who find that MFP contributed in 85% to the growth rate of output per working age population in the Mexican economy during 1995-2000. Contrasting results are obtained by Young (1995), who concludes that growth in Asian countries is determined by the accumulation of capital and not by technological progress (measured by the Solow residual).

These findings, the effects of E and T on the MFP growth rate, suggest two hypotheses subject to further research. First, distortions in the determination of electricity prices and the high charges for electricity consumption lead to a lower use of electricity in relation to other inputs.[21] Second, gains in productivity could be observed through transport; this might be reflected in the relocation of the manufacturing production from the central to the northern and border regions, see Table A6 in the Appendix.

Group Level

As in the case for total manufacturing, we present the growth rates of MFP at the group level, the factor shares and their respective contributions to the VA average growth.

With respect to the average levels of MFP, Table A7 in the Appendix shows that the groups in the first two places are G13 Computer & Electronic Products and G5 Petroleum & Coal. The last two places are for G12 Other Transportation Equipment and G2 Textile, Apparel, Fur, Leather & Footwear. When calculating the average growth rate of MFP with the different combinations of inputs, it is found that, on the one hand, the groups in the first places are G13 Computer & Electronic Products, G5 Petroleum & Coal, G3 Lumber & Wood and G10 Electrical Equipment, Appliances & Components; on the other hand, the groups in the last places are G8 Primary & Fabricated Metal, G12 Other Transportation Equipment, G6 Chemicals, G9 Machinery and G11 Automobiles, see Table A8 in the Appendix.

Similar to the case for total manufacturing, in 11 groups the average growth rate of MFP increases when E is included into the list of inputs, whilst it diminishes when T is added. Thus, in general terms, E (T) seems to continue having, this time at the group level, a negative (positive) effect in the traditional Solow-residual measure.[22]

Regarding factor intensity, it is found that with the $KLET$ combination, the most capital intensive groups are G8 Primary & Fabricated Metal, G7 Non-metallic & Glass, G4 Paper, Printing, Publishing & Reproduction and G11 Automobiles, which in turn are the least labour intensive. The least capital intensive groups are G9 Machinery, G14 Miscellaneous and G12 Other Transportation Equipment, which in turn are the most labour intensive. The most electricity intensive groups are G8 Primary & Fabricated Metal, G7 Non-metallic & Glass and G4 Paper, Printing, Publishing & Reproduction, and the least intensive are G12 Other Transportation Equipment, G13 Computer & Electronic Products, and G14 Miscellaneous. The most transport intensive groups are G11 Automobiles, G1 Food, Beverage & Tobacco, and G7 Non-metallic & Glass, whilst the least intensive are G9 Machinery, G10 Electrical Equipment, Appliances & Components and G2 Textile, Apparel, Fur, Leather & Footwear, see Tables 6 and 7.[23]

Now, we extend the approach described in Cameron *et al.* (1997), to decompose the LP growth as follows

$$\Delta\% \left(\frac{VA}{L}\right)_i = \Delta\% MFP_i + \alpha_i \Delta\% \left(\frac{K}{L}\right)_i + \gamma_i \Delta\% \left(\frac{E}{L}\right)_i + \lambda_i \Delta\% \left(\frac{T}{L}\right)_i . \tag{6}$$

[21] See, for instance, CFE (2006).

[22] G8 Primary & Fabricated Metal and G13 Computer & Electronic Products always increase their MFP average growth rate when inputs are added into the production function, whilst for G3 Lumber & Wood the opposite occurs.

[23] There is no significant Spearman correlation between the ranking of the MFP growth rate and the ranking of factor intensities.

Table 6: Shares and Contributions (KL), 1996-2003

Group		Factor Shares		Contribution to Avg. Growth		MFP	
		K	L	K	L	Level	Growth
G5	Petroleum & Coal	0.33	0.67	0.3%	-2.2%	22.9	6.3%
G13	Computer & Electronic Products	0.31	0.69	3.6%	-0.1%	25.4	6.3%
G3	Lumber & Wood	0.36	0.64	-1.9%	-4.8%	5.6	5.8%
G10	Electrical Equipment, Appliances & Components	0.28	0.72	1.2%	0.0%	17.8	3.9%
G4	Paper, Printing, Publishing & Reproduction	0.39	0.61	-0.1%	0.6%	11.0	3.3%
G1	Food, Beverage & Tobacco	0.29	0.71	1.2%	0.6%	21.7	2.8%
G14	Miscellaneous	0.25	0.75	1.0%	0.5%	13.8	2.7%
G2	Textile, Apparel, Fur, Leather & Footwear	0.29	0.71	-0.2%	-1.6%	9.9	2.6%
G7	Non-metallic & Glass	0.44	0.56	0.6%	-0.2%	11.7	2.2%
G8	Primary & Fabricated Metal	0.46	0.54	1.6%	-0.5%	9.9	1.5%
G12	Other Transportation Equipment	0.26	0.74	-0.1%	0.7%	7.4	1.3%
G6	Chemicals	0.30	0.70	1.4%	-0.1%	22.1	0.3%
G9	Machinery	0.19	0.81	0.5%	-0.5%	20.0	0.2%
G11	Automobiles	0.39	0.61	3.2%	0.4%	16.1	-0.1%
	Total Manufacturing	0.34	0.66	1.3%	-0.1%	16.1	2.1%

Groups ranked with respect to average MFP growth rate.

Table 7: Shares and Contributions (KLET), 1996-2003

Group	Factor Shares				Contribution to Avg Growth				MFP	
	K	L	E	T	K	L	E	T	Level	Growth
Computer & Electronic Products	0.27	0.61	0.02	0.10	3.2%	-0.1%	0.0%	-0.5%	27.2	7.2%
Petroleum & Coal	0.29	0.59	0.03	0.09	0.3%	-1.9%	-0.1%	0.8%	24.4	5.4%
Lumber & Wood	0.30	0.53	0.07	0.10	-1.6%	-3.9%	-0.4%	-0.3%	6.6	5.3%
Electrical Eq., Appl. & Comps.	0.26	0.65	0.04	0.05	1.0%	0.0%	-0.1%	0.1%	19.7	4.0%
Paper, Printing, Publishing & Rep.	0.32	0.53	0.08	0.07	-0.1%	0.5%	-0.1%	0.2%	13.1	3.3%
Food, Beverage & Tobacco	0.25	0.60	0.04	0.11	1.0%	0.5%	0.0%	0.6%	23.9	2.6%
Textile, Apparel, Lther. & Footwr	0.25	0.63	0.06	0.06	-0.2%	-1.4%	-0.2%	0.2%	11.5	2.4%
Miscellaneous	0.23	0.68	0.03	0.06	0.9%	0.5%	0.0%	0.4%	15.2	2.4%
Primary & Fabricated Metal	0.35	0.43	0.15	0.07	1.3%	-0.4%	-0.1%	-0.3%	11.6	2.2%
Non-metallic & Glass	0.33	0.44	0.12	0.11	0.5%	-0.2%	0.0%	0.5%	14.0	1.9%
Other Transportation Equipment	0.24	0.67	0.02	0.07	-0.1%	0.6%	-0.1%	1.0%	8.3	0.5%
Chemicals	0.24	0.59	0.07	0.10	1.1%	-0.1%	-0.1%	0.2%	23.2	0.5%
Machinery	0.18	0.75	0.03	0.04	0.5%	-0.5%	0.0%	0.0%	21.5	0.2%
Automobiles	0.31	0.49	0.04	0.16	2.6%	0.3%	0.1%	0.7%	17.2	-0.1%
Total Manufacturing	0.28	0.56	0.06	0.10	1.0%	-0.1%	-0.1%	0.3%	18.1	2.1%

Groups ranked with respect to average MFP growth rate.

The decomposition consists of two parts: *i*) the change in MFP and *ii*) the change in inputs, capital, electricity and transport per unit of labour (the last three terms of equation (6)). Table 8 shows that, for total manufacturing, 61.8% of the increase in LP is explained by MFP growth. Capital accumulation per unit of labour is the second most important component representing 32.4% of the observed increase in LP. The use of electricity per unit of labour contributes negatively, close to 3%, of the change in LP. The remaining 8.8% is explained by the increase in transport per unit of labour.

At the group level, it is observed, also from Table 8, that for the group with the major increase in LP, G13 Computer & Electronic Products, MFP explains approximately 72%. The groups in which capital accumulation explains most of the growth in LP are G11 Automobiles (84%), and G9 Machinery (74%).[24] The change in the use of electricity per unit of labour has a negative effect in eight groups and almost nil in three groups. The group in which the increase in the use of transport per unit of labour has a greater impact on LP growth is G12 Other Transportation Equipment (94%). MFP plays a major role in explaining LP growth in G4 Paper, Printing, Publishing & Reproduction (117%), G2 Textile, Apparel, Leather, Fur, & Footwear (80%) and G10 Electrical Equipment, Appliances & Components (79%).

Table 8: Decomposition of Labour Productivity Growth Rate

		Contribution				Contribution (% of LP)			
Group	LP	MFP	$\alpha K/L$	$\gamma E/L$	$\lambda T/L$	MFP	$\alpha K/L$	$\gamma E/L$	$\lambda T/L$
Computer & Electronic Products	10.0	7.2	3.2	0.0	-0.5	72.3	32.0	0.2	-4.8
Petroleum & Coal	7.8	5.4	1.2	0.0	1.1	68.7	15.9	0.2	14.4
Lumber & Wood	6.7	5.3	0.7	0.2	0.4	79.5	10.5	2.6	6.6
Electrical Eq., Appl. & Comps.	5.1	4.0	1.1	-0.1	0.1	78.6	20.7	-2.5	2.8
Food, Beverage & Tobacco	3.8	2.6	0.8	-0.1	0.5	67.4	20.9	-1.6	13.0
Primary & Fabricated Metal	3.6	2.2	1.6	0.0	-0.2	60.6	44.4	0.6	-5.6
Miscellaneous	3.5	2.4	0.8	0.0	0.4	67.3	21.7	-0.6	11.4
Textile, Apparel, Lther. & Footwr	3.0	2.4	0.4	-0.1	0.3	79.6	12.0	-1.9	10.2
Non-metallic & Glass	3.0	1.9	0.6	0.0	0.5	62.2	20.1	0.2	17.1
Automobiles	2.8	-0.1	2.3	0.0	0.6	-4.0	83.5	1.3	21.1
Paper, Printing, Publishing & Rep.	2.8	3.3	-0.4	-0.1	0.1	116.8	-15.2	-5.1	4.2
Chemicals	1.7	0.5	1.2	-0.1	0.2	28.9	65.9	-7.8	14.1
Other Transportation Equipment	1.0	0.5	-0.3	-0.1	0.9	56.0	-28.0	-15.3	93.5
Machinery	0.8	0.2	0.6	0.0	0.1	21.8	73.9	-1.4	6.6
Total Manufacturing	3.4	2.1	1.1	-0.1	0.3	61.8	32.4	-2.9	8.8

Groups ranked with respect to average LP growth rate

Finally, Figure A1 in the Appendix shows the position of MFP levels of each group relative to the

[24] The fact that Automobiles shows the highest capital accumulation component is consistent with the fact that, as mentioned in Banco de Mexico's Inflation Report for January-March 2006, in the last few years most of the assembly plants established in the country have made important investments to expand and modernise their production capacities (including the construction of new plants).

average level of the manufacturing sector during 1996-2003. The literature mentions that increases in the dispersion of relative MFP levels through time could be evidence that the development and/or adoption of technology is very specific for some groups and is not being transmitted rapidly to others, see Cameron *et al.* (1997). The dispersion of the relative levels of MFP has increased in Mexican manufacturing; however, this is due exclusively to one group, G13 Computer & Electronic Products, which as mentioned in subsection 4.1, occupies the first place in technology transfers and royalties (technology adoption). Once this is taken into account (excluding G13 Computer & Electronic Products), it is found that the dispersion has remained the same.

5.1.2 Econometric Estimation

Diverse econometric methods are considered to estimate the production functions. For total manufacturing, dynamic specifications are studied by means of a system GMM, following Blundell and Bond (2000), and static specifications by means of Fixed Effects (FE, see Dwyer 1996) and Random Coefficients Method (RCM, see Biorn *et al.* 2002). Due to the reduced number of activity classes for most of the 14 groups, the dynamic specification is not estimated to that level; hence, only static estimations are considered.

In all estimations, logarithms are applied to (4)

$$y_{it} = \alpha k_{it} + \beta l_{it} + a_{it}, \tag{7}$$

where lower-case letters stand for the respective log-variables of the function. The residual, a_{it}, is considered as a measure of MFP. Hence, with the estimated coefficients (α and β), growth accounting exercises, similar to those described in subsection 5.1.1, are undertaken.

With respect to the system GMM, it is assumed that a_{it} can be decomposed as

$$a_{it} = \eta_i + \eta_t + u_{it}, \tag{8}$$

where η_i captures differences in productivity – specific for each activity class and fixed over time, η_t captures common time varying productivity shocks, and u_{it} captures productivity shocks for each activity class.

The static representation can be estimated by OLS and/or fixed effects as in similar studies; however, there is evidence that u_{it} is usually persistent over time, implying that the different activity classes do not adjust instantaneously and/or the existence of omitted variable bias of a particular form (i.e. intangibles). This issue can be taken into account by considering an autoregressive form, that is

$$u_{it} = \phi u_{it-1} + e_{it}; \qquad |\phi| < 1, \tag{9}$$

where e_{it} is an idiosyncratic error term. This allows to obtain a dynamic representation of (7)[25]

$$y_{it} = \delta_1 y_{it-1} + \delta_2 k_{it} + \delta_3 k_{it-1} + \delta_4 l_{it} + \delta_5 l_{it-1} + \eta_i(1-\phi) + (\eta_t - \phi\eta_{t-1}) + e_{it} \tag{10}$$

[25] The lagged dependent variable is a way to capture the fact that when production factors change, it takes time to output, and consequently MFP, to achieve a new long-run level.

where $\delta_1 = \phi$; $\delta_2 = \alpha$; $\delta_3 = -\phi\alpha$; $\delta_4 = \beta$; $\delta_5 = -\phi\beta$. With δ_3 and δ_5 being two non-linear (common factor) restrictions. As stated in Blundell and Bond (2000), given consistent estimates of the unrestricted parameter vector $\delta = (\delta_1, \delta_2, \delta_3, \delta_4, \delta_5)$ and $var(\delta)$, these restrictions can be tested and imposed using minimum distance to obtain the restricted parameter vector (α, β, ϕ).

Results

Persistence

Before commenting on the estimation results, a word should be said about some of the characteristics of our data. When the series are persistent, the instruments used for the difference GMM estimator are weak, so this estimator would be inappropriate given the existence of such persistence.[26] Therefore, under that context, a more appropriate estimation would be achieved by means of a system GMM, see Bond *et al.* (2005).

Hence, to better understand the results determined by the system GMM, a brief analysis of the series is presented. Following Bond *et al.* (2005), unit root tests, based on OLS estimation of an AR(1) process, are presented as it has been shown that such procedure has better power properties than alternative panel unit root tests in the setting of a relatively large cross-section dimension and a small number of time periods.

Table A9 in the Appendix presents tests of the unit root hypothesis for the first set of variables used in the empirical part, being these: Y, VA, K, L, E and T. Table A10 in the Appendix presents a second set of variables that will be considered in Section 5.2.1; these are: MFP, LP, intensities for K, E and T, technology adoption, concentration, human capital intensity and exports.

Specifically, of all the studied variables, the null hypothesis of a unit root is not rejected only for capital and transport when time dummies are included; once individual dummies are included, the null is rejected for these two variables. The other variables show no evidence of a panel unit root. Still, they present a relatively high degree of persistence. Other standard panel unit root tests for the series find no evidence of a unit root.[27] In short, the results show certain degree of persistence and, in few cases, close to random walk processes.[28] Then, this provides further validity to our system GMM estimation results.

Total Sector

With respect to the total manufacturing, using a panel of the 205 activity classes for the period 1996-2003, we focus first on the results based on the system GMM, which present a constant return to scale (Wald) test (labeled as CRS) and a common factor test (labeled as Comfac)[29] of the unrestricted specification, see Table A11 in the Appendix. As can be seen, the test does not reject the null hypothesis of CRS in the different specifications. Therefore, estimations imposing CRS are presented in Table A12 in the Appendix. It is important to mention that the system GMM is also used in section 5.2.1, where further details of this estimator will be provided.

[26] For instance, in the case of a random walk, there would not be correlation between the variables in first differences and the lagged levels, this means that the autoregressive coefficient would not be identified, as the rank condition is not satisfied; thus, the instruments would not add any information.

[27] Unreported in the paper.

[28] The system GMM estimator is preferred (based on both applied research and Monte Carlo simulations), when there are highly persistent processes.

[29] The test is a minimum distance test of the non-linear common factor restrictions imposed in the restricted models. The null hypothesis is that the restrictions are adequate.

Now, in Tables 9 and 10 we show the results for all the different econometric methods obtained when no restrictions are imposed and when CRS are assumed, respectively (including those just found with the system GMM). In addition to the number of worked hours in the input combinations, the specifications in Tables 9 and 10, consider the adjusted number of worked hours (L_{adj}). In the case of the non-restricted coefficients estimations it is found that the null hypothesis of CRS is accepted in most cases.

Table 9: Non-Restricted Econometric Estimations, 1996-2003

	Coefficient				Contribution to Growth				
Method	K	L	E	T	K	L	E	T	MFP Growth
Fixed Effects	0.29**	0.86***			1.1%	-0.1%			2.3%
	0.13**	0.52***	0.45***		0.5%	-0.1%	-0.5%		3.4%
	0.27***	0.73***		0.15***	1.0%	-0.1%		0.4%	1.9%
	0.12**	0.46***	0.40***	0.11***	0.5%	-0.1%	-0.4%	0.3%	3.0%
Random Coefficients	0.36***	0.83***			1.3%	-0.1%			2.0%
	0.28***	0.66***	0.14		1.1%	-0.1%	-0.2%		2.4%
	0.32***	0.48***		0.29***	1.2%	-0.1%		0.9%	1.2%
	0.27***	0.46***	0.07	0.24***	1.0%	-0.1%	-0.1%	0.7%	1.7%
GMM	0.50***	0.77***			1.9%	-0.1%			1.5%
	0.08	0.68***	0.34***		0.3%	-0.1%	-0.4%		3.4%
	0.40***	0.69***		0.12*	1.5%	-0.1%		0.4%	1.5%
	0.11	0.52***	0.32***	0.13**	0.4%	-0.1%	-0.4%	0.4%	2.9%
Fixed Effects	0.21***	0.82***			0.8%	-0.1%			2.5%
(L_{adj})	0.10**	0.49***	0.41***		0.4%	-0.1%	-0.5%		3.4%
	0.19***	0.71***		0.15***	1.0%	-0.1%		0.4%	2.2%
	0.10**	0.45***	0.36***	0.11***	0.4%	-0.1%	-0.4%	0.3%	3.0%
Random Coefficients	0.16**	0.94***			0.6%	-0.1%			2.8%
(L_{adj})	0.09	0.81***	0.13		0.3%	-0.1%	-0.1%		3.2%
	0.13**	0.64***		0.25***	0.5%	-0.1%		0.7%	2.1%
	0.10	0.61***	0.06	0.22***	0.4%	-0.1%	-0.1%	0.6%	2.4%
GMM	0.03	1.05***			0.1%	-0.1%			3.3%
(L_{adj})	0.00	0.63***	0.31***		0.0%	-0.1%	-0.3%		3.7%
	0.00	0.90***		0.15**	0.0%	-0.1%		0.4%	2.9%
	0.00	0.51***	0.29***	0.17***	0.0%	-0.1%	-0.3%	0.5%	3.1%

*, **, *** indicate statistical significance at 10, 5 or 1 percent, respectively

The null hypothesis of CRS was accepted in most cases using a Wald test

Thus, the results assuming CRS are as follows. The coefficients for capital, in contrast with other studies for Mexican manufacturing (see Lopez-Cordova, 2002), have more relevance in the production function, which is consistent with similar studies for other countries. This might suggest that the measure of capital has been adequately constructed. The different estimation methods present some problems when

electricity is included. Either this variable is not statistically significant or capital becomes statistically non-significant. In particular, for the classical specification, with capital and labour, both the RCM and GMM yield very similar coefficients, 0.33 and 0.67 vs 0.37 and 0.63, respectively; whilst with Fixed Effects, the elasticities are 0.23 and 0.77, respectively. For the other input combinations results, see Table 10.[30]

Table 10: Econometric Estimations Imposing CRS, 1996-2003

	Coefficient				Contribution to Growth				
Method	K	L	E	T	K	L	E	T	MFP Growth
Fixed Effects	0.23**	0.77***			0.9%	-0.1%			2.5%
	0.09	0.46***	0.46***		0.3%	-0.1%	-0.5%		3.5%
	0.21**	0.64***		0.15***	0.8%	-0.1%		0.4%	2.1%
	0.09*	0.40***	0.41***	0.11***	0.3%	-0.1%	-0.5%	0.3%	3.1%
Random Coefficients	0.33**	0.67***			1.2%	-0.1%			2.1%
	0.25**	0.57***	0.19*		0.9%	-0.1%	-0.2%		2.6%
	0.30***	0.39***		0.31***	1.1%	-0.1%		0.9%	1.3%
	0.22***	0.43***	0.11	0.24***	0.8%	-0.1%	-0.1%	0.7%	1.9%
GMM	0.37**	0.63***			1.4%	-0.1%			1.9%
	0.07	0.55***	0.38***		0.3%	-0.1%	-0.4%		3.5%
	0.27**	0.55***		0.18**	1.0%	-0.1%		0.5%	1.8%
	0.16*	0.39***	0.29***	0.15**	0.6%	-0.1%	-0.3%	0.4%	2.6%
Fixed Effects	0.20***	0.80***			0.7%	-0.1%			2.6%
(L_{adj})	0.10**	0.49***	0.41***		0.4%	-0.1%	-0.5%		3.4%
	0.17***	0.68***		0.15***	0.6%	-0.1%		0.4%	2.2%
	0.09**	0.44***	0.36***	0.11***	0.3%	-0.1%	-0.4%	0.3%	3.0%
Random Coefficients	0.14**	0.86***			0.5%	-0.1%			2.8%
(L_{adj})	0.09	0.80***	0.11		0.3%	-0.1%	-0.1%		3.1%
	0.14**	0.63***		0.23***	0.5%	-0.1%		0.7%	2.1%
	0.09	0.63***	0.08	0.20***	0.3%	-0.1%	-0.1%	0.6%	2.5%
GMM	0.04	0.96***			0.1%	-0.1%			3.3%
(L_{adj})	0.04	0.71***	0.25**		0.1%	-0.1%	-0.3%		3.6%
	0.00	0.83***		0.17***	0.0%	-0.1%		0.5%	3.0%
	0.08	0.59***	0.17*	0.16***	0.3%	-0.1%	-0.2%	0.5%	2.9%

*, **, *** indicate statistical significance at 10, 5 or 1 percent, respectively

Regarding the inclusion of the adjusted number of worked hours (L_{adj}), in all cases and input combinations, the corresponding estimated coefficient increases. Specifically, it is found that under the basic

[30] The only combination in which all inputs are included and have statistical significance is given by the system GMM.

combination KL, 0.80 is the minimum elasticity for L_{adj}.[31]

Based on the above results, under all specifications and econometric methods, the average MFP growth rate for 1996-2003 increases when adding E to the production function,[32] whilst diminishes when including T into the list of inputs. Again, identical to the growth accounting case, this is an indication that E (T) is contributing negatively (positively) to the traditional Solow-residual measure, see Table 11.[33]

Table 11: Changes in Average Growth Rates, 1996-2003 (CRS)

Estimation Method	KL a KLE	KL a KLT	KLE a KLET	KLT a KLET
Random Coefficients	+	-	-	+
Random Coefficients ($L\ adj$)	+	-	-	+
Fixed Effects	+	-	-	+
Fixed Effects ($L\ adj$)	+	-	-	+
GMM	+	-	-	+
GMM ($L\ adj$)	+	-	-	-

Group Level

Here we present the results obtained through econometric estimation by means of the Fixed Effects method for each of the 14 groups assuming CRS.[34]

After calculating the average MFP growth rate with the different input combinations, we find that, on the one hand, the groups which occupy the first places of the ranking are G13 Computer & Electronic Products, G3 Lumber & Wood and G10 Electrical Equipment, Appliances & Components. On the other hand, the groups which occupy the last places are G8 Primary & Fabricated Metal, G6 Chemicals, and G9 Machinery, see Table A13 in the Appendix.

In fact, results similar to those from the growth accounting approach are encountered. First, when E is added into the production function, the MFP average growth rate increases in 9 out of 11 groups. Second, when including T, the MFP average growth rate decreases in 7 out of 11 groups.[35] Third, G13 Computer & Electronic Products and G8 Primary & Fabricated Metal, always increase their MFP. See Tables A14 and A15 in the Appendix.[36]

[31] The only combination in which all inputs are included and have statistically significant coefficients is given by Fixed Effects.

[32] The only exception arises in the case of the GMM estimation, when adding E to the $KL_{adj}T$ combination.

[33] This same pattern applies also for the non-restricted estimations.

[34] The same econometric exercise without assuming CRS was carried out (unreported). The qualitative results do not change dramatically. In fact, the Spearman correlation coefficient for both rankings (with KL) is 0.92 significant at 1%. As discussed, the dynamic specification by system GMM was not performed at the group level given the very reduced number of observations for most of the groups. The RCM provided, for most of the groups, both insignificant and awkward coefficients.

[35] In both cases, only 11 groups were considered due to the lack of enough observations in the other groups.

[36] Spearman correlation coefficient between the ranking from growth accounting and this one is 0.98, significant at 1%.

Estimations with L_{adj}

For completeness, we present the ranking of the groups under the different combinations of the production functions obtained from econometric estimations for the 14 groups substituting L by L_{adj} and assuming CRS.

Table A16 in the Appendix shows that there are no substantial differences with respect to the ranking that does not present adjustments on the unit of labour.[37] Again, G13 Computer & Electronic Products is the group with the highest MFP growth. More interesting is to focus on the change that the estimated coefficient (L_{adj}) experiences compared to the one obtained with L. On one hand, Table A17 in the Appendix shows that G14 Miscellaneous, G13 Computer & Electronic Products, G7 Non-metallic & Glass, and G10 Electrical Equipment, Appliances & Components are the groups which present the most important positive changes. On the other hand, the groups that present the most important downwards changes are G9 Machinery and G3 Lumber & Wood. These results seem to be consistent with what one might expect: a more qualified labour force should prevail in groups such as G13 Computer & Electronic Products than in groups such as G3 Lumber & Wood.

5.2 Determinants of MFP and LP

In this section, we use both a cross-section approach and a dynamic panel data approach with the intention of identifying, econometrically, some possible determinants of productivity growth.

5.2.1 Econometric Estimation

Single cross-section productivity growth regressions ($N = 205$ activity classes, with averaged data for 1996-2003) are estimated as well as dynamic panel data regressions ($N = 205$ activity classes, $t = 8$ years).

For the static case, we consider the average growth rate for MFP ($\triangle$MFP) and LP ($\triangle$LP) as dependent variables. The explanatory variables are the 1996-2003 averaged variables for factor intensities (K, E and T), concentration, technology adoption and exports.

It is important to bear in mind that when using cross-sectional regressions, one has to take into account that: *i*) reducing time series to a single average observation means that not all available information is being used, *ii*) it is likely that single cross-section regressions suffer from omitted variable bias, and *iii*) one or more of the regressors may be endogenous. Moreover, since we are analysing growth of MFP and LP and given the characteristics of the panel studied here (N large and T small), a dynamic panel data estimation, using a system GMM, is a natural candidate to be considered. This type of estimation is able to account for unobserved individual specific effects and allows for the endogeneity of one or more of the regressors. In particular, the specification takes the following structure

$$p_{it} = \omega + \theta p_{it-1} + \psi x_{it} + \eta_i + \eta_t + v_{it}, \tag{11}$$

where p is the logarithm of either MFP or LP and x_{it} is a vector of explanatory variables.

[37] When the labour input is not adjusted, the Spearman correlations between the rankings of MFP growth obtained by means of growth accounting and econometric estimations (both restricted and non-restricted specifications) are very high, above 0.90, and significant at the 1% level.

As demonstrated in Hsiao (2003), omitting unobserved time invariant individual effects in a dynamic panel data model will cause OLS levels estimates to be biased and inconsistent, as the lagged dependent variable is positively correlated with the permanent effects, η_i. An alternative approach would be to estimate (11) by means of the within groups estimator, however, as shown by Nickell (1981), using such estimator will also provide biased and inconsistent estimates in a dynamic panel model with fixed T. In addition, one or more regressors in (11) could be correlated with either η_i or v_{it}(or both). To solve these issues and the potential persistence of the series, commented earlier, Blundell and Bond (1998) argue that a system GMM is the most appropriate method.

Therefore, in more practical terms, the first step in this context is to first-difference equation (11), as suggested by Anderson and Hsiao (1981), in order to eliminate the individual effects

$$p_{it} - p_{it-1} = \theta\left(p_{it-1} - p_{it-2}\right) + \psi\left(x_{it} - x_{it-1}\right) + \left(\eta_t - \eta_{t-1}\right) + \left(v_{it} - v_{it-1}\right). \tag{12}$$

However, this method of eliminating the individual (activity class) specificity introduces another econometric issue. The first-difference has caused the new error term to be correlated with the lagged dependent variable. This correlation, combined with the potential endogeneity of the explanatory variables, leads to consider the use of instrumental variables as suggested by Arellano and Bond (1991). The estimator that uses those moment conditions is known as the 'difference estimator'. In particular, during the so called 'one-step', it is assumed that the error terms are independent and homoscedastic across individuals and over time. In the 'two-step', the differenced residuals from the one-step are used to construct a consistent estimate of the variance-covariance matrix and relaxing the assumptions of independence and homoscedasticity.[38]

Nonetheless, the difference estimator presents some shortcomings. For instance, under the difference approach, one is eliminating the individual specificity. In addition, such a procedure may increase measurement error biases caused by the decrease in the signal-to-noise ratio as reported by Griliches and Hausman (1986). Furthermore, Blundell and Bond (1998) conclude that when the lagged dependent variable and the explanatory variables are persistent over time, lagged values of these variables are weak instruments for the regression equation in differences, which affects the asymptotic and small-sample performance of the difference estimator.[39]

To solve these issues, Arellano and Bover (1995) and Blundell and Bond (1998) propose the use of the 'system estimator', which is based on asymptotic and small sample properties, to diminish any potential biases in finite samples. This method estimates jointly the regression in differences with the regression in levels. Arellano and Bover (1995) mention that since the lagged levels are considered as instruments in the first step, then in the second step one should use only the most recent difference as instrument. By introducing the regression in levels, a better estimation is achieved since it does not wipe out the cross-section relation nor increase the measurement error. Summarising, the regression in differences uses the same instrumental variables as detailed above, whilst the regression in levels uses as instrumental variables the lagged differences of the respective variables. The two-step GMM system estimator yields consistent and efficient parameters estimates; the calculation of the two-step GMM estimator is analogous to that described before. In short, the system GMM estimator not only improves the precision but also

[38] This means that the two-step estimator is more efficient than the one-step estimator.

[39] Monte Carlo simulations indicate that this weakness leads to biased coefficients in small samples.

reduces the finite sample bias.

To assess the appropriateness of the GMM estimators, various specification tests will be considered. Basically, tests for the validity of the instruments and the validity of the assumption that the error term does not present serial correlation. Therefore, the validity of the instruments is tested by means of the Sargan test and the Difference Sargan test of over-identifying restrictions. The Sargan (S_z) test, where z stands for either the Difference ($Diff$) or the System (Sys) estimator, is distributed as χ^2 with $(J-K)$ degrees of freedom, J being the number of instruments and K the number of regressors. The null hypothesis is that the instruments are valid. The Difference Sargan (DS) is a test of the additional moment conditions used in the system GMM estimators relative to the corresponding first-differenced GMM estimators. The statistic $DS = S_{Sys} - S_{Diff}$ is distributed as χ^2 with $(df_{Sys} - df_{Diff})$ degrees of freedom, where df_{Sys} and df_{Diff} are the degrees of freedom from the system and difference estimators, respectively. The null hypothesis is that the additional instruments used in the system estimator are valid.

Additionally, the assumption of no serial correlation in v_{it}, which is essential for the consistency of the estimators, is tested. Two tests (m_1 and m_2) for first-order and second-order serial correlation in the first-differenced residuals will be reported. If the disturbances v_{it} are not serially correlated, there should be evidence of significant first-order serial correlation in the differenced residuals and no evidence of second-order serial correlation in the differenced residuals. These tests are based on the standardised average residual autocovariances which are asymptotically $N(0,1)$ variables under the null of no autocorrelation. For further details, see Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998).

It is worth mentioning that this econometric method has been used in different studies, in particular, to analyse cross-country economic growth (conditional convergence) and the specific importance that certain variables have on growth (i.e. trade liberalisation, role of secondary education, innovation, etc.).

Results

First, we present the results for the cross-section econometric estimation with 205 activity classes considering the average of the variables during 1996-2003. The average growth rate of MFP ($\triangle$MFP) or LP ($\triangle$LP) are taken as the dependent variables under this approach. The explanatory variables on the baseline equation are: *i*) capital intensity, *ii*) electricity intensity, *iii*) transport intensity, *iv*) technology adoption, *v*) concentration, *vi*) human capital intensity, and *vii*) exports. Due to causality and endogeneity issues we consider another equation that does not include exports.[40]

Second, we present the results for the dynamic econometric specification, estimated by means of the system GMM, taking into account the following: *i*) the likely endogeneity of some regressors, *ii*) the lagged dependent variable as an explanatory variable, *iii*) the possibility of omitted variable bias in the cross section regressions, and *iv*) the specific characteristics of the panel herein studied (N relatively large and T small). The explanatory variables are the same as those considered in the cross-section estimation.

[40] Existing literature studies a causality from exports to productivity as well as the inverse direction (see, for instance, Bernard and Jensen, 1999).

Cross Section

Table 12 presents our initial results and finds that technology adoption is statistically significant and presents the expected positive sign in all the specifications. Thus, more technology adoption would imply increases in the growth rates of both MFP and LP. The F test of goodness of fit rejects the null hypothesis that all coefficients are zero in all cases.

Table 12: Determinants of Productivity, Cross Section

	ΔMFP		ΔLP	
	eq. (1)	eq. (2)	eq. (1)	eq. (2)
Capital Intensity	-0.008	-0.010	0.033	0.035
	(-0.21)	(-0.24)	(0.77)	(0.85)
Electricity Intensity	-0.041	-0.041	-0.008	-0.007
	(-0.51)	(-0.51)	(-0.09)	(-0.08)
Transport Intensity	0.094	0.095	0.106	0.104
	(1.43)	(1.44)	(1.53)	(1.53)
Technology Adoption	0.665**	0.658**	0.778**	0.794**
	(2.54)	(2.50)	(2.04)	(1.97)
Concentration	-0.039	-0.041	-0.031	-0.025
	(-1.28)	(-1.45)	(-0.94)	(-0.71)
Human Capital	-0.006	-0.006	-0.001	-0.001
Intensity	(-0.56)	(-0.54)	(-0.03)	(-0.09)
Exports	-0.009		0.021	
	(-0.37)		(0.74)	
Constant	0.019	0.018	0.002	0.005
	(1.22)	(1.22)	(0.13)	(0.33)
R^2	0.10	0.10	0.11	0.11
Prob > F	0.004	0.01	0.001	0.001

White cross section standard errors. t-statistic in parentheses.

*, **, *** indicate statistical significance at 10, 5 or 1 percent, respectively.

N = 205 for the period 96 – 03.

Given this, more detailed estimations of the previous cross-section specifications are undertaken. That is, statistically non-significant regressors are dropped one by one in both the MFP and the LP equations, until only statistically significant coefficients remain. Such procedure yields the results presented in Table 13. Specifically, technology adoption maintains the expected positive signs in the final equations, and concentration appears with a significantly negative sign in the MFP specification. This last finding would imply that, controlling for technology adoption, those sectors where competition is less intense experience a lower productivity growth. Lastly, the F test of goodness of fit rejects the null hypothesis that all coefficients are zero in all cases.

Table 13: Determinants of Productivity, Cross Section

	ΔMFP	ΔLP
	eq. (1)	eq. (2)
Technology Adoption	0.668***	0.744**
	(4.08)	(2.08)
Concentration	-0.049*	
	(-2.37)	
Constant	0.016***	0.017**
	(2.60)	(2.52)
R^2	0.09	0.09
Prob > F	0.000	0.000

White cross section standard errors. t-statistic in parenthesis.

*, **, *** indicate statistical significance at 10, 5 or 1 percent, respectively.

N = 205 for the period 96 – 03.

The previous results show the importance of technology adoption in explaining productivity, a relationship widely studied in the endogenous growth context. Hence, since technology adoption plays a major role in explaining the MFP and LP variations, we proceed to analyse it in more detail. In this context, we consider a cross-section specification, similar to the previous ones, this time technology adoption being the dependent variable and as the explanatory variables: *i*) capital intensity, *ii*) electricity intensity, *iii*) transport intensity, *iv*) concentration, *v*) human capital and *vi*) exports. The results are presented in Table 14.

Capital and electricity intensities present negative and statistically significant signs. The first result, the capital coefficient, would suggest that the activity classes with higher capital intensity are usually those with a lower degree of expenditure in technology transfers and royalties (i.e. old economy).[41] The second result, the electricity coefficient, could be reflecting the fact that both the electricity fare schedule and the high charges during peak times are affecting, mainly, the activity classes with a higher propensity to innovate (see, for instance, CFE (2006) and IMCO (2004a, 2005, 2007)).[42]

Finally, human capital intensity has a positive relationship with technology adoption, which may be reflecting the existing complementarity between skilled labour and the use of technology.[43] The F test of goodness of fit rejects the null hypothesis that all coefficients are zero in all specifications.

[41] It is worth mentioning that the groups with higher capital intensity, G8 Primary & Fabricated Metal, G7 Non-metallic & Glass and G4 Paper, Printing, Publishing & Reproduction, show low MFP growth rates. This could be also due to the fact that obtaining physical capital is no longer an important restriction; nevertheless, this is not being reflected in greater use or technology adoption.

[42] G8 Primary & Fabricated Metal, G7 Non-metallic & Glass and G4 Paper, Printing, Publishing & Reproduction are the more electricity intensive groups, and also present low MFP growth rates.

[43] These three variables remain statistically significant when eliminating, one by one, the non-significant coefficients.

Table 14: Determinants of Technology Adoption, Cross Section

	Technology Adoption	
	eq. (1)	eq. (2)
Capital Intensity	-0.029**	-0.028**
	(-2.35)	(-2.36)
Electricity Intensity	-0.059***	-0.059**
	(-2.36)	(-2.42)
Transport Intensity	0.034	0.033
	(1.12)	(1.13)
Concentration	0.016	0.019
	(0.95)	(0.98)
Human Capital	0.012**	0.012**
Intensity	(2.44)	(2.28)
Exports	0.011	
	(0.88)	
Constant	0.008**	0.010**
	(1.79)	(2.09)
R^2	0.15	0.15
Prob > F	0.000	0.000

White cross section standard errors. t-statistic in parentheses.

*, **, *** indicate statistical significance at 10, 5 or 1 percent, respectively.

N = 205 for the period 96 – 03.

Dynamic Panel Data

Given the described advantages of the system GMM estimator, Table 15 shows the main findings when we use this econometric approach. Before commenting on the results, it is very important to mention that the estimations satisfy all the required specification tests.

First, regarding the case of the MFP growth rate in equations (1) and (2) in Table 15, it can be observed that some results are similar to those obtained with the cross-section estimations. In particular, concentration presents a negative and significant relationship with MFP, whilst there is a positive and statistically significant relationship between technology adoption and MFP.

However, in contrast to the cross-section estimation, this econometric approach finds two additional statistically significant estimated coefficients; one negative between capital intensity and MFP, and the other one positive between human capital intensity and MFP. Hence, there are signs that physical capital accumulation might not longer be a so relevant productivity enhancing factor – old economy vs new economy. In this sense, it is important to highlight the role of human capital and its contribution to productivity growth.

Summarising our main results so far, on the one hand, we find a positive relationship between technology adoption and productivity, and on the other hand, a negative relationship between concentration

and productivity. These two particular findings are consistent with some of endogenous growth theories, see Aghion and Howitt (1998).

Second, with regards to the case of LP growth, equations (3) and (4) in Table 15, there is a positive and highly significant influence of human capital on it. Thus, the results previously obtained for the MFP specification, are reinforced by the positive relationship between LP and human capital.[44] In addition, technology adoption in equation (4) of Table 15 shows a significant and positive estimated coefficient with LP.

Table 15: Determinants of Productivity, Dynamic Panel Data

	△MFP		△LP	
	eq. (1)	eq. (2)	eq. (3)	eq. (4)
△Capital Intensity	-1.645***	-1.510***	0.001	-0.094
	(-5.69)	(-4.75)	(0.01)	(-0.61)
△Electricity Intensity	1.144	0.858	1.057	0.933
	(1.15)	(0.95)	(1.64)	(1.42)
△Transport Intensity	-0.338	-0.398	0.368	0.295
	(-0.94)	(-1.11)	(1.08)	(0.94)
△Technology Adoption	0.965*	1.019*	0.494	0.709*
	(1.73)	(1.85)	(1.14)	(1.78)
△Concentration	-0.248*	-0.382***	-0.031	-0.073
	(-1.67)	(-2.75)	(-0.19)	(-0.47)
△Human Capital	0.115**	0.119**	0.153***	0.119***
Intensity	(2.28)	(2.24)	(3.34)	(3.03)
△Exports	-0.150		-0.036	
	(-1.33)		(-0.40)	
△MFP (-1)	0.777***	0.792***		
	(18.8)	(18.3)		
△LP (-1)			0.840***	0.875***
			(18.4)	(25.2)
Sargan Test$^{\Diamond}$	0.939	0.596	0.959	0.719
Diff Sargan Test$^{\Diamond}$	0.997	0.961	0.998	0.957
m1$^{\Diamond}$	0.000	0.000	0.000	0.000
m2$^{\Diamond}$	0.685	0.637	0.448	0.452

$^{\Diamond}$p- values. Corrected two-step t-statistics in parentheses.

*, **, *** indicate statistical significance at 10, 5 or 1 percent, respectively.

N=205, T=8. Time dummies included.

[44] This gives further relevance to the challenge faced by the Mexican economy: to generate more and better human capital, which requires long time horizons for its maturity. See Lucas (1988) and Nelson and Phelps (1966), two of the pioneering contributions to the literature on endogenous growth based on the importance of human capital.

Analogous to Table 14, dynamic panel specifications that attempt to identify some of the determinants of technology adoption are presented in Table 16. As in the previous system GMM cases, the results are validated by all the required specification tests.

Table 16: Determinants of Technology Adoption, Dynamic Panel Data

	△ Technology Adoption	
	eq. (1)	eq. (2)
△ Capital Intensity	-0.027*	-0.025*
	(-1.81)	(-1.65)
△ Electricity Intensity	0.000	0.006
	(-0.001)	(0.18)
△ Transport Intensity	0.017	0.017
	(1.09)	(1.13)
△ Concentration	0.022**	0.027**
	(2.09)	(1.96)
△ Human Capital Intensity	-0.002	-0.002
	(-0.55)	(-0.47)
△ Exports	0.010	
	(0.80)	
△ Technology Adoption (-1)	0.719***	0.724***
	(11.3)	(12.7)
Sargan Test$^{\Diamond}$	0.986	0.777
Diff Sargan Test$^{\Diamond}$	0.999	0.738
m1$^{\Diamond}$	0.009	0.008
m2$^{\Diamond}$	0.321	0.323

$^{\Diamond}$ p- values. Corrected two-step t-statistics in parentheses.

*, **, *** indicate statistical significance at 10, 5 or 1 percent, respectively.

N=205, T=8. Time dummies included.

We find that concentration and technology adoption present a positive and statistically significant relationship. This might serve as an evidence of the Schumpeterian idea that, in order to innovate more or adopt more technology, a certain degree of concentration is required, see Aghion and Griffith (2005). Once again, there is some evidence that becoming capital intensive might not contribute much in being more related into innovative and technological activities.[45]

It is worth stressing the statistical significance encountered for the concentration variable in the different specifications, both in these Tables and in the previous ones. In short, concentration has a

[45] The Spearman correlation between technology adoption and capital intensity increases (in absolute value) as we consider the more capital intensive activity classes. It goes from -0.18 ($p = 0.012$) when the full sample is considered to: *i*) -0.23 ($p = 0.021$) when the 100 more capital intensive activity classes are considered; *ii*) -0.25 ($p = 0.079$) when the 50 more capital intensive activity classes are considered; and *iii*) -0.32 ($p = 0.065$) when the 35 more capital intensive activity classes are considered.

positive relationship with technology adoption, but a negative one with MFP growth. Similar results are encountered by Nickell (1996) for the UK manufacturing sector, and Okada (2005) for Japan.[46]

In short, concentration is exerting a positive and significant (at the 5%) influence on innovation (only in the dynamic panel estimation). However, once these two variables are included into the econometric estimation where MFP is the dependent variable, technology adoption is contributing positively, at the 10% level of significance, to MFP, whereas concentration is affecting negatively, at the 1% level of significance, to MFP. Based on the results of Table 15 and Table 16, the net effect of concentration on MFP is negative.[47]

Hence, our results seem to indicate that those sectors where competition is less intense experience a lower MFP growth.

6 Summary

Throughout the diverse dimensions that analysed the evolution of the 14 manufacturing groups, as well as their trends in MFP and LP growth, it was encountered that, in general, on the one hand, G13 Computer & Electronic Products, was one of the best performers; on the other hand, G2 Textile, Apparel, Fur Leather & Footwear and G3 Lumber & Wood, were amongst the worst performers.

We found evidence that labour mobility between both the 14 groups and the 205 activity classes has not been an important source for the overall LP growth as it only contributed with 5.3 percent and 2.3 percent to the observed growth at each aggregation level, respectively. Moreover, those groups in which the real wage growth has been greater than the increase in labour productivity are, precisely, the less productive.

Both the calculated and estimated elasticities found are consistent with those obtained in other studies for developed countries, in particular the ones for capital; this is a good indicator that our measure of capital has been constructed adequately.

The change in MFP has been the main driver in explaining the growth rates changes of both VA and LP. In the case of aggregate output growth, MFP helps explaining between 58 percent and 69 percent; whilst it accounts for 62 percent of aggregate LP growth.

There is evidence that electricity (transport) is contributing , negatively (positively), to the traditional Solow-residual measure (MFP with K and L). However, the fact that transport appears to help in explaining the Solow residual should not mask the overall evolution of this sector. What the results are probably showing is that productivity gains are taking place via transport, which possibly indicate that, for manufacturers, it has been relatively easier to overcome the difficulties posed by this sector, than those prevalent in the electricity sector.

With respect to the identification of some of the determinants of both MFP and LP, the cross-section analysis indicates: *i*) that technology adoption has a positive influence on the productivity measures, whilst market concentration, which implies less competition, is negatively related to MFP growth; and *ii*) when considering some of the factors explaining technology adoption, the cross-section analysis encounters a positive sign for human capital intensity whilst negative signs for capital and electricity intensities.

[46] For some related findings, see Aghion and Griffith (2005).

[47] -0.23 for equations in (1) and -0.35 for equations in (2).

In the dynamic panel data analysis, first, it is found that in addition to the cross-sectional results, on the one hand, there is a negative relation between capital intensity and MFP and a positive one between human capital and MFP; on the other hand, there exists a positive relation between human capital intensity and LP. Second, the dynamic panel estimation finds as determinants of technology adoption, concentration with a positive sign and capital intensity with a negative one.

In sum, using AIS data from 1996 to 2003 at the activity class level, the evidence encountered here seems to suggest that, even after controlling for technology adoption, those sectors characterised by higher levels of concentration (less competition) would experience lower productivity rates.

References

[1] Aghion, P. and R. Griffith. (2005). *Competition and Growth: Reconciling Theory and Evidence.* MIT Press.

[2] Aghion, P. and P. Howitt. (1998). *Endogenous Growth Theory.* MIT Press.

[3] Anderson, T.W. and C. Hsiao. (1981). "Estimation of Dynamic Models with Error Components." *Journal of the American Statistical Association*, 76: 598-606.

[4] Arellano, M. and S. Bond. (1991). "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies*, 58: 277-297.

[5] Arellano, M. and O. Bover. (1995). "Another Look at the Instrumental Variables Estimation of Error-Components Models." *Journal of Econometrics*, 68: 29-51.

[6] Basu, S. and J. G. Fernald. (1995). "Are Apparent Productive Spillovers a Figment of Specification Error?" *Journal of Monetary Economics.* 36: 165-188.

[7] Bergoeing, R., P. J. Kehoe, T. J. Kehoe and R. Soto. (2002). "Decades Lost and Found: Mexico and Chile since 1980". *Federal Reserve Bank of Minneapolis Quarterly Review.* Winter.

[8] Bernard, A. B. and J. B. Jensen. (1999). "Exporting and Productivity". *Working Paper* # 7135. NBER. May.

[9] Biorn, E., K.G. Lindquist and T. Skjerpen. (2002). "Heterogeneity in Returns to Scale: A Random Coefficient Analysis with Unbalanced Panel Data". *Journal of Productivity Analysis*, 18: 39-57.

[10] Blundell, R. and S. Bond. (1998). "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics*, 87:115-143.

[11] Blundell, R. and S. Bond. (2000). "GMM Estimation with Persistent Panel Data: An Application to Production Functions." *Econometric Reviews*, 19(3): 321-340.

[12] Bond, S., C. Nauges and F. Windmeijer. (2005). "Unit Root: Identification and Testing in Micro Panels". *Institute for Fiscal Studies Working Paper* CWP07/05

[13] Calderon-Madrid, A. and A. Voicu. (2004). "Multifactorial Productivity Growth and Job Turnover in Mexican Manufacturing Plants in the 1990s". *Institute for the Study of Labour Working Paper* 993. January.

[14] Calderon-Madrid, A. and A. Voicu. (2005). "Assessing Heterogeneity of Plant Responses to Trade Liberalization: Productivity, Job Creation and Destruction and Survival of Manufacturing Plants in NAFTA". *Mimeo*. July.

[15] Cameron, G., J. Proudman and S. Redding. (1997). "Deconstructing Growth in UK Manufacturing". *Working Paper*. Bank of England.

[16] Casacuberta, C., G. Fachola and N. Gandelman. (2004). "The Impact of Trade Liberalization on Employment, Capital and Productivity Dynamics: Evidence from the Uruguayan Manufacturing Sector". *Inter-American Development Bank Working Paper* R-479. February.

[17] CFE. (2006). *Factores de ajuste a las tarifas de baja, media y alta tensión por variaciones en los precios de combustibles y la inflación nacional*. Subdirección de Programación. Mexico. Available on http://aplicaciones.cfe.gob.mx/aplicaciones/ccfe/tarifas/factores/factores.asp

[18] Disney, R., J. Haskel and Y. Heden. (2003). "Restructuring an Productivity growth in UK Manufacturing." *The Economic Journal*, 113:666-694.

[19] Dwyer, D. W. (1996). "Are Fixed Effects Fixed?". *Working Paper*. Center for Economic Studies, U.S. Bureau of the Census.

[20] Eslava, M., J. Haltiwanger, A. Kugler and M. Kugler. (2004). "The Effects of Structural Reforms on Productivity and Profitability Enhancing Reallocation: Evidence from Colombia." *Journal of Developments Economics*, 75: 333-371.

[21] Faal, E. (2005). "GDP Growth, Potential Output, and Output Gaps in Mexico". *International Monetary Fund Working Paper* WP/05/93. May.

[22] Griffith, R. (1999). "Using the ARD Establishment Level Data at Foreign Ownership and Productivity in the United Kingdom." *The Economic Journal,* 109: F416-F442.

[23] Griliches, Z. and J. A. Hausman. (1986). "Errors in Variables in Panel Data." *Journal of Econometrics*, 31: 93-118.

[24] Harrison, A. and G. Hanson. (1999). "Who Gains From Trade Reform? Some Remaining Puzzles" *Journal of Development Economics* Vol. 59: 125–154.

[25] Hsiao, C. (2003) *Analysis of Panel Data*. 2nd Edition. Cambridge University Press, Cambridge.

[26] IMCO. (2004a). *Análisis de la Competitividad de México*. Mexico.

[27] IMCO. (2004b). *Elementos para Mejorar la Competitividad del Transporte de Carga en México*. Mexico.

[28] IMCO. (2005). *Mercado de Factores Eficientes: Energía*. Mexico.

[29] IMCO. (2007). "Competitividad de las Tarifas del Sector Eléctrico en México". Presentation in *Ciclo de Conferencias con Legisladores*. Mexico.

[30] International Energy Agency and Organisation for Economic Cooperation and Development. (2005). *Energy Prices and Taxes Quarterly Statistics*. Volume 2005 Issue 4.

[31] Klette, T. J. (1999). "Market Power, Scale Economies and Productivity: Estimates from a Panel of Establishment Data". *The Journal of Industrial Economics*, Vol. 47(4): 451-476.

[32] Lopez-Cordova, E. (2002). "NAFTA and Mexico's Manufacturing Productivity: An Empirical Investigation using Micro-level Data." *Working Paper presented at the Latin American and Caribbean Economic Association Meeting*, Madrid.

[33] Lopez-Cordova, E. and M. Mesquita-Moreira. (2003). "Regional integration and Productivity: the Experiences of Brazil and Mexico". *The Institute for the Integration of Latin America and the Caribbean Working Paper* 14. July.

[34] Lucas, R. E. (1988). "On the Mechanics of Economic Development." *Journal of Monetary Economics* 22(1): 3-42.

[35] Mairesse, J. and B. H. Hall. (1996). "Estimating the Productivity of Research and Development: An Exploration of GMM Methods using Data on French and United States Manufacturing Firms". *Working Paper* # 5501. NBER. March.

[36] Mena-Campos, D. (1997). "Acervos y Rendimiento del Capital en México, 1960-1997". *BSc. Thesis in Economics.* ITAM. July.

[37] Nelson, C. and E. Phelps. (1966). "Investment in Humans, Technological Diffusion, and Economic Growth." *American Economic Review* 61: 69-75.

[38] Nickell, S. J. (1981). "Biases in Dynamic Model with Fixed Effects" *Econometrica* 49: 1417-1426.

[39] Nickell, S. J. (1996). "Competition and Corporate Performance." *Journal of Political Economy*, Vol. 104(4): 724-746.

[40] OECD. (2001). "Measurement of Aggregate and Industry-Level Productivity Growth". OECD Manual. Paris.

[41] Okada, Y. (2005). "Competition and Productivity in Japanese Manufacturing Industries". *Working Paper* # 11540. NBER. August.

[42] Pavcnik, N. (2002). "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants." *Review of Economic Studies*, 69: 245-276.

[43] Perez-Gonzalez, F. (2004). "The Impact of Acquiring Control on Productivity: Evidence from Mexican Manufacturing Plants." *Mimeo*, Columbia University.

[44] World Bank. (2006). "Mexico's Competitiveness: Reaching Its Potential." *World Bank Report No.* 35388-*MX*. Washington, D.C. August.

[45] World Economic Forum. (2006). *The Global Competitiveness Report* 2006-2007.

[46] Young, A. (1995). "The Tyranny of Numbers: Confronting the Statistical Realities of the East Asian Growth Experience." *Quarterly Journal of Economics* 110: 641-680.

Appendix

Groups Composition

Each manufacturing group is composed mainly by the following activities and products:

G1. Food, Beverage & Tobacco: Meat processing, dairy, cereals, bakery, tortilla, sugar industry, sweets, coffee, alcohol, beverages, tobacco.

G2. Textile, Apparel, Fur, Leather & Footwear: Fibers, fabrics, clothes, leather goods, fur, shoes.

G3. Lumber & Wood: Wood processing, construction supplies and containers.

G4. Paper, Printing, Publishing & Reproduction: Manufacturing of paper products, prints, newspapers, books, magazines.

G5. Petroleum & Coal: Coke, mineral oils and additives.

G6. Chemicals: Basic oil chemistry, fertilizers, insecticides, resins, paints, pharmaceutical, perfumes, tires, rubber, tubing, plastic house supplies.

G7. Non-metallic & Glass: Construction materials, glass, cement, concrete, ceramic.

G8. Primary & Fabricated Metal: Iron, steel, alloys, aluminium, heaters.

G9. Machinery: Tractors, machinery, agricultural supplies, pumps, filters.

G10. Electrical Equipment, Appliances & Components: stoves, ovens, refrigerators, washing machines, heaters, boilers, batteries, bulbs, automotive electric components.

G11. Automobiles: Production, assembly and repair of automobiles, trucks, engines, motors, transmissions, suspensions, brakes.

G12. Other Transportation Equipment: Production, assembly and repair of navigation ships and boats, railroad equipment, motorcycles, bicycles and parts.

G13. Computer & Electronic Products: Computers, radios, TV sets, photography, medical equipment, measurement equipment, lenses.

G14. Miscellaneous: Jewelry, toys, office supplies, mattresses, furniture.

Tables

Table A1. Group Shares in Total Output and Worked Hours (Percent)

		Output			Worked Hours		
		1996	2003	Change	1996	2003	Change
G13	Computer & Electronic Products	3.7	8.6	4.9	2.0	2.0	0.0
G10	Electrical Equipment, Appliances & Components	4.3	5.1	0.8	5.3	5.3	0.0
G1	Food, Beverage & Tobacco	26.4	26.5	0.1	27.3	29.2	1.9
G5	Petroleum & Coal	0.6	0.6	0.0	0.4	0.3	-0.1
G12	Other Transportation Equipment	0.1	0.1	0.0	0.4	0.4	0.0
G14	Miscellaneous	1.1	1.0	0.0	2.8	3.0	0.2
G3	Lumber & Wood	0.4	0.3	-0.1	1.0	0.6	-0.4
G4	Paper, Printing, Publishing & Reproduction	4.8	4.7	-0.1	6.6	7.2	0.5
G9	Machinery	2.0	1.9	-0.1	3.1	3.0	-0.1
G7	Non-metallic & Glass	5.0	4.7	-0.4	5.7	5.6	-0.1
G11	Automobiles	16.5	15.8	-0.7	7.8	8.2	0.5
G8	Primary & Fabricated Metal	12.3	11.0	-1.3	8.9	8.4	-0.5
G2	Textile, Apparel, Fur, Leather & Footwear	5.6	4.1	-1.5	13.1	11.3	-1.8
G6	Chemicals	17.0	15.5	-1.5	15.5	15.4	-0.1

Groups ranked with respect to change in output share.

Table A2. Exports by Group (as Percentage of Total Sales)

	Group	1996	1999	2003	Avg.
G13	Computer & Electronic Products	72.9	80.3	79.0	77.9
G11	Automobiles	73.5	64.7	69.3	67.0
G10	Electrical Equipment, Appliances & Components	36.9	35.5	43.4	38.2
G9	Machinery	34.1	34.0	37.7	35.9
G3	Lumber & Wood	34.4	35.7	24.8	30.0
G15	Total Manufacturing	29.4	29.0	27.6	28.9
G8	Primary & Fabricated Metal	23.7	21.8	22.8	22.3
G12	Other Transportation Equipment	18.4	14.9	14.4	18.4
G14	Miscellaneous	18.4	19.6	14.2	17.6
G2	Textile, Apparel, Fur, Leather & Footwear	17.4	18.1	16.3	17.4
G6	Chemicals	19.0	16.3	15.6	16.5
G7	Non-metallic & Glass	15.3	11.7	10.3	12.2
G1	Food, Beverage & Tobacco	6.4	6.7	6.1	6.5
G4	Paper, Printing, Publishing & Reproduction	3.8	3.5	3.6	3.6
G5	Petroleum & Coal	3.3	4.0	2.4	3.1

Groups ranked with respect to exports performance in 2003.

Table A3. Herfindahl-Hirschman Index: Descriptive Statistics

		1996				2003			
	Group	Min	Max	Median	Group	Min	Max	Median	Group
G12	Other Transportation Equipment	1841	6107	3422	1041	1744	7145	5578	1234
G13	Computer & Electronic Products	1390	9973	4281	1810	2271	10000	5115	1579
G5	Petroleum & Coal	713	4971	2842	802	967	5994	3481	948
G10	Electrical Equipment, Appliances & Components	535	8866	1895	226	884	7395	2288	267
G9	Machinery	716	5683	1360	253	703	5207	1735	250
G2	Textile, Apparel, Fur, Leather & Footwear	233	4620	1055	67	476	7222	1551	114
G7	Non-metallic & Glass	305	6952	1270	158	344	6031	1502	160
G1	Food, Beverage & Tobacco	210	10000	1227	40	231	10000	1454	50
G14	Miscellaneous	265	3849	994	117	330	6407	1368	157
G6	Chemicals	200	5832	1229	58	295	4203	1261	69
G8	Primary & Fabricated Metal	426	6058	1306	228	599	7805	1216	224
G3	Lumber & Wood	415	925	756	374	960	1669	1137	486
G11	Automobiles	456	2125	1147	646	583	1838	1118	839
G4	Paper, Printing, Publishing & Reproduction	309	2775	726	107	366	2543	798	103

Groups ranked with respect to the median in 2003.

Min, max and median values represent HH indices for activity classes in their respective group.

Table A4. Ranking: Average Expenditure on Technology Transfers and Royalties

	Group
G13	Computer & Electronic Products
G6	Chemicals
G10	Electrical Equipment, Appliances & Components
G9	Machinery
G5	Petroleum & Coal
G7	Non-metallic & Glass
G4	Paper, Printing, Publishing & Reproduction
G2	Textile, Apparel, Fur, Leather & Footwear
G1	Food, Beverage & Tobacco
G14	Miscellaneous
G11	Automobiles
G12	Other Transportation Equipment
G8	Primary & Fabricated Metal
G3	Lumber & Wood

As share of VA.

Table A5. Human Capital Intensity and Real Wage

		Human Capital	Real Wage
	Group	Avg. Level 96-03	Avg. Growth 96-03
G5	Petroleum & Coal	1.62	3.70%
G6	Chemicals	1.44	2.30%
G11	Automobiles	1.34	1.52%
G13	Computer & Electronic Products	1.17	0.69%
G9	Machinery	1.08	1.04%
G8	Primary & Fabricated Metal	1.03	0.48%
G7	Non-metallic & Glass	1.01	2.42%
G4	Paper, Printing, Publishing & Reproduction	0.94	1.50%
G10	Electrical Equipment, Appliances & Components	0.90	2.05%
G1	Food, Beverage & Tobacco	0.88	2.78%
G12	Other Transportation Equipment	0.87	4.04%
G14	Miscellaneous	0.62	3.67%
G2	Textile, Apparel, Fur, Leather & Footwear	0.59	1.73%
G3	Lumber & Wood	0.51	2.00%

Groups ranked with respect to average human capital intensity.

Table A6: Regional Shares in Manufacturing Production

	1996	2001	2004
Border	27.6%	28.6%	30.1%
North	26.8%	26.3%	27.9%
Center	40.5%	39.6%	36.3%
South	5.2%	5.5%	5.8%

Source: INEGI.

Table A7. Ranking of Average MFP Levels, 1996-2003

	Group	KL	KLE	KLT	KLET	Mode
G13	Computer & Electronic Products	1	1	1	1	1
G5	Petroleum & Coal	2	2	2	2	2
G6	Chemicals	3	3	4	4	3
G1	Food, Beverage & Tobacco	4	4	3	3	3
G9	Machinery	5	5	5	5	5
G10	Electrical Equipment, Appliances & Components	6	6	6	6	6
G11	Automobiles	7	7	7	7	7
G14	Miscellaneous	8	8	8	8	8
G7	Non-metallic & Glass	9	9	9	9	9
G4	Paper, Printing, Publishing & Reproduction	10	10	10	10	10
G8	Primary & Fabricated Metal	11	11	12	11	11
G2	Textile, Apparel, Fur, Leather & Footwear	12	12	11	12	12
G12	Other Transportation Equipment	13	13	13	13	13
G3	Lumber & Wood	14	14	14	14	14

Table A8. Ranking: Average MFP Growth Rates, 1996-2003

	Group	KL	KLE	KLT	KLET	Mode
G13	Computer & Electronic Products	2	1	1	1	1
G5	Petroleum & Coal	1	2	3	2	2
G3	Lumber & Wood	3	3	2	3	3
G10	Electrical Equipment, Appliances & Components	4	4	4	4	4
G4	Paper, Printing, Publishing & Reproduction	5	5	5	5	5
G1	Food, Beverage & Tobacco	6	6	6	6	6
G14	Miscellaneous	7	7	7	8	7
G2	Textile, Apparel, Fur, Leather & Footwear	8	8	8	7	8
G7	Non-metallic & Glass	9	9	10	10	9
G8	Primary & Fabricated Metal	10	10	9	9	10
G12	Other Transportation Equipment	11	11	11	11	11
G6	Chemicals	12	12	12	12	12
G9	Machinery	13	13	13	13	13
G11	Automobiles	14	14	14	14	14

Table A9. Persistence – First Set of Variables –

		Y	VA	K	L	E	T
T dummies	Lagged	1.010	1.013	1.002	1.008	1.004	0.999
included	variable (χ)	(0.000)	(0.000)	(0.166)	(0.009)	(0.081)	(0.994)
T and I dummies	Lagged	0.732	0.718	0.782	0.773	0.758	0.604
included	variable (χ)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

°OLS: $W_{it}=\chi W_{it-1}+\xi_i+\xi_t+\epsilon_{it}$

H_0: $\chi = 1$. p-value Wald Test in parenthesis.

Table A10. Persistence – Second Set of Variables –

		MFP	LP	K Int.	E Int.	T Int.	Hum. Cap.	Tech.	Conc.	Exp.
T dummies	Lagged	0.889	0.901	0.920	0.937	0.922	0.930	0.818	0.908	0.909
included	variable (χ)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T and I dummies	Lagged	0.575	0.653	0.673	0.709	0.631	0.621	0.529	0.590	0.591
included	variable (χ)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

°OLS: $W_{it}=\chi W_{it-1}+\xi_i+\xi_t+\epsilon_{it}$

H_0: $\chi = 1$. p-value Wald Test in parenthesis.

Table A11. Non-Restricted Production Function Estimates (SYS T-2)

	KL	KLE	KLT	KLET	KL_{adj}	$KL_{adj}E$	$KL_{adj}T$	$KL_{adj}ET$
δ_1	0.814***	0.811***	0.773***	0.777***	0.754***	0.795***	0.715***	0.742***
	(.086)	(.100)	(.083)	(.081)	(.099)	(.117)	(.090)	(.088)
δ_2	0.454***	0.088	0.304*	0.027	0.028	-0.074	-0.073	-0.169
	(.175)	(.151)	(.179)	(.137)	(.149)	(.121)	(.130)	(.117)
δ_3	-0.331**	-0.039	-0.213	0.025	-0.020	0.074	0.057	0.163
	(.152)	(.120)	(.167)	(.121)	(.126)	(.104)	(.122)	(.104)
δ_4	0.692***	0.579***	0.677***	0.419**	0.938***	0.587***	0.847***	0.462***
	(.203)	(.189)	(.195)	(.192)	(.175)	(.180)	(.167)	(.151)
δ_5	-0.050*	-0.374	-0.514**	-0.253	-0.642***	-0.347*	-0.558**	-0.236
	(.259)	(.282)	(.263)	(.260)	(.228)	(.217)	(.231)	(.192)
δ_6		0.320***		0.340***		0.293***		0.330***
		(.093)		(.085)		(.096)		(.076)
δ_7		-0.272***		-0.331***		-0.291***		-0.340***
		(.091)		(.086)		(.093)		(.064)
δ_8			0.094	0.104*			0.085	0.099*
			(.080)	(.063)			(.078)	(.059)
δ_9			-0.010	-0.001			-0.004	0.002
			(.069)	(.056)			(.078)	(.057)
$m_1^{\Diamond}$	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000
$m_2^{\Diamond}$	0.950	0.400	0.759	0.582	0.042	0.059	0.078	0.145
Sargan$^{\Diamond}$	0.057	0.196	0.232	0.232	0.031	0.105	0.204	0.349
Diff Sargan$^{\Diamond}$	0.093	0.504	0.628	0.473	0.052	0.217	0.315	0.477
α	0.496***	0.077	0.401***	0.111	0.025	-0.095	-0.002	-0.063
	(.173)	(.145)	(.153)	(.120)	(.148)	(.115)	(.105)	(.095)
β	0.770***	0.680***	0.689***	0.524***	1.052***	0.631***	0.904***	0.508***
	(.155)	(.125)	(.122)	(.120)	(.133)	(.161)	(.107)	(.107)
γ		0.336***		0.320***		0.313***		0.285***
		(.091)		(.077)		(.091)		(.064)
λ			0.124*	0.128**			0.152**	0.168***
			(.074)	(.062)			(.061)	(.053)
ρ	0.886***	0.914***	0.885***	0.897***	0.815***	0.925***	0.828***	0.894***
	(.063)	(.095)	(.051)	(.037)	(.080)	(.062)	(.049)	(.037)
Comfac$^{\Diamond}$	0.406	0.686	0.102	0.014	0.428	0.428	0.430	0.042
CRS$^{\Diamond}$	0.141	0.473	0.192	0.499	0.480	0.137	0.594	0.173

*, **, *** indicate statistical significance at 10, 5 or 1 percent, respectively. Time and group dummies included. Corrected two-step standard errors in parenthesis. $^{\Diamond}$p-values.

Table A12. Production Function Estimates Imposing CRS (SYS T-2)

	KL	KLE	KLT	KLET	KL_{adj}	$KL_{adj}E$	$KL_{adj}T$	$KL_{adj}ET$
δ_1	0.822***	0.804***	0.804***	0.797***	0.755***	0.758***	0.741***	0.741***
	(.104)	(.113)	(.087)	(.090)	(.106)	(.124)	(.099)	(.110)
δ_2	0.399***	0.109	0.273**	0.100	0.037	0.029	-0.021	0.005
	(.152)	(.115)	(.118)	(.098)	(.155)	(.117)	(.112)	(.100)
δ_3	-0.265**	-0.032	-0.185	-0.037	0.021	0.053	0.044	0.064
	(.124)	(.093)	(.123)	(.092)	(.138)	(.101)	(.130)	(.103)
δ_6		0.351***		0.342***		0.240*		0.263**
		(.112)		(0.097)		(.141)		(.113)
δ_7		-0.313***		-0.320***		-0.264*		-0.289***
		(.122)		(.095)		(.140)		(.104)
δ_8			0.115	0.102			0.115*	0.113*
			(.085)	(.074)			(.067)	(.066)
δ_9			-0.044	-0.029			-0.045	-0.038
			(.080)	(.068)			(.072)	(.067)
$m_1^{\Diamond}$	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000
$m_2^{\Diamond}$	0.798	0.377	0.599	0.650	0.039	0.022	0.138	0.127
Sargan$^{\Diamond}$	0.048	0.085	0.468	0.449	0.004	0.041	0.254	0.239
Diff Sargan$^{\Diamond}$	0.074	0.020	0.756	0.382	0.009	0.072	0.312	0.301
α	0.367**	0.073	0.274**	0.161*	0.037	0.038	-0.002	0.079
	(.150)	(.111)	(.113)	(.091)	(.155)	(.116)	(.098)	(.090)
β	0.633***	0.551***	0.551***	0.391***	0.963***	0.709	0.833	0.590
	(.187)	(.165)	(.153)	(.127)	(.233)	(.181)	(.110)	(.109)
γ		0.376***		0.294***		0.253**		0.167*
		(.100)		(.085)		(.121)		(.091)
λ			0.175**	0.154**			0.169***	0.164***
			(.078)	(.066)			(.054)	(.054)
ρ	0.866***	0.851***	0.895***	0.898***	0.768***	0.870***	0.821***	0.902***
	(.099)	(.106)	(.069)	(.079)	(.105)	(.111)	(.080)	(.074)
Comfac$^{\Diamond}$	0.184	0.498	0.107	0.061	0.515	0.129	0.344	0.212

*, **, *** indicate statistical significance at 10, 5 or 1 percent, respectively. Time and group dummies included. Corrected two-step standard errors in parenthesis. $^{\Diamond}$p-values.

Table A13. Ranking: MFP Average Growth Rates, 1996-2003

	Group	KL	KLE	KLT	KLET
G3	Lumber & Wood	1	-	-	-
G13	Computer & Electronic Products	2	1	1	1
G10	Electrical Equipment, Appliances & Components	3	2	3	2
G12	Other Transportation Equipment	4	6	4	6
G4	Paper, Printing, Publishing & Reproduction	5	5	7	4
G2	Textile, Apparel, Fur, Leather & Footwear	6	7	5	5
G1	Food, Beverage & Tobacco	7	9	8	8
G7	Non-metallic & Glass	8	10	9	9
G14	Miscellaneous	9	11	10	11
G11	Automobiles	10	8	6	7
G8	Primary & Fabricated Metal	11	4	12	3
G6	Chemicals	12	12	11	10
G9	Machinery	13	-	-	-

Table A14. Shares and Contributions (KL), 1996-2003

Group		Factor Shares		Contribution to Average Growth		MFP Avg	
		K	L	K	L	Level	Growth
G13	Computer & Electronic Products	0.33***	0.67***	3.9%	-0.1%	28.9	6.7%
G3	Lumber & Wood	0.06***	0.94**	-0.3%	-7.0%	2.3	5.3%
G10	Electrical Equipment, Appliances & Components	0.31***	0.69***	1.3%	0.0%	30.5	4.5%
G1	Food, Beverage & Tobacco	0.37***	0.63***	1.5%	0.5%	52.4	3.6%
G4	Paper, Printing, Publishing & Reproduction	0.22***	0.78**	-0.1%	0.8%	15.2	3.2%
G14	Miscellaneous	0.47***	0.53**	1.9%	0.4%	12.9	2.6%
G2	Textile, Apparel, Fur, Leather & Footwear	0.15***	0.85***	-0.1%	-1.9%	8.7	2.6%
G8	Primary & Fabricated Metal	0.42***	0.58***	1.5%	-0.5%	21.6	2.3%
G7	Non-metallic & Glass	0.28***	0.72**	0.4%	-0.3%	16.3	2.3%
G12	Other Transportation Equipment	0.46***	0.54**	-0.1%	0.5%	3.6	1.5%
G6	Chemicals	0.28***	0.72***	1.3%	-0.1%	41.3	1.1%
G11	Automobiles	0.14***	0.86***	1.1%	0.6%	14.3	-0.3%
G9	Machinery	0.27***	0.73***	0.8%	-0.5%	7.5	-0.7%

*, **, *** indicate statistical significance at 10, 5 or 1 percent, respectively.

Tables A15. Shares and Contributions (KLET), 1996-2003

Group	Factor Share				Contribution to Avg. Growth				MFP	
	K	L	E	T	K	L	E	T	Level	Growth
Computer & Electronic Products	0.21***	0.31**	0.30***	0.17**	2.5%	0.0%	0.2%	-0.9%	48.5	9.1%
Elec. Eq., Appliances & Comps.	0.12***	0.46***	0.42***	0.00	0.5%	0.0%	-1.3%	0.0%	24.9	5.1%
Paper, Printing, Pub. & Rep.	0.08*	0.66**	0.15***	0.10**	0.0%	0.7%	-0.1%	0.3%	9.9	3.9%
Primary & Fabricated Metal	0.20***	0.33***	0.36***	0.12***	0.7%	-0.3%	-0.3%	-0.4%	37.1	3.5%
Textile, Apparel, Lthr. & Ftwr.	0.00	0.38***	0.55***	0.07***	0.0%	-0.8%	-1.8%	0.2%	16.8	3.3%
Food, Beverage & Tobacco	0.28***	0.46***	0.23***	0.03	1.2%	0.4%	-0.1%	0.2%	26.5	2.8%
Chemicals	0.13**	0.40**	0.30**	0.17	0.6%	-0.1%	-0.7%	0.4%	41.0	2.7%
Miscellaneous	0.30***	0.31*	0.20**	0.19***	1.2%	0.2%	0.0%	1.4%	29.1	2.4%
Non-metallic & Glass	0.27***	0.27**	0.31***	0.15***	0.4%	-0.1%	-0.1%	0.6%	16.4	2.3%
Other Transportation Eq.	0.34***	0.30*	0.34**	0.01	-0.1%	0.3%	-1.8%	0.2%	7.7	0.1%
Automobiles	0.11***	0.37**	0.36***	0.17***	0.9%	0.3%	0.6%	0.7%	19.1	0.0%

*, **, *** indicate statistical significance at 10, 5 or 1 percent, respectively.

Table A16. Ranking: MFP Average Growth Rates, 1996-2003 (L_{adj})

	Group	KL	KLE	KLT	KLET
G13	Computer & Electronic Products	1	1	1	1
G3	Lumber & Wood	2	-	-	-
G10	Electrical Equipment, Appliances & Components	4	2	3	2
G4	Paper, Printing, Publishing & Reproduction	5	6	4	5
G14	Miscellaneous	6	8	6	8
G2	Textile, Apparel, Fur, Leather & Footwear	7	5	8	6
G1	Food, Beverage & Tobacco	8	7	5	4
G7	Non-metallic & Glass	9	10	9	9
G11	Automobiles	10	11	10	10
G8	Primary & Fabricated Metal	11	9	7	7
G12	Other Transportation Equipment	12	3	12	3
G6	Chemicals	13	12	11	11
G9	Machinery	14	-	-	-

Table A17. Changes in Estimated Coefficients Between L and L_{adj}

	Group	KL
G14	Miscellaneous	0.32
G13	Computer & Electronic Products	0.22
G7	Non-metallic & Glass	0.08
G10	Electrical Equipment, Appliances & Components	0.06
G2	Textile, Apparel, Fur, Leather & Footwear	0.06
G8	Primary & Fabricated Metal	0.01
G1	Food, Beverage & Tobacco	0.01
G11	Automobiles	0.00
G6	Chemicals	-0.02
G12	Other Transportation Equipment	-0.05
G4	Paper, Printing, Publishing & Reproduction	-0.06
G3	Lumber & Wood	-0.15
G9	Machinery	-0.19

Figures

Figure A1: Relative MFP Levels