

TECHNICAL EFFICIENCY, TECHNOLOGICAL DEVELOPMENT, AND THE LABOR PRODUCTIVITY GAP IN MEXICAN MANUFACTURING

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Abstract

This paper applies a stochastic frontier approach to analyze the evolution of technical efficiency in Mexican manufacturing and its effect on the labor productivity gap among states over the period 1988-2008. The model allows for heterogeneity in technological development by introducing region-specific effects in the econometric specification. The main findings of our analysis are threefold. First, technical efficiency was both increasing and converging over time and across states in a context where labor productivity was also converging. Second, there are considerable differences in the levels of technological development of the north and the central regions with respect to the south that partially explains the labor productivity gap. Third, the dynamics of technical efficiency contributed to reduce inequality in productivity among states over the analyzed period.

Keywords: Manufacturing; Mexican regions; Labor productivity; Stochastic frontier; Structural efficiency; Technical efficiency

JEL Classification: D24; L60; O18

1. Introduction

Regional disparities are pervasive in Mexico, and manufacturing is not an exception. While this sector represents 22% of total economic activity in the north, its participation is about 8.1% in the south (Banxico, 2011a).¹ Differences are also observed in terms of labor productivity (measured as value added per worker) in manufacturing: productivity is about 55% higher in the north than in the south.² Not surprisingly, average household income is about 67% higher in the former region than in the latter.³

Regional differences in labor productivity can be partially attributed to differences in technical efficiency, which refers to the ability of an economic unit to avoid waste by producing as much output as technology and input usage allow (Fried, Lovell and Schmidt, 2008). For the measurement of technical efficiency it is necessary to compare actual performance with optimal (efficient) performance, which is represented by a set of points that lie on the production frontier (the upper boundary of the production possibilities set). The central problem in the measurement of technical efficiency is to measure the distance between the production frontier and the input-output combination of each economic unit (Kumbhakar and Lovell, 2003). Since the true frontier is unknown,

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¹Mexico is divided in four regions by applying the regionalization proposed by Banco de Mexico (2011a). **North:** Baja California, Chihuahua, Coahuila, Nuevo Leon, Sonora and Tamaulipas; **North-Central:** Aguascalientes, Baja California Sur, Colima, Durango, Jalisco, Michoacan, Nayarit, San Luis Potosi, Sinaloa and Zacatecas; **Central:** Federal District, State of Mexico, Guanajuato, Hidalgo, Morelos, Puebla, Queretaro and Tlaxcala; **South:** Campeche, Chiapas, Guerrero, Oaxaca, Quintana Roo, Tabasco, Veracruz and Yucatan.

²Own calculations based on the 2009 Economic Census produced by INEGI, the national statistical office.

³Own calculations based on the 2010 National Household and Expenditure Survey (INEGI).

the empirical approximation to it is commonly defined as best practice frontier. Most studies related to the measurement of technical efficiency have applied either non-parametric or parametric methods to estimate the frontier (Murillo and Vega, 2001).

The non-parametric approach is basically represented by data envelopment analysis (DEA) (Coelli, 2005), a mathematical programming approach to the construction of frontiers. It constructs a frontier envelopment surface that literally envelops the data set. The surface is determined by those economic units that lie on it (efficient units), while those units that lie beneath the surface are considered inefficient. One caveat of DEA is that all deviations from the efficient frontier are assumed to be under the control of the economic units. This assumption can produce biases in the estimated efficiency, since factors such as weather, luck, and uncertainty are not distinguished from the rest of the factors affecting technical efficiency. In order to separate the effects of efficiency from the effects of noise on output a parametric approach, the so-called stochastic frontier analysis, is usually applied (Aigner, Lovell and Schmidt 1977, Meeusen and van Den Broeck 1977, Khumbakar and Lovell, 2003).

Another methodological challenge in the analysis of production frontiers is to separate region-specific technological characteristics from technical efficiency (Alvarez, 2007). Under standard frontier analysis, it is usually assumed that different regions use the same kind of technology. However, technological characteristics can be associated to historical and institutional factors (Acemoglu and Johnson, 2001) as well as being related to the interaction of location, scale economies and transportation costs (Krugman 1991, Schmutzler 1999). For instance, the most concentrated and largest industries in Mexico tend to be located in the north and the central regions (Trejo, 2010) and are better connected to the U.S. than those located in the south (Dávila, Kessel and Levy, 2002). Some authors, such as Alvarez (2007) and Kumbhakar and Wang (2005), have incorporated the possibility of heterogeneous technical characteristics into the traditional stochastic frontier model by allowing for level differences in the deterministic part of the frontier instead of assuming a single national frontier function.

Our research is related to other studies that have measured technical efficiency for Mexican manufacturing at different levels of regional aggregation. Bannister and Stolp (1995) analyzed technical efficiency in a set of manufacturing industries for a cross section of Mexican states in 1985. By applying the DEA approach, they found that those states with a high concentration of industrial activity were closer to the frontier, particularly the Federal District and the State of Mexico, while less industrialized states, such as Guerrero, Michoacan, Nayarit and Yucatan, were consistently less efficient. Braun and Cullman (2011) used a panel of municipality-level data to estimate technical efficiency in Mexican manufacturing (including oil-related industries) using data from the years 1989, 1999 and 2004. They applied the so called "true" random effects model (Greene, 2005) to overcome the problem that any unobserved and time-invariant municipality-specific effect is considered as technical inefficiency. Not only did they find considerable differences in terms of efficiency of the south with respect to the central region and the north, but they also found a pronounced variation of efficiency within states. However, none of these studies presented results dealing with the evolution of technical efficiency across time and space, particularly convergence across states, neither did they explicitly estimate level differences of technological development at the regional

level. Therefore, their results cannot be used to evaluate the impact of both efficiency dynamics and technological development on the labor productivity gap in regional manufacturing.

The aim of the paper is twofold. Firstly, to analyze the evolution of technical efficiency in manufacturing, particularly the presence of convergence (divergence) of technical efficiency over time and across states, taking regional differences in technological development into account. Secondly, to evaluate the role of technical efficiency as a mechanism to reduce (increase) inequality in labor productivity among states. In order to do so, this study adopts a stochastic frontier specification that allows for time-varying technical efficiency based on the model proposed by Battese and Coelli (1992). Under the assumption that regional technical characteristics are deterministic and time invariant, it is possible to identify and separate both technical efficiency and technical characteristics to calculate their respective contributions to productivity differentials. The model is estimated for the manufacturing sector using a panel over the period 1988-2008 where the units of analysis are the Mexican states.

The remainder of the paper is organized as follows. Section 2 introduces the stochastic frontier model and its corresponding econometric specification. Section 3 describes the data on regional manufacturing. Section 4 presents the main empirical results. Finally, section 5 concludes.

2. Methodology

2.1 Technical and structural efficiency

An economy is geographically divided in m regions and n states. Region $j = 1, \dots, m$ is composed by a group of n_j states, such that

$$\sum_{j=1}^m n_j = n$$

In period $t = 0, \dots, T$, state $i \in j$ produces based on its *stochastic* production frontier⁴

$$Y_{it}^s = \phi_j f(K_{it}, L_{it}, t; \beta) \exp(v_{it}) \quad (1)$$

where K_{it} , and L_{it} are, respectively, capital and labor; t is a time trend serving as a proxy for technical change; β is a parameter vector characterizing the structure of production technology; instead of assuming a single national frontier function for all states, heterogeneity is allowed by having region-specific shift parameters, ϕ_j , indicating the relative level of technological development or *structural efficiency* of region j . This type of efficiency is related to time-invariant characteristics (weather, proximity to markets, institutional framework, etc.) observed in the regions where the states are located; $\exp(v_{it})$ takes into account all those factors that are not directly under the control of economic units by introducing random shocks v_{it} into the production process.

⁴As in most regional studies, we assume the sum of all micro-units within each state as a single production unit.

Economic units often produce less than they might because they are not making the most of their inputs given the current state of technological development. Based on Debreu (1951) and Farrell (1957) *technical efficiency* is defined as the ability to obtain maximum (potential) output from a given input vector. Formally, technical efficiency, E_{it} , is measured as the ratio of observed output Y_{it} to potential output Y_{it}^* (output at the frontier). Therefore, observed output is given by

$$Y_{it} = Y_{it}^* E_{it} \quad (2)$$

where $E_{it} \in (0,1]$. Clearly, state i is operating at its maximum capacity in period t if $E_{it} = 1$; otherwise it would be technically inefficient.

2.2 Econometric specification

Taking the natural log of both sides of equation (2)

$$y_{it} = \alpha_j + \ln \{f(K_{it}, L_{it}, t; \beta)\} + v_{it} - u_{it} \quad (3)$$

Where $y_{it} = \ln Y_{it}$, $\alpha_j = \ln \phi_j$ and $u_{it} = -\ln E_{it}$. Notice that $u_{it} \geq 0$ since $E_{it} \in (0,1]$; hence $u_{it} \geq 0$ represents a deviation from the frontier (technical inefficiency).

One caveat of this approach is that it requires the definition of a specific functional form for the employed technology. A widely accepted specification characterized by its flexibility is the translog production frontier (Coelli, 2005):

$$y_{it} = \alpha_j + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 k_{it}^2 + \beta_4 l_{it}^2 + \beta_5 k_{it} l_{it} + \beta_6 t + v_{it} - u_{it} \quad (4)$$

where k_{it} , and l_{it} are, respectively, the logs of capital, and labor; t is a time trend capturing technical progress in the model. Note that it nests within the Cobb-Douglas function when $\beta_3 = \beta_4 = \beta_5 = 0$.

We follow Battese and Coelli [1992] by assuming $u_{it} = \eta_t u_i = \exp[-\eta(t-T)]u_i$. This specification has the advantage of having only one additional parameter to estimate, making computation simpler. Since $\partial \ln u_{it} / \partial t = -\eta$, technical inefficiency decreases, remains constant or increases over time, if $\eta > 0$, $\eta = 0$ or $\eta < 0$, respectively. Assuming a half-normal distribution for u_i : i.e. $u_i \sim \text{iid } N^+(\mu, \sigma_u^2)$, and a normal distribution for v_{it} : i.e. $v_{it} \sim \text{iid } N(0, \sigma_v^2)$, the model can be estimated by maximum likelihood to obtain estimators for μ , σ_u^2 , σ_v^2 , η , the parameters of equation (4) and technical efficiency E_{it} .

3. Data

The empirical model is estimated for the manufacturing sector, excluding oil-related industries, using a balanced panel for the 31 Mexican states and the Federal District for the years 1988, 1993, 1998, 2003 and 2008. We use gross value added as a proxy for output (from now on we use the terms value added and output indistinctly), Y_{it} , and the stock of private capital as a measure of capital input, K_{it} (both Y_{it} and K_{it} are measured in constant 2003 pesos). Labor input, L_{it} , was obtained from the unadjusted total employment in manufacturing. These variables were obtained from the Economic Census

of INEGI (the Mexican statistical office). Similar to Duffy and Papageorgiou (2000) and Kneller and Stevens (2003), we weight labor force by the mean years of schooling of the workforce. Specifically, we define $S_{it}L_{it}$ as a proxy measure for the human capital-adjusted labor input, where S_{it} is defined as the mean years of schooling of the population aged 15 and older. The sources of the schooling data are the General Censuses and the Counts of Population and Housing, which are also produced by INEGI.

Table 1 presents the regional share of gross value added, employment, and the stock of capital, as well as the mean years of schooling per region.

Table 1. Summary statistics at the regional level

	Year	North	North Central	Central	South
Gross value added ^a (Y)	1988	0.26	0.13	0.56	0.06
	1993	0.25	0.16	0.53	0.06
	1998	0.31	0.17	0.46	0.05
	2003	0.34	0.16	0.44	0.06
	2008	0.35	0.17	0.41	0.06
Total employment ^b (L)	1988	0.28	0.16	0.48	0.08
	1993	0.30	0.17	0.45	0.09
	1998	0.35	0.17	0.40	0.08
	2003	0.36	0.18	0.38	0.08
	2008	0.34	0.19	0.38	0.09
Private capital ^a (K)	1988	0.25	0.19	0.43	0.13
	1993	0.27	0.23	0.39	0.10
	1998	0.29	0.19	0.41	0.10
	2003	0.31	0.19	0.40	0.09
	2008	0.30	0.22	0.40	0.08
Mean years of schooling ^c (S)	1988	7.17	6.14	6.30	5.25
	1993	8.07	7.04	7.21	6.25
	1998	8.17	7.30	7.75	6.50
	2003	8.87	8.07	8.23	7.30
	2008	9.32	8.62	8.75	7.88

^a Regional Share.

^b Normalized by $\max \{Y_j / L_j\}$ at each period.

^c Population aged 15 and over. Source: INEGI, own calculations.

This table also introduces output per worker which, to make comparison easier, is expressed as the ratio to the maximum observed value across regions. The central region observed the highest level and the south the lowest level of output per worker all over the period. The north-central and the north regions increased their labor productivity relative to the central region between 1988 and 2008.

The north and the north-central regions increased their share in total gross value added and employment over the analyzed period, particularly the north, whose share in total value added went from 26% in 1988 to 35% in 2008. In the case of the north-central region, its participation went from 13% to 17% in the generation of value added, and its participation in the labor market went from 16% to 19% over the same period. In contrast, the central region considerably reduced its share in both total value added and total employment: its participation went from 56% to 41% in the former case, and from 48% to 38% in the latter one. Finally, the south stagnated maintaining its participation in total

value added and total employment around 6% and 9%, respectively, all over the 20-year period. This pattern was observed, to a lesser extent, in the stock of capital during the 1988-2008 period. The north and the north-central regions increased their share in the stock of capital from 25% and 19% to 30% and 22%, while the participation of the central region and the south was reduced by 3 and 5 percentage points, respectively.

Table 2. Summary statistics at the state level (1988)

	Gross Value	Capital	Employment ^a	Value added	Average years
	added ^a	Stock ^a		per worker ^b	of schooling ^c
Aguascalientes	0.007	0.009	0.013	0.163	6.6
Baja California	0.019	0.009	0.031	0.201	7.3
Baja California Sur	0.001	0.001	0.002	0.171	7.2
Campeche	0.001	0.001	0.003	0.118	5.7
Coahuila	0.058	0.072	0.041	0.468	7.1
Colima	0.001	0.001	0.002	0.139	6.5
Chiapas	0.004	0.004	0.006	0.188	4.1
Chihuahua	0.039	0.029	0.067	0.192	6.7
Distrito Federal	0.219	0.117	0.194	0.372	8.5
Durango	0.008	0.009	0.017	0.151	6.2
Guanajuato	0.028	0.025	0.042	0.217	5.1
Guerrero	0.002	0.001	0.006	0.130	4.9
Hidalgo	0.016	0.018	0.015	0.349	5.4
Jalisco	0.064	0.053	0.068	0.310	6.3
Mexico	0.199	0.164	0.148	0.442	6.9
Michoacan	0.013	0.086	0.022	0.197	5.1
Morelos	0.035	0.010	0.011	1.000	6.6
Nayarit	0.003	0.001	0.004	0.211	5.9
Nuevo Leon	0.102	0.093	0.078	0.429	7.8
Oaxaca	0.005	0.010	0.009	0.184	4.4
Puebla	0.032	0.055	0.042	0.247	5.5
Queretaro	0.024	0.032	0.019	0.413	6
Quintana Roo	0.001	0.001	0.002	0.145	6.2
San Luis Potosi	0.023	0.029	0.020	0.383	5.7
Sinaloa	0.006	0.006	0.011	0.178	6.6
Sonora	0.020	0.032	0.025	0.258	7.2
Tabasco	0.002	0.007	0.004	0.183	5.8
Tamaulipas	0.021	0.013	0.036	0.195	6.9
Tlaxcala	0.008	0.011	0.010	0.275	6.4
Veracruz	0.033	0.096	0.035	0.313	5.3
Yucatan	0.008	0.007	0.012	0.209	5.6
Zacatecas	0.001	0.001	0.003	0.123	5.3

^a State's share ^b Normalized by $\max \{Y_j / L_j\}$. ^c Population aged 15 and over.

Source: INEGI, own calculations.

Table 3. Summary statistics at the state level (2008)

	Gross value added	Capital Stock	Employment	Value added per worker	Average years of schooling
Aguascalientes	0.019	0.027	0.016	0.770	9.23
Baja California	0.044	0.026	0.061	0.463	9.26
Baja California Sur	0.001	0.001	0.002	0.267	9.40
Campeche	0.001	0.001	0.004	0.157	8.51
Coahuila	0.069	0.079	0.044	1.000	9.47
Colima	0.002	0.005	0.003	0.543	8.95
Chiapas	0.004	0.005	0.010	0.241	6.67
Chihuahua	0.054	0.042	0.075	0.458	8.82
Distrito Federal	0.096	0.069	0.087	0.703	10.54
Durango	0.010	0.008	0.013	0.479	8.58
Guanajuato	0.049	0.051	0.057	0.541	7.73
Guerrero	0.002	0.002	0.012	0.083	7.27
Hidalgo	0.018	0.027	0.018	0.638	8.10
Jalisco	0.075	0.068	0.082	0.577	8.78
Mexico	0.145	0.122	0.115	0.804	9.10
Michoacan	0.020	0.043	0.024	0.511	7.42
Morelos	0.013	0.012	0.011	0.712	8.90
Nayarit	0.002	0.002	0.004	0.287	8.61
Nuevo León	0.104	0.099	0.077	0.863	9.81
Oaxaca	0.005	0.014	0.014	0.241	6.94
Puebla	0.047	0.065	0.051	0.594	7.95
Queretaro	0.036	0.038	0.026	0.872	8.92
Quintana Roo	0.002	0.002	0.003	0.437	9.12
San Luis Potosi	0.028	0.044	0.023	0.757	8.26
Sinaloa	0.008	0.010	0.013	0.406	9.08
Sonora	0.039	0.031	0.035	0.708	9.42
Tabasco	0.003	0.005	0.005	0.467	8.64
Tamaulipas	0.042	0.026	0.050	0.532	9.12
Tlaxcala	0.011	0.013	0.013	0.539	8.78
Veracruz	0.037	0.043	0.027	0.890	7.67
Yucatan	0.008	0.010	0.019	0.266	8.22
Zacatecas	0.006	0.010	0.006	0.597	7.90

^a State's share ^b Normalized by $\max \{Y_j / L_j\}$. ^c Population aged 15 and over. Source: INEGI, own calculations.

Tables 2 and 3 present the states' share of total value added, stock of capital and employment for the years 1988 and 2008, respectively. These tables also introduce output per worker expressed as the ratio to its maximum observed value across states. For instance, Morelos observed the highest level and Campeche the lowest level of output per worker in 1988. In 2008, it was Coahuila which showed the highest level of labor

productivity and Campeche the lowest. According to these tables, value added per worker in Campeche was about 25.2% of that in Coahuila in 1988, but only 15.7% in 2008.

With respect to the average years of schooling, there are important regional differences for this indicator: while the average years of education in the north were 9.3 in 2010, individuals living in the south spent, on average, 7.9 years in school (Table 1). These differences become more noticeable once we compare average years of schooling between states. For instance, while the average years of education in the Federal District was about 10.5 in 2010, in Chiapas, one of the poorest states in Mexico, individuals spent just 6.7 years in school (Table 3).

4. Empirical results

4.1 Technical efficiency and technological development

Table 4 reports maximum likelihood estimates of the model of equation (4) and, for comparison purpose, a Cobb Douglas specification ($\beta_3 = \beta_4 = \beta_5 = 0$), with (Models 2 and 4) and without (Models 1 and 3) regional fixed effects.

We conduct a series of misspecification tests to identify an appropriate functional form for the frontier. The first test shows that the translog functional form is preferred to the Cobb-Douglas: the likelihood ratio test rejects the hypothesis that $\alpha_2 = \beta_4 = \beta_5 = 0$ at the 1% level ($\chi^2_3 = 12.73$) (the Cobb-Douglas specification has also been rejected by other studies in the context of efficiency analysis (Kumbhakar and Wang 2005, Kneller and Stevens, 2003). The second test rejects the hypothesis of homogeneous production frontiers: the likelihood ratio test rejects the hypothesis that $\alpha_i = \alpha_j, i \neq j$, at the 1% level for both the translog ($\chi^2_3 = 11.75$) and Cobb-Douglas ($\chi^2_3 = 15.76$) specifications. Given these results, the translog specification with regional fixed effects (Model 2) represents the best specification among the 4 analyzed models presented in Table 4.

The significant value obtained for $\gamma = \frac{\sigma_u^2}{\sigma_\varepsilon^2 + \sigma_u^2}$ indicates that technical efficiency contributes to explain the difference in production across states that is not accounted for by the input variables. Therefore, ignoring this fact would imply assuming that deviations from the production frontier are totally due to factors beyond the control of the economic units when they are not. Similar to Kneller and Stevens (2003) and Kumbhakar and Wang (2005), the coefficient related to the trend variable, commonly known as technical change, is negative. It is associated to the output variation that is not explained by either a change in input usage or efficiency improvements.

Using the estimates presented in Table 4, it is possible to estimate technical efficiency for each state i and each period t , E_{it} , by applying the minimum-squared-error predictor developed by Battese and Coelli (1992). Technical efficiency of region j at t , E_{jt} , is obtained as the ratio of observed to efficient regional output. Formally,

$$E_{jt} = \frac{\sum_{i \in j} Y_{it}}{\sum_{i \in j} Y_{it}^*} = \frac{\sum_{i \in j} Y_{it}}{\sum_{i \in j} E_{it}^{-1} Y_{it}} \quad (5)$$

where $Y_{it}^E = E_{it}^{-1}Y_{it}$ comes from equation (2). Analogously, overall technical efficiency in period t , E_t , is given by

$$E_t = \frac{\sum_i Y_{it}}{\sum_i E_{it}^{-1} Y_{it}} \quad (6)$$

Table 4. Estimation results

	Translog		Cobb-Douglass	
	Model 1	Model 2	Model 3	Model 4
k	-0.243	-0.189	0.468***	0.463***
	(0.412)	(0.395)	(0.045)	(0.042)
l	0.741	0.799	0.652***	0.587***
	(0.585)	(0.563)	(0.053)	(0.054)
k^2	-0.093***	-0.083***		
	(0.026)	(0.026)		
l^2	-0.075**	-0.072*		
	(0.039)	(0.038)		
kl	0.192***	0.173***		
	(0.056)	(0.056)		
Trend	-0.111***	-0.085**	-0.126***	-0.097***
	(0.038)	(0.035)	(0.041)	(0.035)
North-Central		-0.167*		-0.164*
		(0.095)		(0.096)
Central		0.078		0.096
		(0.086)		(0.086)
South		-0.231**		-0.278***
		(0.105)		(0.105)
Constant	0.175	-0.142	-2.715***	-2.045***
	(2.675)	(2.521)	(0.414)	(0.475)
η	0.028***	0.036**	0.031**	0.045***
	(0.011)	(0.014)	(0.013)	(0.016)
$\sigma_v^2 + \sigma_u^2$	0.053	0.047	0.058	0.049
	(0.007)	(0.006)	(0.008)	(0.006)
$\gamma = \frac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2}$	0.240***	0.148**	0.223***	0.121*
	(0.087)	(0.072)	(0.088)	(0.066)
Log-likelihood	7.292	13.166	-1.078	6.801
N	160	160	160	160

s.e. in parenthesis. Significance: *** = 1% level; ** = 5% level; * = 10%.

Technical efficiency observed a positive pattern along the period 1988-2008 for all states (Table 5). This pattern becomes evident even after considering uncertainty in the estimation (see Figure 1). The lower bound of the 95% confidence bands is above 60% for all states in 2008 and, with the exception of Morelos, their corresponding confidence bands for the years 1988 and 2008 do not overlap: the upper limit of the confidence interval on technical efficiency in 1988 is smaller than the lower limit of the confidence

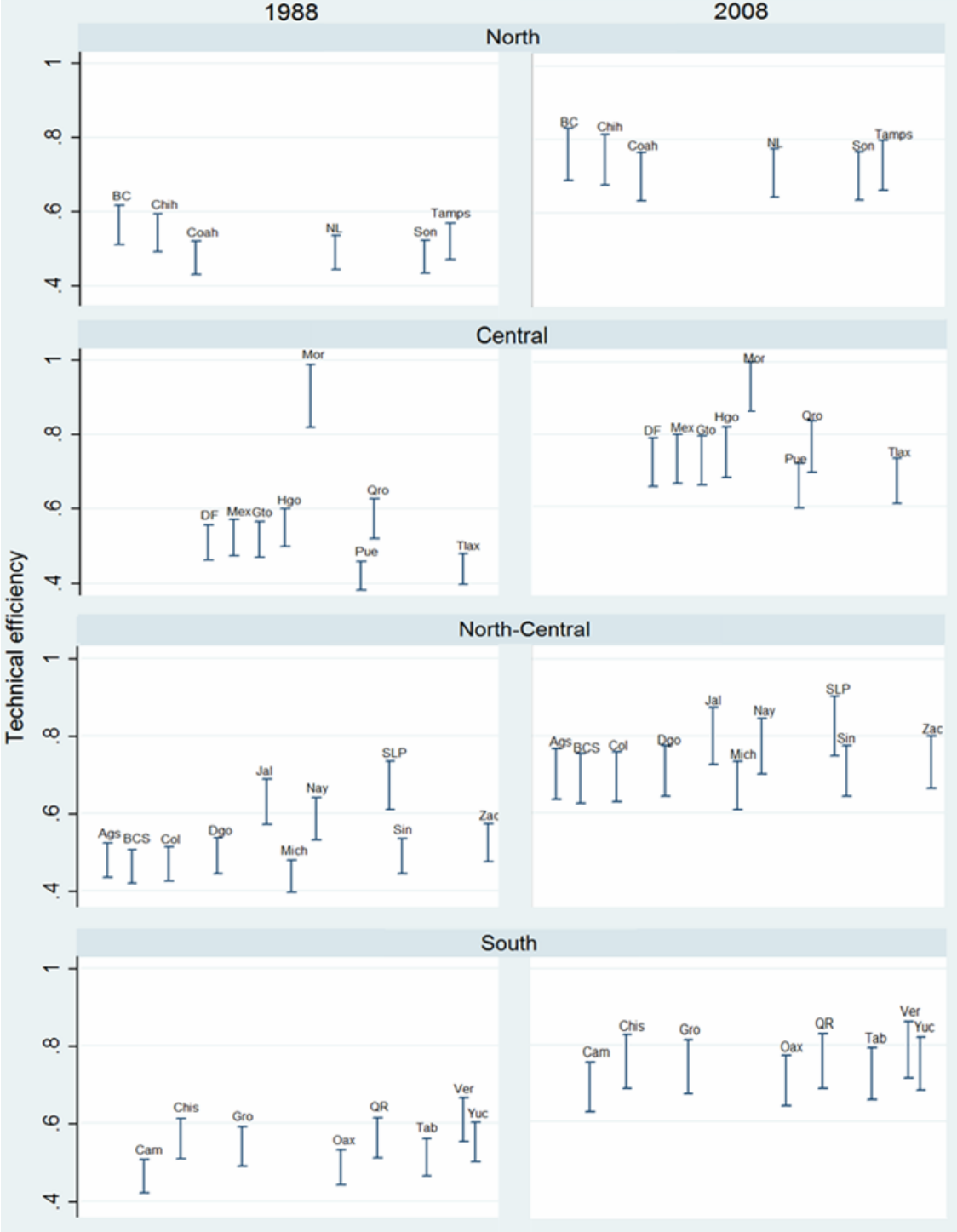
interval on technical efficiency in 2008.⁵

Table 5. Technical and structural efficiency in manufacturing

	Technical (E_{it})					Structural Efficiency (θ_{it})
	1988	1993	1998	2003	2008	
North	0.506	0.566	0.624	0.673	0.720	0.925
BC	0.565	0.621	0.671	0.717	0.757	
Coahuila	0.544	0.601	0.654	0.701	0.743	
Chihuahua	0.477	0.539	0.596	0.649	0.697	
Nuevo León	0.491	0.552	0.609	0.661	0.707	
Sonora	0.480	0.542	0.599	0.652	0.699	
Tamaulipas	0.521	0.580	0.634	0.684	0.728	
North-Central	0.579	0.631	0.677	0.720	0.758	0.783
Aguascalientes	0.479	0.541	0.599	0.651	0.699	
Baja California Sur	0.463	0.526	0.584	0.639	0.688	
Colima	0.470	0.533	0.591	0.644	0.693	
Durango	0.491	0.552	0.609	0.661	0.707	
Jalisco	0.629	0.679	0.724	0.763	0.798	
Michoacan	0.439	0.503	0.563	0.619	0.670	
Nayarit	0.586	0.640	0.688	0.732	0.771	
San Luis Potosi	0.673	0.718	0.758	0.793	0.824	
Sinaloa	0.490	0.551	0.608	0.660	0.707	
Zacatecas	0.525	0.583	0.638	0.687	0.730	
Central	0.534	0.589	0.640	0.686	0.730	1.000
Federal District	0.510	0.570	0.625	0.675	0.721	
Guanajuato	0.524	0.582	0.637	0.686	0.730	
Hidalgo	0.519	0.578	0.633	0.682	0.727	
State of Mexico	0.550	0.607	0.659	0.706	0.748	
Morelos	0.880	0.899	0.914	0.928	0.939	
Puebla	0.420	0.485	0.546	0.604	0.656	
Queretaro	0.575	0.630	0.679	0.724	0.764	
Tlaxcala	0.439	0.502	0.563	0.619	0.670	
South	0.574	0.622	0.673	0.718	0.764	0.735
Campeche	0.464	0.526	0.585	0.639	0.688	
Chiapas	0.561	0.617	0.668	0.714	0.754	
Guerrero	0.541	0.598	0.651	0.699	0.741	
Oaxaca	0.487	0.549	0.606	0.658	0.705	
Quintana Roo	0.563	0.618	0.669	0.715	0.756	
Tabasco	0.513	0.572	0.627	0.678	0.722	
Veracruz	0.610	0.661	0.708	0.749	0.786	
Yucatan	0.553	0.609	0.661	0.707	0.749	
Overall	0.537	0.594	0.645	0.691	0.735	
Standard deviation	0.085	0.077	0.069	0.061	0.053	

⁵ Confidence intervals on technical efficiency were calculated using the computer program developed by Merryman (2010).

Figure 1. 95% confidence intervals on technical efficiency



The overall technical efficiency went from 0.537 in 1988 to 0.735 in 2008 (an annual rate of growth of 1.7%). That is, in 1988 Mexican states produced 53.7% of maximum attainable output, while in 2008 this value increased to 73.6%. A back of the envelope calculation shows that

Mexico could increase its output in manufacturing by 36% without increasing capital and/or labor. Specifically, the north, the north-central, the central, and the south regions could increase their output by 38.9%, 32.0%, 37.0%, and 30.9%, respectively, without adding more inputs to the production process. This result shows the ample potential that improvements in efficiency could imply for economic growth.

Our estimates indicate that the most technically efficient regions in 2008 were the north-central (0.758) and the south (0.764). These regions observed annual growth rates of technical efficiency of 1.4% and 1.5%, respectively, from 1988 to 2008. The central region (0.730) and the north (0.720) obtained the greatest gain in efficiency, growing at an annual rate of 1.7% and 1.9%, in that order. Coincidentally, economic activity in the central region and the north is more associated to the dynamics of the U.S. economy than the rest of the country (Banxico, 2011b). This fact is consistent with other studies concluding that a higher degree of integration to international markets, especially after the implementation of the North American Free Trade Agreement (NAFTA) in 1994, enhanced manufacturing productivity in Mexico, particularly on firms located in northern states (López-Córdoba, 2003).

The best performing states in terms of technical efficiency were Morelos, San Luis Potosi and Jalisco, while Puebla, Michoacan and Tlaxcala showed the lowest level of technical efficiency. However, our specification explicitly considered the possibility of heterogeneous frontier functions at the regional level. If we define *total efficiency* as the product of technical and structural efficiency (the product of ϕ_i and E_{it}), the best performing states were Morelos, Queretaro and Hidalgo, while Campeche, Oaxaca, and Michoacan observed the lowest level of total efficiency. In fact, the 10 best performing states in terms of total efficiency were either northern or central states, which is consistent with the findings of Bannister and Stolp (1995) and Braun and Cullmann (2011).

Table 5 also presents structural efficiency estimates for the four regions, which are expressed as the ratio to the structural efficiency of the central region. Our calculations imply the existence of technical characteristics that systematically make the north, the north-central, and the south regions produce about 92.5%, 78.3%, and 73.5%, respectively, of the output that they would have produced if they had showed the same level of structural efficiency as the central region.

4.2 Efficiency dynamics and the labor productivity gap

The estimated value of the parameter η is associated to the existence of two widely applied concepts of convergence: β -convergence and σ -convergence (Young, Higgins and Levy 2008, Barro and Sala-i-Martin, 1992). In the present context, β -convergence in efficiency scores occurs when less efficient states tend to improve efficiency faster than more efficient ones. When the dispersion of technical efficiency across states falls over time, there is σ -convergence in efficiency scores. In particular, it can be shown that if η

is strictly positive then both types of convergence are guaranteed (see Appendix). Hence, the estimated value of η (0.036) implies the existence of β -convergence and σ -convergence for the analyzed data set. This result is in coherence with the evolution of the standard deviation of efficiency scores (Table 5), and the correlation between technical efficiency in 1988 and its rate of growth over the studied period (-0.981).

Although improvements in technical efficiency are related to the growth rate of value added per worker⁶, the existence of convergence in technical efficiency does not guarantee convergence in labor productivity. To analyze the effect of the dynamics of technical efficiency on convergence in labor productivity, we estimate the following equations:

$$\frac{\ln(Y_{i2008}/L_{i2008}) - \ln(Y_{i1988}/L_{i1988})}{\Delta t} = \lambda_0 + \lambda_1 \ln(Y_{i1988}/L_{i1988}) + \epsilon_i \quad (7)$$

$$\frac{\ln E_{i2008} - \ln E_{i1988}}{\Delta t} = \alpha_0 + \alpha_1 \ln(Y_{i1988}/L_{i1988}) + \zeta_i \quad (8)$$

where $\Delta t = 2008 - 1988 = 20$ and $\frac{Y_{it}}{L_{it}}$ is the level of value added per worker in state i at period t .

Table 6 presents the results of the OLS estimation of equations (7) and (8) with and without regional fixed effects. The results appearing in the third and fourth rows of Table 6 show the existence of a β -convergence process in output per worker: the negative and significant estimate of λ_1 implies a negative relationship between the initial level of value added per worker and the growth rate of labor productivity.

The empirical evidence supports the existence of convergence in both technical efficiency and value added per worker. However, convergence in technical efficiency does not necessarily contribute to convergence in labor productivity. Its contribution will depend on the sign of the parameter α_1 (Gumbau-Albert, 2000). The results presented in the first and second rows of Table 6 indicate that technical efficiency acted as a mechanism for convergence in labor productivity since the estimate of α_1 is both negative and statistically significant for both specifications: on average, states with lower initial levels of labor productivity observed higher growth rates of technical efficiency, which contributed to close the labor productivity gap among Mexican states.

⁶It is clear from (2) that technical efficiency and labor productivity are positively associated since

$\left(\frac{\dot{Y}}{Y}\right) = \left(\frac{\dot{Y}^*}{Y^*}\right) + \dot{\epsilon}$, where a dot over a variable indicates the rate of change (e.g. $\dot{x} = d \ln x / dt$).

Table 6. Productivity convergence and technical efficiency

	Efficiency growth		Productivity growth	
$\ln(Y_{1988} / L_{1988})$	-0.006***	-0.004***	-0.022***	-0.025***
	(0.001)	(0.001)	(0.008)	(0.008)
North-Central	-0.001		-0.004	
	(0.002)		(0.010)	
Central	0.002		-0.008	
	(0.002)		(0.011)	
South	0.000		-0.030	
	(0.002)		(0.010)	
Constant	-0.014*	-0.008	-0.144***	-0.170
	(0.008)	(0.006)	(0.048)	0.044
Adjusted R^2	0.308	0.322	0.386	0.218
N	32	32	32	32

s.e. in parenthesis. Significance: *** = 1% level; ** = 5% level; * 10% level.

5. Conclusions

In this paper we have estimated a translog stochastic frontier function to measure technical and structural efficiency in regional manufacturing over the period 1988-2008. To take into account the possibility of region-specific production frontiers, regional fixed effects were incorporated into the econometric specification. Under the assumption that regional technical characteristics are time invariant, it was possible to identify and separate technical efficiency from technical characteristics. Three main findings emerge.

First, technical efficiency was both increasing and converging across states over the period 1988-2008. In particular, we found empirical evidence of beta and sigma convergence in efficiency scores in a context where labor productivity in manufacturing was also converging. Second, there are considerable differences in the levels of technological development of the north and the central regions with respect to the south that partially explains the labor productivity gap among regions. Therefore, state differences in technical efficiency decrease over time in a context where northern and central states tend to be more technologically developed.

Third, the evolution of technical efficiency contributed to reduce inequality in labor productivity among states: *i.e.* states with lower initial levels of labor productivity observed higher growth rates of technical efficiency.

In sum, the results indicate that the period 1988-2008 was characterized by the existence of convergence in labor productivity across states in regional manufacturing, with technical efficiency as an important driving force behind convergence. However, there are structural, time-invariant factors that systematically make southern states less productive than the rest of the states.

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Appendix: Convergence in Efficiency Scores

Since $u_{it} = \eta_t u_t = \exp[-\eta(t-T)]u_t$ and $u_{it} = -\ln(E_{it})$, we have

$$\begin{aligned}\ln(E_{it}) &= -\eta_t u_t \\ &= -\exp(-\eta t) \exp(\eta T) u_t \\ &= \exp(-\eta t)(-u_{t0}) \\ &= \exp(-\eta t) \ln(E_{t0})\end{aligned}\tag{9}$$

For $\eta > 0$ we have

$$\frac{\partial \ln E_{it}}{\partial t \partial E_{t0}} = \frac{-\eta \exp(-\eta t)}{E_{t0}} < 0\tag{10}$$

Therefore, there is an inverse relationship between the growth in technical efficiency and its initial level (β -convergence) as long as $\eta > 0$.

Finally, we show that $\eta > 0$ implies σ -convergence. From (5) we have $E_{it} = \exp(\eta_t u_t)$. By the Delta method

$$\text{Var}(E_{it}) \approx \eta_t^2 \exp(2\eta_t E[u_t]) \sigma_u^2\tag{11}$$

Since η_t is decreasing in t when $\eta > 0$, and $E[u_t] \geq 0$ ($u_t \geq 0$), we obtain σ -convergence.