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Could Mexico become the new 'China'? Policy drivers of competitiveness and productivity[1]

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Abstract

Over the last decade, Mexico's unit labour costs decreased relative to other emerging markets', especially compared to China's. This decrease boosted Mexico's trade competitiveness, particularly in the manufacturing sector. However, Mexico's increasing competitiveness masks one of the country's fundamental concerns, which is the absence of productivity improvements. The aim of this paper is two-fold: first, we examine the evolution of total factor productivity in Mexico's manufacturing sector, as compared to China's. Firm-level data is employed to analyse the distribution and characteristics of productivity across Mexico's regions. Second, using regional data for the period 2005–2012, we study the policy impediments behind sluggish productivity improvements, particularly to determine how labour informality may have contributed. The study takes advantage of Mexico's heterogeneity across regions in terms of productivity, market regulation, financial constraints and firm size to identify economic policies that can help to boost productivity in the future.

JEL: E26, O17, O43, O54, L25.

Keywords: Productivity, microdata, sub-national policy analysis, informality, allocative efficiency.

1. Introduction

In recent years, shifts in global competitive conditions have caused China to lose competitiveness in some of its dominant export sectors. This has allowed Mexico's unit labour costs to become increasingly competitive with those of China. China has experienced a yearly growth of more than five per cent in unit labour costs, while Mexico's costs have increased at only half that rate. Mexico's catch-up in unit labour costs emerged primarily from a slowdown in China's productivity gains as its workers' wages grew rapidly, while at the same time the RMB appreciated against the USD (OECD, 2013, 2015a).

This change in costs boosted Mexico's trade competitiveness, particularly in the manufacturing sector, where China's average wage now exceeds Mexico's (Sirkin et al., 2014). In addition, total landed costs for the US market, which

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include taxes, tariffs and regulatory compliance, as well as transportation and storage, have considerably increased for products made in China since 2005, while they have fallen for products made in Mexico (AlixPartners, 2013; Wang and Hu, 2014). As a consequence, there are increasing incentives for manufacturers to shift parts of their production process from China to Mexico, particularly in light of the proximity to final goods markets in North America.[2]

Mexico's increasing competitiveness and attractiveness masks, however, one of the countries' fundamental concerns, which is the absence of productivity improvements. Mexico's productivity lags behind that of other major emerging economies, and it has suffered from a negative growth trend. One prominent feature of the Mexican economy as compared with China's is much more extensive employment informality and smaller average firm size (Dougherty, 2015; OECD, 2015a, 2015b). In order to fully take advantage of the increasing cost of production in China, identifying policies to improve productivity is essential for Mexico.

Firms differ in productivity within even narrowly defined industries in a country. For example, in US manufacturing, the productivity of the 90th percentile plant is almost twice that of the 10th percentile plant (Syverson, 2004). The gap in productivity between high and low productive plants is five to six times larger in Mexico than in the United States (Hsieh and Klenow, 2014). These differences may indicate misallocation of resources across firms with negative effects at the aggregate level (Bartelsman et al., 2013; Hsieh and Klenow, 2009). Differences in productivity across countries can thus be explained by cross-country variation in the distribution of firm productivity.

Multiple factors influence a firm's productivity, both internal and external to the firm. Among the internal factors, better management practices are associated with productivity gains (Bandiera et al., 2009; Bloom and Van Reenen, 2007). In addition to management quality, the quality of labour and capital influences productivity. Productivity is increasing in workers' education and age (Ilmakunnas et al., 2004), but differences in labour quality across firms only explain a small part of productivity dispersion (Fox and Smeets, 2011). Differences in capital quality are difficult to assess, and therefore, some studies have focused on information technology (IT) capital. IT productivity gains contributed to the acceleration of US productivity growth in the mid-1990s, in particular for IT-intensive industries (Bloom et al., 2012). There is also evidence that product innovation and intangible capital leads to productivity gains (OECD, 2015c). Indeed, the number of products and patent grants are positively correlated with total factor productivity (TFP) (Balasubramanian and Sivadasan, 2011; Bernard et al., 2010).

[2] The presence and linkages of global value chains also play an important role in manufacturing locational decisions, and these can sometimes dominate unit labour costs concerns for intermediate parts of production processes (OECD, 2015c).

In this paper, we focus on the external or contextual factors that influence productivity because they are more related to policy design. Even if contextual factors do not operate directly on productivity, they may influence producers' incentives based on internal factors and, thus, the productivity distribution across firms (Syverson, 2011). External factors influence the productivity of individual firms, but they can also influence aggregate productivity if more efficient firms grow faster than less efficient ones.

Among the external factors, the literature highlights the importance of geography and foreign direct investment (FDI) since they influence technology and knowledge transfers (Bloom et al., 2013; Keller and Yeaple, 2009; Ciccone and Hall, 1996). Market regulation and competition are other important external factors that influence productivity. Competition increases the market share of more efficient firms, reducing that of less efficient firms and sometimes forcing them to exit (Melitz, 2003). In addition, competition may influence productivity through innovation; however this effect may follow an inverted U-shaped relationship (Aghion et al., 2005). Trade liberalisation is also a source of competition that fosters productivity growth through factor reallocation (Bloom et al., 2011); moreover, trade facilitates access to overseas' knowledge through the imports of intermediate inputs and supply networks (Goldberg et al., 2010). Finally, financial frictions reduce productivity because they hamper firms' investment and technology adoption decisions, as well as generate capital misallocation (Midrigan and Xu, 2014).

One form of misallocation is informality, which can distort market competition. Informality is a symptom of poor institutional quality such as a burdensome regulatory framework and weak monitoring or enforcement power of the state (La Porta and Schleifer, 2014). Moreover, informal firms avoid taxes and benefit from low hiring and firing costs, allowing them to produce more cheaply than formal firms that face more regulations (Gonzalez and Lamanna, 2007). Second, informality may create labour market distortions: since formal labour is subject to regulatory and tax burdens that generate monetary costs for firms, the marginal cost of a worker increases with a firm's size (Busso et al., 2012; Levy, 2008). Thus, while large firms mostly hire workers legally and are taxed, smaller firms tend to hire less-skilled workers in the informal sector, limiting their productivity. We view informality as an intermediate outcome that may be subject to intervention using a variety of policy tools (Dougherty and Escobar, 2013).

The aim of this paper is two-fold. First, motivated by the inversion of the unit labour cost differential between China and Mexico, we examine the growth and distribution of total factor productivity at the firm level, to better understand the extent to which inefficiency and misallocation are determining outcomes. Second, the study takes advantage of Mexico's heterogeneity across regions and sectors in terms of productivity, market regulation, and other constraints to identify economic policies that can help to boost productivity in the future.

Among various findings, the results imply a strongly negative relationship between informality and productivity, which we investigate further to identify causality. More productive states and industries are found to suffer more from informality than less productive ones, and the negative effects of informality on productivity rise as the level of productivity increases.

2. Productivity patterns in Mexico and China

2.1 The data

Chinese and Mexican microdata are used in this study to measure productivity. For Mexico, plant-level data from the Annual Survey of Industries (EIA) and the Annual Survey of Manufacturing Industry (EAIM) – both conducted by Mexico's Institute of Statistics and Geography (INEGI) – were used remotely with INEGI's support. Although the data is plant-level, they can be considered as effectively firm-level because more than 97 per cent of Mexico's firms are single-plant firms (Dougherty, 2014). Since the EIA evolved to become the EAIM, we use EIA data for years 2005–2008 and EAIM data for years 2009–2012. For most industries, the sample is representative of the industry. INEGI selects plants according to their share in an industry's output until they obtain at least 80 per cent of the industry's total. In the cases where a small group of plants covers an industry's output, all of industry's plants are in the sample. In addition, all plants with more than 250 workers are sampled with certainty. Hence, we can expect that the smaller plants are generally excluded from the sample. A second limitation of these data is that we are unable to build a plant-level panel due to lack of plant identifiers. However, the data provide information about plants' location that allows us to match them with state-level policy measures.

An important difference between EIA and EAIM is the shift in NAICS code classification. EAI uses NAICS 2002 version and EAIM the 2007 version. There are no major changes when considering 4-digit level data. There are 16 minor 6-digit industries for which changes in the NAICS version affect the 4-digit industry, which we then exclude from the sample.

For China, manufacturing microdata from the industrial firm database of the Chinese National Bureau of Statistics (NBS) is used, from the data provider GTA. These longitudinal data cover the 2000 to 2007 period and include non-state firms with annual sales in current yuan of five million or higher, and all state-owned firms. These data are widely considered to be the best available company data for China during the period (Dougherty et al., 2007; Hseih and Klenow, 2009; Brandt et al., 2014). During the economic census year 2004, about 97% of firms were single-plant, similar to the Mexican data. While the dataset covers only about 20% of firms, these produce over 90% of output. The raw number of firms varies from 160,000 in 2000 to 335,000 in 2007. As a result of exit and entry to the database, about 80% of the firms in a given year can be observed in the previous year. In order to utilize the maximum number of firm observations, the unbalanced panel consisting of all firms with valid data is used in the analysis that follows.

The Chinese and Mexican data provide information about plant output, several labour input measures, book values and depreciation of the capital stock, and expenditure on intermediate inputs. We use these data (in logs) to calculate a plant's TFP as its output minus a weighted sum of its capital, labour and intermediate inputs:

$$TFP = \frac{Y}{K^{\alpha_k} L^{\alpha_l} M^{\alpha_m}} \tag{1}$$

where the weights α_j are each input $j \in \{K, L, M\}$ elasticities. To measure these elasticities, we use industry-level input cost shares. We compute cost shares, at NAICS 4-digit level, using Mexico's input-output table for the year 2008 from INEGI System of National Accounts (SCNM). For China, we compute cost shares by industry using the 2003 input-output table from the China Industrial Productivity (CIP) Database Round 2.0 developed by the Research Institute of Economy, Trade and Industry (Japan). Following OECD (2001), for each industry, we use data on total output (Y), expenditures on intermediate inputs (M), compensation of employees (W), net taxes (T), gross operating surplus and mixed income ($GOS + I$), and the number of employees and self-employed.

To compute the cost share of labour (α_l), in addition to the compensation of employees, we need to compute the proprietors' income and the share of labour on net taxes. In the case of proprietors, it is difficult to distinguish between income from labour and income from capital in the mixed income; we calculate the proprietors' income as $I_L = \frac{W}{Employees} \times Selfemployed$. Net taxes are allocated proportionately to labour and capital, thus the net taxes of labour are $T_L = \frac{W+I_L}{W+GOS+I} \times T$. The share of labour on output is then $\alpha_l = \frac{W+I_L+T_L}{Y}$.

Knowing proprietors' income and net taxes of labour, we can easily compute the capital component of mixed income and net taxes, and then the cost share of capital. The capital part of mixed income is calculated residually from the labour part as $\mathrm{I_K} = \mathrm{I} - \mathrm{I_L}$. Similarly, the capital part of net taxes is $\mathrm{T_K} = \mathrm{T} - \mathrm{T_L}$. Thus, the cost share of capital is $\alpha_k = \frac{GOS+I_K+T_K}{Y}$. Finally, the cost share of intermediate inputs is $\alpha_m = \frac{M}{Y}$.[3]

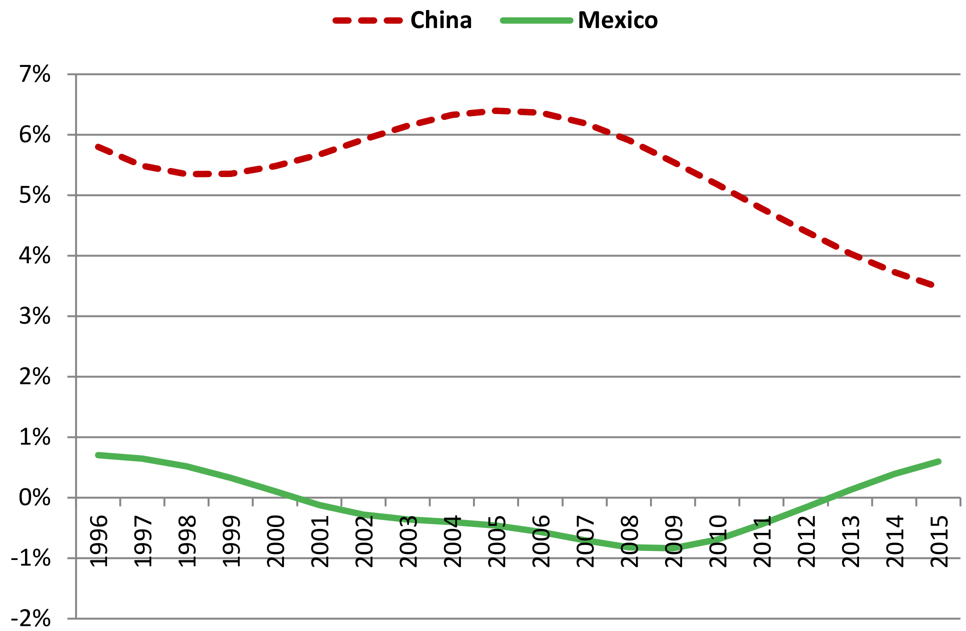
[3] The Chinese input-output tables do not provide information on mixed income (I). We then did not calculate proprietor's income (I_L) nor the part of capital (I_K) for this country. The net taxes for China are then computed as $T_L = \frac{W}{W+GOS} \times T$. Thus, we calculate the share of labour and capital as $\alpha_l = \frac{W+T_L}{Y}$ and $\alpha_k = \frac{GOS+T_K}{Y}$ respectively.

To obtain a measure of TFP in real terms, we use producer price indexes of final and intermediate goods reported by the INEGI. INEGI reports monthly data based on June 2012 prices; for simplicity we use, for each year, the data of June. For China, we use analogous NBS producer price deflators.

2.2 Productivity patterns in Mexico and China

This subsection presents estimates of TFP for Mexico, compares these estimates to those of China, and analyses the different patterns of TFP among Mexico's federal entities. Figure 1 presents aggregate estimates of TFP for both China and Mexico for the period 1996—2015, using OECD estimates. Whereas China experienced a TFP growth rate of more than 5 per cent for most of the years during this period, Mexico experienced negative TFP growth for most of these years. China's TFP growth slowed since 2006, while Mexico's bottomed out during the financial crisis in 2009, and started rising since 2013, but differences between these countries remain important. TFP in manufacturing followed a similar pattern. According to OECD (2014), between 2000 and 2008, China experienced remarkable manufacturing TFP growth of above 7%, while Mexico's stagnated. As a consequence, Mexico, which had a smaller gap in manufacturing TFP levels relative to the United States in 2000, was overtaken by China in 2008.

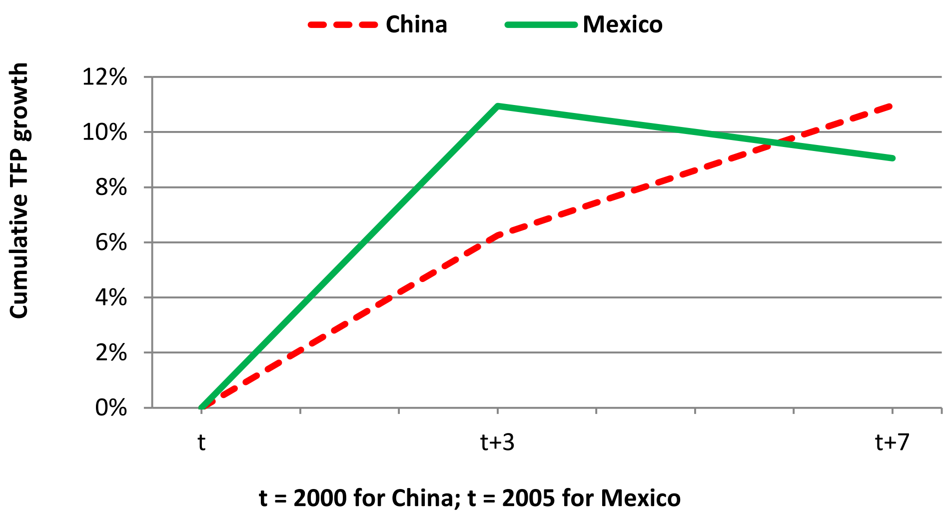
Figure 1. Aggregate TFP growth in Mexico and China



Notes: For each country, TFP growth is calculated as the growth of Solow residual. For both countries, this residual was estimated as the residual of a production function with labour-augmenting technological progress using data from OECD Economic Outlook database. Factor shares are common and fixed over time for both countries, which may overstate TFP growth if the labour share falls.

Differences in TFP dynamics between the two economies are much less evident when comparing average firm-level TFP growth, among sizable manufacturing firms. Figure 2 illustrates the cumulative TFP growth for a seven-year period for China and Mexico. Note that the starting year is not the same for each country because of data availability. The cumulative TFP growth of China's firms is around 13 per cent, while for Mexico's it is around 9 per cent. However, before 2008, Mexico's firms experienced a higher growth rate of average TFP than China. Mexico's TFP growth suffered a downturn since 2008; since the Chinese data that we use end in the year 2007, the worldwide financial crisis is not reflected in its TFP growth rate. Hence, we can infer that the average of firm-level TFP growth is vaguely similar for both countries. So, how can we explain the large differences in aggregate TFP growth between Mexico and China?

Figure 2. Firm-level TFP growth in Mexico and China



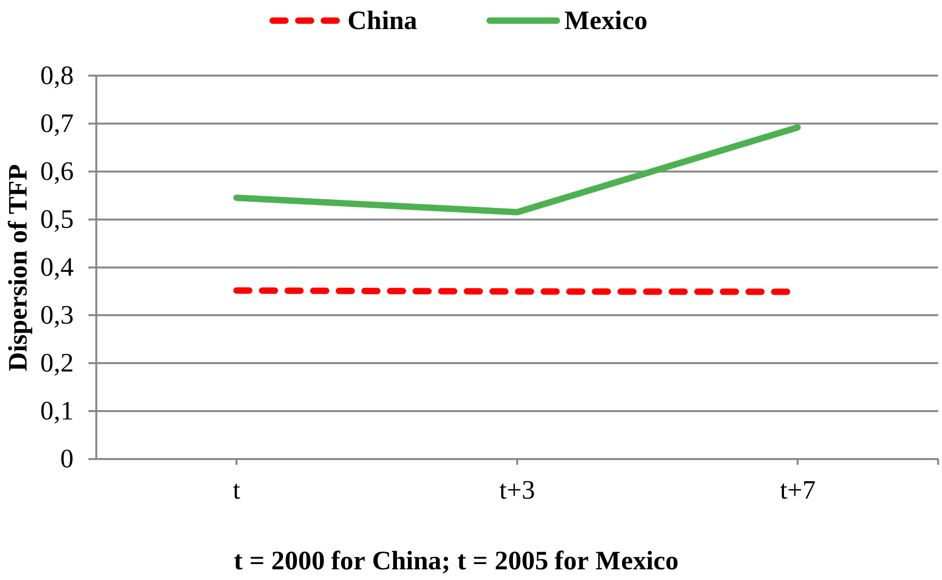
Notes: For each country, TFP growth is calculated as the growth of the average of manufacturing firms' TFP. Because of data availability, the starting point differs between the two countries.

The answer is probably differences in the extent of misallocation of resources across firms, with negative effects at the aggregate level (Bartelsman et al., 2013; Hsieh and Klenow, 2009). Following Hsieh and Klenow (2009, 2014), we use the standard deviation of firms' TFP to illustrate this misallocation.4 A larger dispersion means that low-productivity firms are employing resources that could be allocated to more productive firms, hence reducing overall productivity.

[4] Hsieh and Klenow (2009) make a distinction between physical productivity (TFPQ) and revenue productivity (TFPR). TFPQ is obtained using plant-specific deflator, while TFPR uses an industry-level deflator. In our case, we use TFPR. Hsieh and Klenow (2009) demonstrate that dispersion in TFPR reflects the extent of misallocation. There is also an underlying distribution of TFPQ, which reflects the dispersion of the underlying technologies and that is unrelated to misallocation.

Figure 3 illustrates the evolution of the dispersion of TFP in Mexico and China. Dispersion in Mexico is almost twice as large as in China. From Figures 1 to 3, we can deduce that Mexico's larger and more productive firms are raising their productivity, but there is an apparent misallocation issue, which may be an important source of the differences in aggregate TFP growth between Mexico and China. Indeed, Mexico's average firm-level TFP is growing whereas TFP differences between the most productive and the least productive plants are increasing. Thus, even if average firm-level TFP had grown at the same rate in both China and Mexico, China would still be experiencing important aggregate productivity gains, while Mexico's aggregate TFP could be stagnant or decreasing.

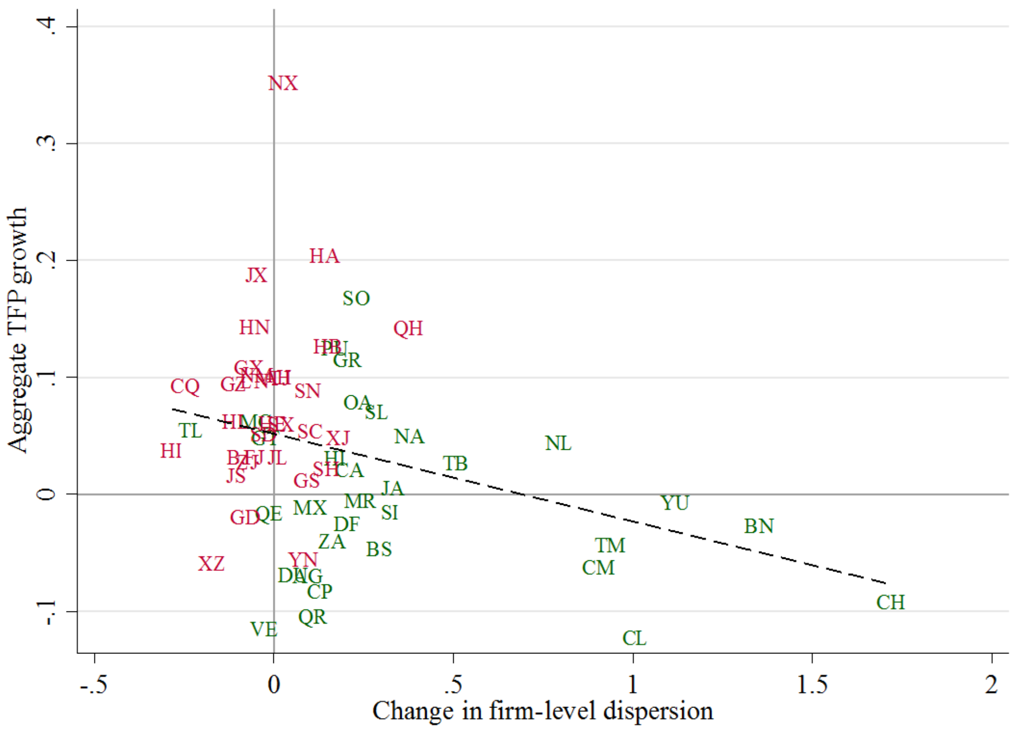
Figure 3. Dispersion of TFP in Mexico and China



Notes: For each country, dispersion of TFP is calculated as the standard deviation of manufacturing firms' TFP. Because of data availability, the starting point differs between the two countries.

To identify if firm-level dispersion is a source of misallocation, we deepen the analysis on the relationship between firm-level dispersion and aggregate productivity in manufacturing, using sub-national data for both countries. Mexico is a federal country with 32 state-level entities, and China has 34 administrative divisions or provinces. We use INEGI's economic census aggregate data to estimate aggregate TFP for manufacturing by Mexican state following the methodology described in the previous section, over approximately the t+3 to t+7 period. The economic census is carried out every five years and covers all plants in the country. Hence, we can compute aggregate TFP growth for the period 2008–2013. For China, we generate aggregated data for the 31 provinces where data is available. To generate aggregates for output, capital, labour, and intermediate inputs, as well as for all the variables needed to compute α_l, α_k, and α_m, we sum the values for all the firms of each variable by province for the years 2003 and 2007. We then estimate aggregate TFP growth for the period 2003–2007.

Figure 4. Scatterplot of aggregate TFP growth and firm-level TFP dispersion in China and Mexico's regions

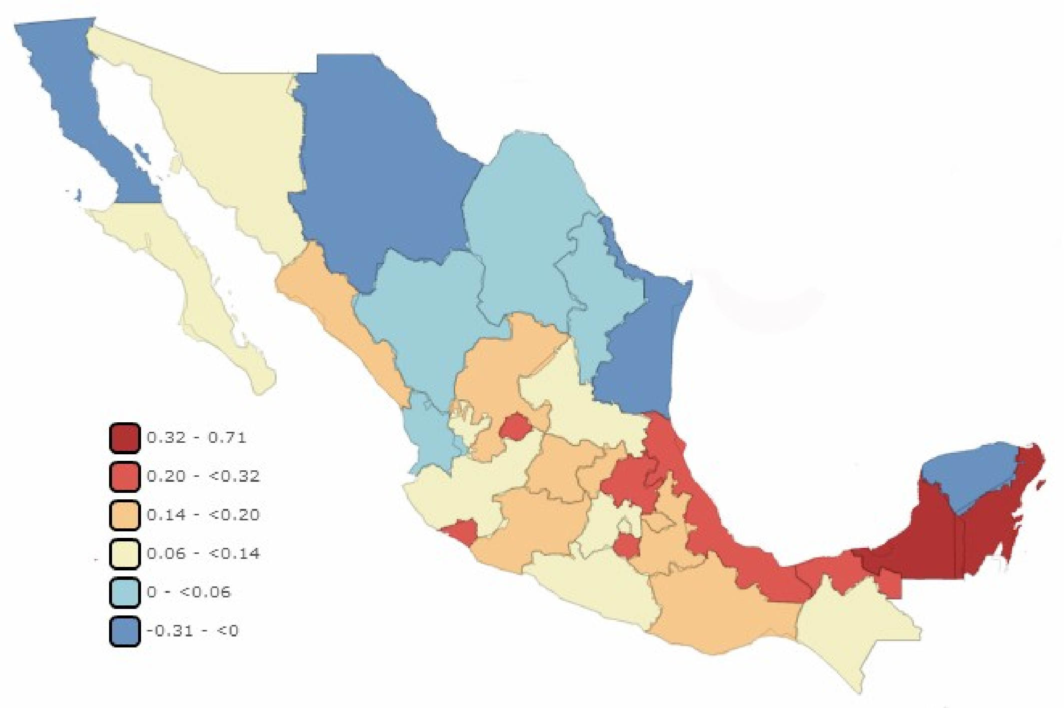


Notes: China's provinces are in red and Mexico's states in green. Because of data availability, periods are different between the two countries. Aggregate growth and change in firm-level dispersion is for the period 2003-2007 for China. For Mexico, aggregate TFP growth is computed for the period 2008-2013, and change in firm-level dispersion for the period 2008-2012. The dashed line represents the line of best fit.

Figure 4 shows the evolution of aggregate TFP and firm-level TFP for both China and Mexico's regions. There is a larger heterogeneity among Mexico's states than among China's provinces in the evolution of firm-level TFP dispersion. Moreover, firm-level TFP dispersion increases for most of Mexico's states, while most of China's provinces experienced a reduction in firm-level TFP dispersion. As a consequence, among China's provinces, only three experienced a decrease in aggregate TFP, while most of Mexico's states 18/32 experienced a decrease in aggregate TFP. The line of best fit suggests that there is a negative correlation between firm-level TFP dispersion and aggregate TFP.5 Hence, we confirm that differences between Chinese and Mexican TFP are in part due to Mexico's misallocation issues.

Figure 4 shows that there are large differences in TFP performance across Mexico's states. This is also the case when analysing firm-level TFP. Figure 5 shows firm-level average TFP growth between 2005 and 2012. There are three states that experienced a decrease in TFP, which are located on the northern border. The rest of the northern border states also have TFP growth issues, as they have among the lowest TFP growth rates. Since these states are supposed to be the most attractive to shift manufacturing production from China to Mexico when considering consumer markets in North America, this suggests that Mexico is still far from becoming the new 'China'. On the other hand, there are the states on the Gulf of Mexico, which experienced TFP growth of more than 20 per cent over the seven year period, which could be because of their specialisation in certain parts of the value chain.

Figure 5. Firm level TFP growth of Mexico's states, 2005-2012



Notes: For each state, TFP growth is calculated as the growth of the mean of manufacturing firms' TFP.

[5] The slope of this line is -0.075 with a robust standard error of 0.016, which implies a correlation at the 0.10% significance level.

Comparing firm-level TFP to aggregate TFP, we can see that firm-level productivity performance is far more positive. At the country level, aggregate productivity decreased between 2005 and 2012 (Figure 1) whereas firm-level productivity experienced a cumulative growth of nine per cent (Figure 2). At the state level, most states have experienced a decline in aggregate productivity, but most of them experienced an increase in average firm-level productivity. These results may be driven by the fact that the most productive plants are doing well. Indeed, the productivity of the most productive plant increases in most of the states, by 58 per cent on average, and it decreases in only five states. In contrast, the productivity fluctuations for the least productive plants are larger and more heterogeneous. TFP decreases for the least productive firms of 19 states' by 185 per cent on average, and it increased in 13 states by 116 per cent on average. In the northern border states, productivity growth of the most productive plant follows similar patterns as at the country-wide level, but the decrease in productivity in the least productive plants is quite large, at 308 per cent.

Summarising this section's findings, productivity, measured as TFP, differs considerably across plants and regions in Mexico. Mexico's most productive plants are performing relatively well, and can compete with China's. However, there is a group of plants, the least productive ones, that is struggling to perform better without success. In this scenario, we might expect a reallocation of resources from least productive to most productive firms. However, evidence suggests that there are problem of misallocation of resources across firms, which is generating negative effects on productivity at the aggregate level.

3. Policy drivers of competitiveness

The aim of this section is to identify the policies that drive productivity improvements. We take advantage of Mexico's administrative divisions, as a federal country with comparable policy data at the subnational level. Since policy data is at the state level, firm-level productivity is aggregated at the industry-state level. Indeed, firm-level productivity depends on its internal factors such as management skills and the quality of labour and capital (Bandiera et al., 2009; Bloom and Reenen, 2007; Ilmakunnas et al., 2004; Bloom et al., 2012), which are difficult to control for in the empirical analysis because of data availability. This would lead to biased estimates due to omitted variable problems. Thus, the empirical analysis of the policy drivers of productivity is conducted at the state-industry level by means of panel data for the period 2005–2012. As described previously, an important difference between EIA and EAIM is the shift in NAICS code classification. However, there are no major changes when considering 3-digit level data. Hence, we exclude from the sample those 6-digit industries for which changes in the NAICS version affected the 3-digit industry. More precisely, we exclude 16 industries. Then, for each Mexican state, we aggregate firm-level data to the NAICS 3-digit level. State-industry level TFP is computed following the same procedure as in Section 2.

3.1 Theoretical framework

Following Restuccia and Rogerson (2008), consider an economy endowed with K units of capital and L units of labour, both of which are supplied inelastically. There is a representative household that has preferences that are increasing in consumption. The unit of production is the plant $i = 1, \ldots, n$, and plants are heterogeneous. The plant output is given by a Cobb-Douglas production function

$$y_i = a_i k_i^{\alpha} l_i^{1-\alpha}, \tag{2}$$

where a_i is plant-specific productivity, k_i is the plant's capital stock, and l_i is the plant's labour input. We assume that, in an equilibrium without distortions, capital to labour ratios are the same across plants. Thus, heterogeneity among plants is given by differences in productivity. There is also a fixed cost of operation c_f, measured in units of output. Only the plants that pay the fixed cost remain in existence. The net output produced by the plant i is therefore given by $y_i - c_f$.

In this framework, poor policy reduces aggregate productivity through two channels. First, poor policy reduces plant-level productivity a_i, and thus economy's average productivity $A = \frac{\sum_i^n a_i}{n}$. Second, poor policy may drive a misallocation of resources. In the model, an efficient allocation will maximize final output $Y = \sum_i^n y_i$ holding the values of a_i fixed. Indeed, an efficient allocation allows only the most competitive plants to remain in existence, and determines the allocation of capital and labour among those plants (Hsieh and Klenow, 2009, 2014; Restuccia and Rogerson, 2008).

3.2 Policy variables and data

Institutional quality influences productivity. An important aspect of Mexico's economy is informality (Busso et al., 2012; Dougherty and Escobar, 2013; Leal Ordóñez, 2014), which is directly related to institutional quality (Dreher et al., 2014). Informality is more prevalent when the regulatory framework is burdensome, when the quality of government services for formal firms is low, and when authorities' monitoring and enforcement power are weak (Loayza et al., 2009). Moreover, informality is also considered as reflecting labour market distortions, as informal employment is often concentrated in the smallest firms, particularly microenterprises. One study found that informal microenterprises contributed to negative productivity growth in Mexico's manufacturing (MGI, 2014). We use data on informal employment from Dougherty and Escobar (2013) to measure informality using household data, which follows the ILO definition based on social security coverage. Informal jobs also tend to be more precarious in general, and play a relatively minor role in China and most OECD countries (OECD, 2015b).

In addition, regulatory enforcement and regulatory costs are institutional characteristics that have an important influence on productivity through competition (Nicoletti and Scarpetta, 2003). To measure regulatory enforcement, we use a rule of law index from the Mexican Institute for Competitiveness (IMCO).[6] To measure regulatory costs, we employ the cost to start a business as a share of income from the World Bank's Sub-national Doing Business data for Mexico. These refer to the *de jure* requirements for setting up a business in each state's capitol.

The literature suggests that technology and knowledge transfers improve productivity (Bloom et al., 2013; Keller and Yeaple, 2009). We use data on multinational enterprises' (MNEs) activity and on imported inputs as measures of contact with foreign technology and knowledge. We compute MNEs activity at the state-industry level. This activity is measured as MNEs' workers share of total workers using data from the ENOE. Data on imported inputs are available from the EIA and EAIM, and we measure the intensity of imported inputs as imported inputs' share of total intermediates. In the empirical specification, to take into account plants that use only national inputs, we compute this variable as $logarithm(\frac{1+Imported\ inputs}{Total\ inputs})$. In addition, we use data on *Maquiladora* services, which consist of assembling imported inputs into final outputs for a foreign client (Bergin et al., 2009), to measure this low-technology export regime. Moreover, *Maquiladoras* are often engaged in competition with China (Utar and Torres, 2013). We measure the size of *Maquiladoras* at the state-industry level as the share of their services income to total income.

A greater absorptive capacity helps to facilitate productivity improvements. Mexico's heterogeneity among states in absorptive capacity can be captured by their differences in human capital. To control for differences in human capital quality, we use a measure of the level of human capital as well as the quality of human capital. To measure the level of human capital, we use data at the state-industry level on average years of schooling from ENOE. To measure the quality of human capital, we use PISA score data from the OECD, based on test performance of 14-year-olds.

Financial frictions reduce productivity because they hamper a firms' investment and technology adoption decisions, as well as generate capital misallocation (Midrigan and Xu, 2014). To control for differences in financial frictions among Mexico's states, we use data from the National Banking and

[6] IMCO computed states' competitive indexes in 2012 and 2014. The 2012 version includes indexes for years 2005 to 2010 and the 2014 version includes indexes for the 2009–2012 period. The variables employed by IMCO to construct the rule of law index vary among versions. We adjust then data for the years 2011 and 2012 of the 2014 version to the levels of the 2012 version using years 2009 and 2010 (available in both versions) as reference.

Securities Commission (CNBV) on the number of loans granted to private enterprises and self-employed entrepreneurs per 1,000 habitants.

Finally, it is widely accepted that physical capital accumulation is a determinant of productivity growth, although it is partially controlled for in the measurement of TFP (de Long et al., 1992). To measure capital accumulation, we use data from EIA and EAIM on fixed assets relative to the sales of the industry, which can also be considered as a measure of each industry's capital intensity.

Table 1. Pooled summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
State-industry level				
Total factor productivity (TFP)	3.723	1.609	0.002	12.081
MNEs workers	16.757	21.301	0	100
Imported inputs	0.239	0.232	0	0.982
Maquila intensity	0.111	0.244	0	1
Years of schooling	9.597	1.693	3.308	14.4
Capital intensity	0.503	0.517	0.013	12.502
Observations	2970			
State level				
Rule of law	51.885	10.36	24.577	84.167
Cost to start a business	0.142	0.066	0.06	0.453
PISA	410.25	19.359	353.667	455
Number of loans	6.949	10.193	0.39	89.275
Informality	0.473	0.095	0.261	0.698
Informality of firms up to 10 workers	0.813	0.076	0.554	0.942
Informality of firms with more than 10 workers	0.167	0.042	0.082	0.304
Informality of firms with more than 50 workers	0.106	0.035	0.035	0.201
Observations	256			

Notes: All variables are in values.

Table 1 presents descriptive statistics, pooled over 2005–2012. There are important differences in TFP levels, which we use in log form as our dependent variable, at the state-industry level. Some of the variables are only available at the state level. We compute different measures of informality for robustness tests: informality, informality of firms up to 10 workers, informality of firms with more than 10 workers, and informality of firms with more than 50 workers. Informality in firms up to 10 workers is highest, as expected. Informality of firms with more than 50 workers is on average 10 per cent, but it can be up to 20 per cent in some states. Table 1 also illustrates the substantial heterogeneity among Mexico's states concerning other policy related variables employed in this paper.

4. Empirical analysis

4.1 Empirical specification

This paper's aim is to analyse the policy drivers of productivity growth. Hence, we specify a model where TFP is a function of policy and other variables,

$$TFP_{i,s,t} = \alpha_{i,s} + X_{i,s,t}\beta + \epsilon_{i,s,t} \tag{3}$$

where $TFP_{i,s,t}$ is the logarithm of total factor productivity by 3-digit industry i in state s in year t. $X_{i,s,t}$ is a vector of control variables such as state-level policy variables and state-industry variables, $\alpha_{i,s}$ represents state-industry specific effects, and $\epsilon_{i,s,t}$ is the error term. This specification suffers, however, from a potential endogeneity issue when linking policy and productivity variables. Because causality may run from productivity to informality, the latter variable may be correlated with the error term. This issue may also apply to the other control variables, too. For each explanatory variable, we conduct the Durbin-Wu-Hausman endogeneity test using one-year lag of all explanatory variables as instruments. The results (see Table A.1 in the Appendix) suggest that only the rule of law and number of loans variables are not affected by endogeneity. To handle endogeneity, we can use instrumental variables (IV) techniques. In addition to endogeneity, we suspect that the estimates suffer from multicollinearity because MNEs activity and cost to start business are among the major determinants of informality (Dougherty and Escobar, 2013). We estimate the variance inflation factor (VIF) for the exogenous variables, and the highest value is for informality (2.02); VIF values for the other variables are lower than two (see Table A.1 for further details). These values are far from the rule of thumb VIF > 10 that indicates high collinearity.

There are also potential autocorrelation issues. The error term may be within-cluster correlated over time due to omitted factors that evolve progressively over time. We test for AR(1) serial correlation using the t-test discussed by Wooldridge (2002). We find that residuals are significantly correlated to one-year lagged residuals with a coefficient value of 0.980 and a t-statistic equal to 65.60. This serial correlation can be handled by adding time-lagged TFP as an explanatory variable. Indeed, using lagged TFP allows us to control for unobservable factors that influence both current and past TFP. We also apply the t-test for serial correlation in the specification with lagged TFP as dependent variable, and the estimated coefficient of the time-lagged residual is not significant. Its coefficient is 0.040 and the t-statistic is 0.84, which is not significant. Another advantage of using a lagged dependent variable is that it reduces omitted variable bias (Wooldridge, 2002). For instance, if one explanatory variable is correlated with an omitted variable, then this explanatory variable is correlated with the error term. Moreover, the lagged TFP variable captures inertial effects. We then add one-year lagged TFP to our model:

$$TFP_{i,s,t} = \alpha_{i,s} + TFP_{i,s,t-1}\delta + X_{i,s,t}\beta + \mu_{i,s,t} \tag{4}$$

We estimate the model of Equations 3 and 4 as a benchmark using FGLS. These estimates, presented in Table A.2 of the Appendix, show that there are important differences depending on whether we control by state-industry specific effects or not. For instance, the coefficient of informality is significant in both specifications, but the sign of this coefficient depends on the specification. Differences in the chi-squared of these two specifications suggest that controlling for specific effects improves the model. The Hausman test also suggests that there are large differences between the two estimates. This result highlights the heterogeneity among states and sectors in Mexico, and underlines the importance of controlling for this heterogeneity by including specific effects. Adding time-lagged TFP improves the model and reduces omitted variables bias. For instance, without lagged TFP the results suggest that TFP decreases with years of schooling, but this result does not hold when adding lagged TFP. However, adding lagged TFP also generates some inconsistency (Wooldridge, 2002). Adding lagged TFP to the model makes OLS estimates biased. Moreover, lagged TFP is potentially endogenous to the fixed effect in the error term, which could create a problem of dynamic bias.

Arellano and Bond (1991) propose a method to handle the issues presented in this section. The first step consists of applying first-differencing to the model to eliminate the unobserved fixed effects from the error term. Hence, our model becomes:

$$\Delta TFP_{i,s,t} = \Delta TFP_{i,s,t-1}\delta + \Delta X_{i,s,t}\beta + \Delta\epsilon_{i,s,t} \tag{5}$$

where Δ represents the variation of the variables. Thus, the growth of TFP is given by a dynamic tendency (lagged TFP) and by the variation in policy. We use the Arellano and Bond (1991) difference GMM estimator, which addresses the issue of endogeneity using the lagged levels of the endogenous regressors, including the lagged dependent variable, as instruments. Endogenous variables are then predetermined and not correlated with the error term, and the number of valid instruments increases as the length of the panel progresses. We test for the validity of these instruments using the Hansen *J-test*.

4.2 Results

The results of Arellano and Bond (1991) difference GMM estimator are shown in Table 2, using the 2006/07 to 2011/12 dataset (we lose the first period, 2005/06). For all estimates, we cluster standard errors by state and industry to allow for heteroskedasticity. The row for the Hansen *J-test* reports the *p*-values for the null hypothesis of the validity of the over-identifying restrictions. We do not reject the null hypothesis of instrument validity. The values reported for the autoregressive AR(1) and AR(2) terms are the *p*-values for the first-order and second-order autocorrelated disturbances. As expected, there is high first-order autocorrelation, and no evidence for significant second-order autocorrelation. These test statistics imply a proper specification.

The results suggest that a reduction of 10 per cent in the informality rate would increase TFP by 2.5 per cent in the short term or 3.2 per cent in the long term.[7] Hence, reducing average informal employment (47 per cent in our sample) to the much lower levels estimated by ILO (2014) for China's informal employment in manufacturing (14 per cent) would increase Mexico's TFP by approximately 10.3 per cent. Rule of law also has a significant and positive effect on productivity growth, although regulatory cost does not. MNEs workers and the intensity of imported inputs variables have a positive and significant effect on productivity, which highlights the importance of foreign technology and knowledge transfers. On the other hand, increasing low value added activities or *Maquila* activity limits productivity growth. This suggests that in industries where Mexico faces strong competition from China, Mexico is suffering from a lack of productivity. Results also show that productivity increases with education quality, as measured by PISA scores. Moreover, this is the variable with the strongest impact. China's PISA scores in mathematics are 34 per cent higher than those of Mexico (550 vs. 410). Thus, according to column (1) estimates, improving education quality to the levels of China would increase Mexico's TFP by 22 per cent. However, results on average years of schooling are not significant, suggesting quality is dominant. Results also suggest that facilitating access to capital in Mexico does not have a significant effect on productivity, but increasing capital intensity drives productivity improvements.

[7] The long term coefficient from Equation 5 is calculated as $= \left(\frac{\beta}{1-\delta}\right)$.

Our results suggest that among the policy drivers, after education, informality is the variable with the strongest effect on productivity. Moreover, informality is among the policy variables that one could tackle in the short run. However, the effects of informality may differ according to the size of the firms that employ informal workers. Indeed, since larger firms tend to be more productive, labour allocated to informal jobs in small and less productive firms may have a stronger effect on overall productivity than labour allocated to informal jobs in larger firms. We then estimate Equation 4 using the Arellano and Bond (1991) difference GMM estimator for different rates of informality: in firms with up to ten workers; in firms with more than ten workers; and in firms with more than 50 workers. Recall that the informality data come from household surveys, and thus cover microenterprises; in contrast, the smallest firms are not fully covered in the TFP data.

Estimates for informality in different sizes of firms are shown in Columns (2) to (4) of Table 2. As expected, informality of firms up to ten workers has the strongest impact, suggesting that the main driver of the results for informality is from microenterprises. Compared to informality in firms with more than ten workers presented in column (3), the effects of informality in firms up to 10 workers is almost twice as large (-0.162 against -0.082). The effects of informality in firms with more than 50 workers on productivity are weaker, but still significant and negative. Finally, concerning control variables, the results are robust to different measures of informality, which implies the absence of multicollinearity between informality and control variables.[8]

One important issue concerning informality is the potential for reverse causality, which could bias our results. We re-estimate the model replacing informality by its one-year lag. Table 3 shows the estimates using the new specification, which confirms that informality has a negative and significant effect on productivity. Lagged informality estimates are larger compared to non-lagged estimates (-0.340 for the former vs. -0.248 for the later). We can interpret these results as evidence of bi-directional causation between productivity and informality. Indeed, reducing informality increases productivity, which in turn reduces informality. Thus, from a given reduction of informality, only a proportion of the change increases productivity directly, while the remainder of the observed effect is due to positive feedback from productivity to informality. For instance, suppose that from a decrease of informality by 10 per cent, only half (5 per cent) of this increases productivity directly and the other half is the second-round effect of this productivity improvement via informality; thus, the true effect of a decrease of informality would be two times larger than the estimated one. The coefficient value of informality then underestimates the true effect of informality on productivity because of bi-directional causation.

[8] We also estimate VIF to detect multicollinearity; all VIF values are lower than 2.10.

Table 2. Policy drivers of productivity

Dependent variable: Total factor productivity (TFP)								
	(1)		(2)		(3)		(4)	
Lagged TFP	0.215	**	0.224	**	0.216	**	0.213	**
	(0.012)		(0.011)		(0.011)		(0.011)	
Informality								
all firms	-0.248	**						
	(0.041)							
firms with< 10 workers			-0.162	**				
			(0.062)					
firms with> 10 workers					-0.082	**		
					(0.016)			
firms with> 50 workers							-0.028	**
							(0.008)	
Rule of law	0.125	**	0.132	**	0.105	**	0.131	**
	(0.023)		(0.020)		(0.024)		(0.022)	
Cost to start a business	0.013		-0.012		0.014		-0.002	
	(0.010)		(0.010)		(0.010)		(0.010)	
MNEs workers	0.011	**	0.008	**	0.012	**	0.009	**
	(0.002)		(0.002)		(0.002)		(0.002)	
Imported inputs	0.011	**	0.010	**	0.011	**	0.010	**
	(0.002)		(0.002)		(0.002)		(0.002)	
Maquila intensity	-0.033	**	-0.032	**	-0.031	**	-0.033	**
	(0.002)		(0.002)		(0.002)		(0.002)	
PISA	0.504	**	0.264	*	0.486	**	0.348	**
	(0.112)		(0.104)		(0.109)		(0.110)	
Years of schooling	-0.011		-0.012		-0.020		-0.018	
	(0.016)		(0.017)		(0.016)		(0.016)	
Number of loans	-0.001		-0.006		-0.004		-0.007	
	(0.004)		(0.004)		(0.004)		(0.004)	
Capital intensity	0.255	**	0.262	**	0.243	**	0.251	**
	(0.011)		(0.012)		(0.012)		(0.012)	
Observations	2116		2116		2116		2116	
Instruments	226		226		226		226	
Groups	406		406		406		406	
Hansen J p-value	0.174		0.153		0.163		0.247	
AR(1) p-value	0.000		0.000		0.000		0.000	
AR(2) p-value	0.524		0.573		0.559		0.554	

*Notes. * significant at the 5% level, ** significant at the 1% level. State-industry clustered standard errors are in parentheses. Excepting dummy variables, all variables are expressed in log form. We use the Arellano-Bond two-step difference GMM estimator. We treat the explanatory variables as endogenous, and use lags of endogenous variables in levels as instruments. The Hansen J test reports the p-values for the null hypothesis of instrument validity. The p-values reported for AR(1) and AR(2) are the p-values for first and second-order autocorrelated disturbances. Each regression includes a constant and time dummies, not reported here.*

Table 3. Policy drivers of productivity, robustness test

Dependent variable: Total factor productivity (TFP)	(1)	(2)	(3)	(4)
Lagged TFP	0.204 **	0.221 **	0.185 **	0.197 **
	(0.011)	(0.012)	(0.011)	(0.011)
Lagged informality				
all firms	-0.340 **			
	(0.040)			
firms with< 10 workers		-0.190 **		
		(0.063)		
firms with> 10 workers			-0.174 **	
			(0.019)	
firms with> 50 workers				-0.065 **
				(0.009)
Rule of law	0.161 **	0.122 **	0.211 **	0.162 **
	(0.024)	(0.024)	(0.026)	(0.026)
Cost to start a business	0.006	-0.013	0.012	0.012
	(0.011)	(0.010)	(0.011)	(0.011)
MNEs workers	0.007 **	0.007 **	0.005 *	0.007 **
	(0.002)	(0.002)	(0.002)	(0.002)
Imported inputs	0.011 **	0.009 **	0.010 **	0.009 **
	(0.002)	(0.002)	(0.002)	(0.002)
Maquila intensity	-0.031 **	-0.032 **	-0.031 **	-0.032 **
	(0.002)	(0.002)	(0.003)	(0.002)
PISA	0.335 **	0.243 *	0.580 **	0.442 **
	(0.119)	(0.112)	(0.121)	(0.115)
Years of schooling	-0.006	-0.019	-0.033	-0.022
	(0.017)	(0.017)	(0.017)	(0.017)
Number of loans	-0.002	-0.006	-0.007	-0.007
	(0.004)	(0.004)	(0.004)	(0.004)
Capital intensity	0.266 **	0.258 **	0.260 **	0.248 **
	(0.012)	(0.012)	(0.013)	(0.012)
Observations	2116	2116	2116	2116
Instruments	220	220	220	220
Groups	406	406	406	406
Hansen J p-value	0.118	0.120	0.280	0.290
AR(1) p-value	0.000	0.000	0.000	0.000
AR(2) p-value	0.502	0.559	0.447	0.523

*Notes. * significant at the 5% level, ** significant at the 1% level. State-industry clustered standard errors are in parentheses. Excepting dummy variables, all variables are expressed in log form. We use the Arellano-Bond two-step difference GMM estimator. We treat the explanatory variables as endogenous, and use lags of endogenous variables in levels as instruments. The Hansen J test reports the p-values for the null hypothesis of instrument validity. The p-values reported for AR(1) and AR(2) are the p-values for first and second-order autocorrelated disturbances. Each regression includes a constant and time dummies, not reported here.*

In the case of time-lagged informality, reverse causality is much less of a problem, and the coefficient represents the effect of a decrease in informality on future productivity improvements. These results hold for our alternative measures of productivity. In addition, the results confirm that among informality rates by firm sizes, informality in firms with up to ten workers have the largest effect on productivity. Finally, results on the other control variables are close to those presented in Table 2, which implies the absence of multicollinearity.

4.3 Non-parametric estimates of informality

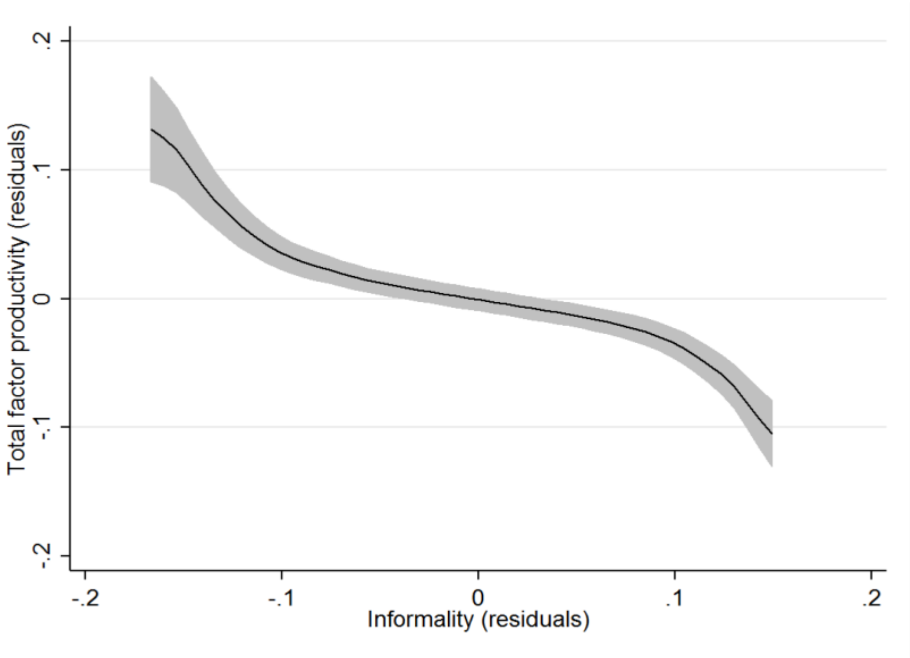
Our results show that informality is one of the major determinants of productivity growth. However, this is only a partial view of the relationship between informality and productivity. In this section, we employ non-parametric techniques to deepen and validate our previous findings. Non-parametric estimation methods allow the model to vary depending on the point of evaluation (Ichimura and Todd, 2007). Indeed, we have seen that there is considerable heterogeneity in TFP among Mexico's manufacturing industries, even within the same state. It is thus possible that the effects of informality differ across groups. Hence, we use a Kernel regression estimator and quantile regression estimator to validate the relationship between informality and productivity, as well as to evaluate if the effects of informality differ according to the level of productivity, which would be a unique finding to our study.

We start by implementing a Kernel regression with an Epanechnikov kernel function conditional on state-industry specific characteristics. More precisely, we first subtract the state-industry specific mean from each observation for productivity and informality variables. We then plot a graph (Figure 6) of the residuals with local zero-degree polynomial smoothing, which corresponds to regressing TFP on a single explanatory variable, informality. [9] The solid curve represents the estimates, and the shaded grey area represents the 95 per cent confidence intervals.

Figure 6 confirms the negative relationship between informality and productivity. Moreover, it shows that the effects of informality on TFP are strongest at the extremes. When informality is low, productivity is higher, but an increase in informality has a stronger negative effect on productivity than when informality and productivity are at their mean levels. Conversely, when informality is high, productivity is lower, and the positive effects of a decrease in informality are also stronger compared when at the mean levels of informality and productivity.

[9] An earlier version of Figure 6 with preliminary results appeared as Figure 1.12 in OECD (2015a).

Figure 6. Effects of informality on productivity, conditional on state-industry fixed-effects



Notes: Total factor productivity (residuals) represents residual variations in the log of TFP after subtracting state-industry specific effects. Informality (residuals) represents residual variations in the log of informality after subtracting state-industry specific effects. The sample is identical to the sample used for the regressions reported in Table 2. The figure is plotted using a nonparametric Kernel regression method with an Epanechnikov kernel function, with local zero-degree polynomial smoothing (bandwidth 0.05). Confidence bands use a 95% confidence level.

From Figure 6, we can infer that there are important differences in productivity and on the effects of informality between the first and last deciles. We then extend the analysis using quantile regression model to evaluate differences in the coefficient of informality variable. More precisely, we estimate the following specification:

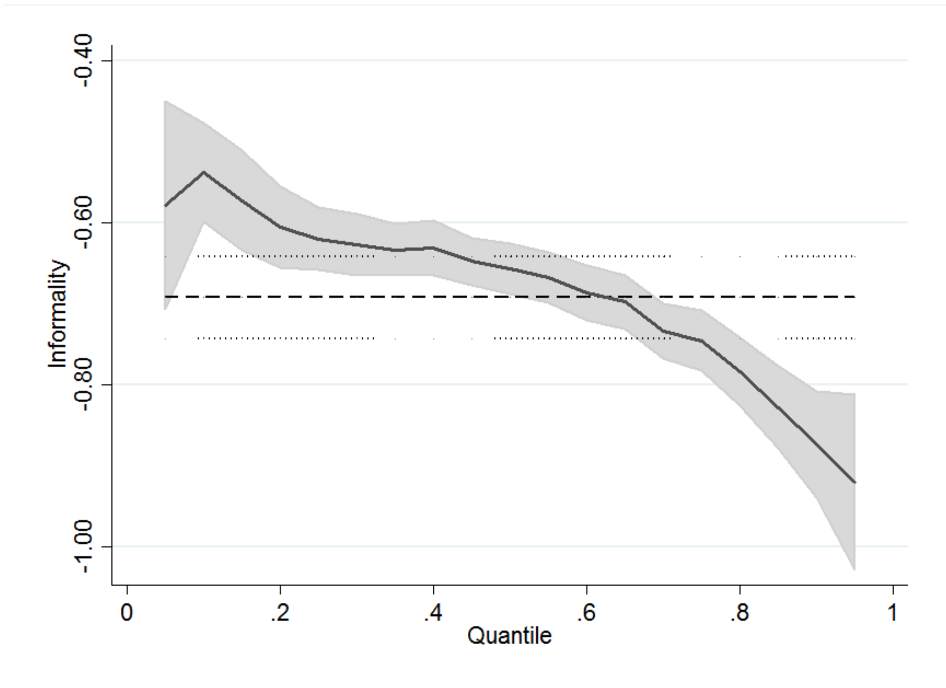
$$\mathrm{TFP}_{i,s,t} = \alpha^{\tau}\mathrm{Informality}_{s,t} + X_{i,s,t}\beta^{\tau} + \eta_{i,s} + \epsilon_{i,s,t} \quad (6)$$

where α^{τ} and β^{τ} are the parameters that characterizes the conditional quantile. We estimate the model under the restriction that the τ-th conditional quantile ($\tau \in (0,1)$) of TFP given $X = x$ is $x'\beta^{(\tau)}$. There are however some econometric issues to estimate specific effects ($\eta_{i,s}$) of Equation 6. We can use individual-specific dummies, but it creates inconsistent coefficients and is also a computational burden.

We employ Canay (2011) two-step estimator to handle specific effects on quantile regressions. In the first step, we estimate Equation 3 using the standard fixed-effects within estimator, we use these estimates to compute the fixed effects $\hat{\alpha}_{i,s} = T^{-1}\sum_{t=1}^{T} TFP_{i,s,t} - \hat{\alpha} Informality_{s,t} + X_{i,s,t}\hat{\beta}$, and we subtract these fixed effects from the dependent variable $\widehat{TFP}_{i,s,t} = TFP_{i,s,t} - \hat{\alpha}$. In the second step, we estimate a standard quantile regression on $\widehat{TFP}_{i,s,t} = \alpha^{\tau} Informality_{s,t} + X_{i,s,t}\beta^{\tau} + \epsilon_{i,s,t}$. Figure 7 presents a summary of simultaneous-quantile regression results for the informality variable. We plot the distinct quantile regression estimates for τ ranging from 0.05 to 0.95 as the solid curve. These point estimates may be interpreted as the impact of a one-unit change of informality on productivity holding other variables fixed. Thus, each of the plots has a horizontal quantile scale, and the vertical scale indicates the effects of informality. The shaded grey area depicts a 95 per cent point-wise confidence band for the quantile regression estimates. The dashed line shows the fixed-effects estimates reported in Table A.2, column (2), and the two dotted lines represent its confidence intervals.

Figure 7 illustrates how the effects of informality vary over quantiles, and how the magnitude of the effect at various quantiles differs from the fixed-effects coefficient, even in terms of the confidence interval around the coefficient.

Figure 7. Estimated parameter of informality by TFP quantile



Notes: The horizontal scale is the (increasing) quantile in the TFP distribution, and the vertical scale is the coefficient value for the effect of informality. The dashed line shows the fixed-effects estimates. Quantile regression estimates use the same control variables used in Table 2.

We see that the effect of informality differs considerably across quantiles; however the median estimate is similar to the fixed-effects estimate. We estimate, but do not report, the Wald test to evaluate the equality of the estimated coefficients of informality for different deciles, and the estimates reject this equality. The Figure shows that the negative effects of informality on TFP increase with the level of productivity. Thus, the benefits of tackling informality are higher for the most productive industries and states.

5. Discussion

Over the last decade we observed a shift in global competitive conditions that allowed Mexico to gain cost competitiveness compared to China. However, Mexico's potential is limited by the lack of aggregate growth of productivity. In this paper, we show that productivity, measured as TFP, differs considerably across Mexico's plants and regions. While Mexico's most productive plants are performing relatively well, and can compete with China's, most plants are struggling to perform better with limited success. A similar situation is observed in other OECD countries where there is a rising gap in productivity between the most advanced firms and the laggards, and the gains in productivity of the most advanced firms are not enough to improve aggregate productivity (OECD, 2015c).

We take advantage of Mexico's political administration to study the drivers of productivity using different econometric techniques to control for heterogeneity, endogeneity, and differences in coefficient values. Our findings suggest that among other factors, stronger rule of law increases productivity in Mexico. This is robust to previous evidence, which suggests that firms in Mexico's states with more effective legal systems tend to be substantially larger and more productive (Dougherty, 2014). Our results also show that among the institutional quality-related variables, informality has the strongest effect on productivity. Moreover, we consider informality as a source of distortions that drive to misallocation of resources. Our results are robust to different methods and imply a strongly negative relationship between informality and productivity. These results confirm and go beyond previous findings for Mexico's case that relied upon calibrated general equilibrium models (Leal Ordóñez, 2014; Prado, 2011). Among different size firms, informality in firms up to 10 workers has the strongest negative effects on productivity. The results also suggest, for the first time that we know of, that the effects of informality are heterogeneous according to the level of productivity in a sector. Moreover, the negative effects of informality on productivity rise with a higher level of productivity. In other words, more productive states and industries suffer more from informality than less productive ones. This is likely due to resources being perversely tied up in informal activities, akin to the 'Zombie firm' literature (Caballero et al., 2008).

Results also suggest that the presence of MNEs improves aggregate productivity. MNEs favour technology and knowledge transfers, as well as competition that could lead to improved innovation and productivity (Bloom et al., 2013; Keller and Yeaple, 2009; OECD 2015c). Since MNEs are more productive than local firms (Helpman et al., 2004), their presence would be sufficient to increase average productivity even without technology and knowledge transfers, which we also see through a positive effect of capital intensity. Commercial relationships with foreign companies through intermediates and value chains are important to improve overall productivity. However, it is important to continue to improve the absorptive capacity of foreign knowledge and technology. Indeed, education quality is one of the major determinants of productivity in Mexico.

Finally, *Maquila* industries, which face the strongest competition from China, are not performing well. Despite the gains in unit labour costs, these industries are missing out on productivity gains – likely due to an undue emphasis on low-end, low-skill assembly operations. Hence, we can conclude that Mexico is not a 'China', yet.

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Appendix

Table A.1 Estimated parameter of informality by TFP quantile

Variable	Durbin-Wu-Hausman		Variance inflation factor	
	χ^2	*p*-value	without lagged TFP	With lagged TFP
Lagged TFP	10.81	0.001		1.09
Informality	3.48	0.062	2.00	2.02
Rule of law	1.20	0.273	1.05	1.06
Cost to start a business	43.46	0.000	1.43	1.38
MNEs workers	21.11	0.000	1.75	1.78
Imported inputs	16.77	0.000	1.5	1.51
Maquila intensity	41.75	0.000	1.66	1.65
PISA	34.11	0.000	1.9	1.75
Years of schooling	60.48	0.000	1.4	1.41
Number of loans	0.22	0.640	1.49	1.34
Capital intensity	71.99	0.000	1.05	1.06

Notes: Durbin-Wu-Hausman computed using lagged values of all explanatory variables as instruments for each explanatory variable. VIF estimated for two different specifications. The first one without lagged TFP and the second one with lagged TFP.

Table A.2 Policy drivers of productivity, benchmark results

Dependent variable: Total factor productivity (TFP)	**(1) OLS**	**(2) FE**	**(3) FGLS**	**(4) FGLS-FE**	**(5) FGLS**	**(6) FGLS-FE**
Lagged TFP					0.971**	0.453**
					(0.004)	(0.011)
Informality	0.411 *	-0.693**	0.164**	-0.151**	0.032**	-0.130**
	(0.164)	(0.138)	(0.040)	(0.037)	(0.011)	(0.033)
Rule of law	0.056	-0.027	0.034	0.021	-0.012	0.025
	(0.093)	(0.051)	(0.031)	(0.021)	(0.008)	(0.016)
Cost to start a business	-0.146	-0.068**	-0.039*	-0.040**	0.003	-0.006
	(0.081)	(0.014)	(0.018)	(0.009)	(0.004)	(0.008)
MNEs workers	-0.093 *	0.001	-0.009**	0.004**	0.001	0.004*
	(0.038)	(0.005)	(0.003)	(0.001)	(0.001)	(0.002)
Imported inputs	0.008	0.019**	-0.001	0.012**	-0.001	0.003**
	(0.014)	(0.006)	(0.002)	(0.001)	(0.001)	(0.001)
Maquila intensity	-0.008	-0.046**	-0.013**	-0.025**	0.000	-0.015**
	(0.005)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
PISA	2.196**	0.292	0.406*	0.133	0.147*	0.115
	(0.496)	(0.250)	(0.162)	(0.096)	(0.059)	(0.079)
Years of schooling	-0.205**	-0.035	-0.077**	-0.021**	-0.044**	-0.001
	(0.070)	(0.028)	(0.020)	(0.006)	(0.011)	(0.006)
Number of loans	0.002	-0.008	-0.001	-0.002	0.000	-0.014**
	(0.022)	(0.005)	(0.005)	(0.003)	(0.002)	(0.003)
Capital intensity	-0.031	0.221**	0.185**	0.243**	0.012**	0.177**
	(0.054)	(0.010)	(0.008)	(0.005)	(0.003)	(0.005)
Observations	2960	2960	2958	2958	2531	2531
F-statistic or Wald χ^2	4.03e+04	1.21e+04	879	1.54e+05	63626	4.64e+05
Hausman χ^2		653.90**				692.47**

Notes. * *significant at the 5% level,* ** *significant at the 1% level. Standard errors robust to heteroskedasticity across panels and autocorrelation within panels are in parentheses. Columns (1) and (2) report estimates using pooled and fixed-effects regressions with Driscoll-Kraay standard errors. Columns (3) to (6) present estimates using the feasible generalized least squares estimator. Each regression includes a constant and time dummies that are not reported here. F-statistic or Wald* χ^2 *row presents the statistics for joint significance. In columns (1) and (2) we use F-statistic, and in columns (3) to (6) we report Wald* χ^2. *The Hausman* χ^2 *is the statistic of the standard Hausman test. This test is computed by estimating the variance covariance matrix of the difference between the fixed-effects and pooled estimators.*