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Unconditional Convergence in the Mexican Manufacturing Sector (1988-2018)

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Abstract

In this paper, I digitize economic census data to study unconditional convergence in manufacturing labor productivity across Mexican states from 1988 to 2018. I document its existence in three-digit industries at a rate of convergence of 1.22% per year. However, this result does not hold at the aggregate level: I find no unconditional convergence in manufacturing-wide labor productivity across states. Shift-sharing analysis reveals that the primary reason is the lack of labor reallocation towards more productive industries and the underperformance of some of the largest ones. Unconditional convergence at all levels only occurred during 1988-1998. Afterward, the convergence process broke down and was only observed at disaggregated levels. I provide evidence that one possible cause of this breakdown is the so-called "China shock". Additionally, I show that the convergence process, when it happened, tended to exhibit a catching-down feature, where past leaders have seen their labor productivity decline.

JEL Classification— O40, O14, O54

Keywords— Growth; Convergence; Manufacturing; Mexico

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1 Introduction

Through the lens of the neoclassical growth model and under certain technological restrictions, regions with lower income levels would grow faster and catch up with their richer counterparts, regardless of their initial conditions. However, contrary to the experience of other countries like the US (Barro and Sala-i Martin (1992)), unconditional income convergence within Mexico has not occurred. In fact, as Figure 1 shows, there is even a tendency towards divergence.

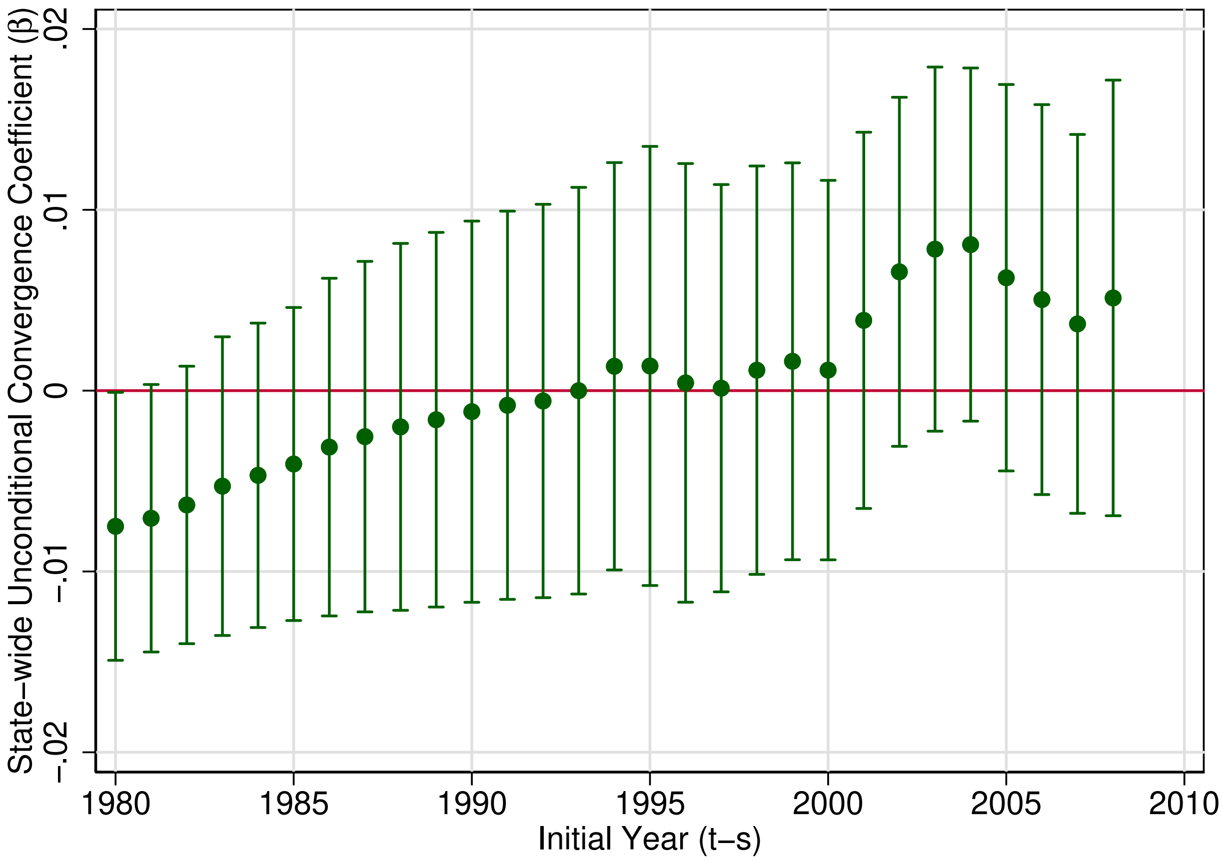


Figure 1: Convergence State-wide GDP per capita

Notes: The sample excludes the state of Campeche. GDP per capita is deflated using the GDP deflator. Estimates from regressing $\hat{y}_{t,s} = \alpha + \beta \ln(y_{t-s}) + \epsilon_{i,t}$, for different initial values of GDP per capita, $\ln(y_{t-s})$, $s \in \{10, 11, \ldots, 38\}$, where $\hat{y}_t$ is the compound growth rate between t and $t - s$, with $t = 2018$. 95% confidence intervals constructed from robust standard errors. Data sources: INEGI; CONAPO.

Is this experience general to all economic sectors? Rodrik (2012) shows that at the cross-country level, unconditional convergence occurs in the manufacturing sector at both the aggregate and disaggregated levels. If this phenomenon prevails at the international level, it is likely to be stronger within a country where barriers to capital and labor reallocation are expected to be smaller. Yet, in this paper, I show that convergence in the manufacturing sector is only mildly present in the Mexican economy. From 1988 to 2018, the convergence rate at the sub-sectorial level was 1.22% per year. Furthermore, as for the whole economy, convergence in aggregate manufacturing labor productivity has not occurred.

In fact, the process of manufacturing convergence broke down around the early 2000s. From 1988 to 1998, unconditional convergence was strong at both the sub-sector and aggregate manufacturing levels. Afterward, it continued to occur only at the sub-sector level, although at a slower pace. To understand this lack of aggregation, I perform a shift-sharing decomposition analysis. Overall, I show that contrary to what happened during 1988-1998, both the underperformance of certain critical industries and the lack of resource reallocation across them have prevented convergence from occurring at the aggregate level.

I also show that there is substantial heterogeneity in convergence across manufacturing subsectors. For instance, from 1988 to 2018, only 5 out of 11 industries displayed unconditional convergence, even though each sector showed signs of it at some point during the three decades of analysis. However, this convergence tends to exhibit a downward feature. That is, former leaders have underperformed in labor productivity growth, exhibiting, in some cases, even negative growth rates, contributing to the convergence process.

The primary source for this analysis is economic census data. However, since digital versions of these censuses are only available from 1998, I digitized and standardized the 1988 and 1993 ones from physical records. This is important as I cover the subsequent dynamics of two critical moments in Mexico's trade liberalization: its entry into GATT (1986) and NAFTA (1994). I complement my analysis using GDP data and employment surveys, although only for recent periods. Moreover, due to methodological differences between these sources, I consider the potential existence of measurement error and use an IV approach. This exercise suggests that the baseline OLS estimates are an upper bound of the convergence process.

Although this paper focuses on beta-convergence, the relation between growth and initial value-added per worker, I also report estimates of convergence in productivity levels, the so-called sigma-convergence. Consistent with the former, I show that sigma-convergence occurred only from 1988 to 2003, while afterward, the standard deviation of the log of labor productivity across states increased.

To the best of my knowledge, this is the first paper that documents unconditional convergence in manufacturing labor productivity for Mexico. Regional studies in the past like Mallick and Carayannis (1994) have documented some degree of aggregate convergence for short periods during the 1970s, although not studying sub-sectoral convergence. Recently, Cabral et al. (2020) have also studied manufacturing productivity convergence across states and municipalities. However, several critical differences separate this work from theirs, aside from their emphasis on spatial analysis. First, despite their claims, the authors estimate conditional convergence, as they include locality-fixed effects in their regressions. Second, they only consider manufacturing-wide productivity instead of the detailed sub-industry analysis I do here. Third, they do not focus on the forces behind the convergence process. Finally, my study period is longer and includes an analysis by decade.

The literature on convergence is quite extensive, but Johnson and Papageorgiou (2020) offer a recent review of it. Overall, cross-country studies tend to show the absence of unconditional convergence, although recently, Patel et al. (2021) have shown that it started to occur from the late 1990s onwards. For the Mexican case, there is also a long tradition of convergence studies[1]. Regarding income convergence across states, notable works include Esquivel (1999), Esquivel and Messmacher (2002), and Chiquiar (2005), which show that convergence existed until 1980, after which it either stopped or showed signs of divergence. More recent studies with different estimation techniques include Rodríguez-Oreggia (2007), Carrion-i Silvestre and German-Soto (2009), Fonseca et al. (2018), and Mendoza-Velázquez et al. (2020), but in general, they tend to show the lack of unconditional convergence, from the 1980s onwards. As emphasized before, the contribution of this paper is the study of convergence in manufacturing, a topic that has received much less attention.

[1] Cabral et al. (2020) offer a detailed summary of studies around the topic.

Indeed, studies of convergence in manufacturing industries within a country and extensive periods are generally scarce. Thus, this work also stands out as one of the few papers that have revisited Rodrik (2012) empirical findings. In that sense, it is somewhat surprising that manufacturing productivity convergence has not received proper attention in the case of Mexico or, in general, in other countries. As the latter mentions, manufacturing industries possess several characteristics not shared by others that facilitate their convergence process. For instance, they produce tradable goods that can more easily integrate into global production networks, which could help with technological adoption. However, this paper's results highlight that convergence could be elusive even in this promising sector. Particularly if both external shocks hit star industries and the reallocation process is limited, as happened in Mexico.

In that respect, I also examine the impact of various economic forces and shocks on the manufacturing convergence process, focusing on the past decade. While these estimates cannot definitively establish a causality link, the analysis provides some insight into the factors that may accelerate or hinder convergence. Specifically, I investigate the influence of informality and the so-called China shock (Autor et al. (2013)) on convergence. The results suggest that cross-regional variation in informality does not significantly impact convergence in manufacturing, either at the aggregate level or by sub-industry. In contrast, I find evidence that the China shock slowed the convergence process from 2008 to 2018. Specifically, instrumental variable estimates indicate that when shock values exceed the 25th percentile of the distribution, manufacture-wide convergence starts to be compromised. Moreover, I also show that the service sector did not exhibit that sort of convergence break-up in the early 2000s. This, in addition to the slowdown in manufacturing exports around that time, strengthens the idea that in the 2000s, a significant shock hit the Mexican manufacturing industry, as also reflected by the deceleration of the economy-wide aggregate manufacturing labor productivity.

This paper is organized as follows. The next section discusses both the methodology and data used. Section 3 shows the results. Section 4 shows the relation of different economic forces on convergence. Section 5 concludes.

2 Data and Methodology

2.1 Estimation Framework

Similar to Rodrik (2012), I assume that the convergence process takes the following form,

$$\hat{y_{ijt,s}} = \beta(\ln y^*_{it} - \ln y_{ijt-s}) + \epsilon_{ijt} \tag{1}$$

where $\hat{y_{ijt,s}}$ is real labor-productivity growth rate of industry i, in state j, between periods t and $t-s$; y^*_{it} represents the technological frontier of industry i at period t; and y_{ijt-s} is the initial real labor-productivity. Equivalently, one can rewrite (1) as[2],

$$\hat{y_{ijt,s}} = -\beta \ln y_{ijt-s} + D_{it} + \epsilon_{ijt} \tag{2}$$

where D_{it} is a set of industry×time fixed effects, which accounts for potentially time-varying differences in the technological frontier (y^*_{it}) across industries. Note that (2) implicitly assumes the usage of a stack panel for different periods. However, one can also estimate the convergence process for a specific cross-section,

$$\hat{y_{ij}} = -\beta \ln y_{ij} + D_i + \epsilon_{ij} \tag{3}$$

I follow both approaches. One can also include state-fixed effects, D_j, to these specifications. However, when including them, the estimate of β reflects *conditional convergence*. The test of *unconditional convergence* lies in estimating either (2) or (3), without including state-fixed effects. Hence, unless otherwise stated, I omit controlling for any regional differences.

2.2 Data

I principally use Economic Censuses (*Censos Económicos*, CE) tabulates for 1988-2018, quinquennially reported by the Mexican Statistics Institute (*Instituto Nacional de Estadís-*

[2]This is the standard empirical specification in the convergence literature, also known as Barro regression (Durlauf et al. (2005)), although slightly modified to account for convergence within sub-industries.

tica y Geografía, INEGI). Data from 1998 onwards reports, whenever confidentiality allows it, aggregate information by state at 6-digit industry codes, using the North America Industrial Classification System for Mexico (*Sistema de Clasificación Industrial de America del Norte*, SCIAN). These data can be downloaded from INEGI's webpage. Tabulates for both 1988 and 1993 were instead digitized from physical records. As they are reported in pre-SCIAN industry codes (*Clasificación Mexicana de Actividades y Productos*, CMAP), I employ INEGI's conversion tables to map them into SCIAN. Appendix A describes additional details.

Table 1: Mapping between SCIAN 3-digit and s3-digit industries

	SCIAN s3-digit	SCIAN 3-digit	Description
1	311	311	Food Manufacturing
2	312	312	Beverage and Tobacco Product Manufacturing
3	313-314	313	Textile Mills
		314	Textile Product Mills
3	315-316	315	Apparel Manufacturing
		316	Leather and Allied Product Manufacturing
5	321	321	Wood Product Manufacturing
6	322-323	322	Paper Manufacturing
		323	Printing and Related Support Activities
7	324-326	324	Petroleum and Coal Products Manufacturing
		325	Chemical Manufacturing
		326	Plastics and Rubber Products Manufacturing
8	327	327	Nonmetallic Mineral Product Manufacturing
9	331-332	331	Primary Metal Manufacturing
		332	Fabricated Metal Product Manufacturing
10	333-336	333	Machinery Manufacturing
		334	Computer and Electronic Product Manufacturing
		335	Electrical Equipment, Appliance, and Component Manufacturing
		336	Transportation Equipment Manufacturing
11	337	337	Furniture and Related Product Manufacturing
12	339	339	Miscellaneous Manufacturing

Notes: Industry grouping for comparability purposes.

The levels of aggregation considered in this analysis are from 3-digit industries up to 1-digit, i.e., the whole manufacturing sector. In particular, I follow a similar approach to INEGI's state GDP report (*PIB por entidad Federativa*, PIBE) and aggregate certain 3-digit codes into one category. I do this for two reasons. First, it allows me to compare results from CE with the latter. Second, it creates an almost balanced panel, as some states have either negligible production or report negative census value added for certain 3-digit industries. This leaves 12 SCIAN semi-3-digit (s3) manufacturing industries instead of the 21 3-digit ones. Table 1 summarizes this aggregation.

I complement PIBE's yearly information with employment data from the Mexican Employment Survey (*Encuesta Nacional de Ocupación y Empleo*, ENOE). I use ENOE's quarterly microdata to calculate total employment and total hours worked by industry. Then, I compute yearly data as a simple average of the corresponding quarterly aggregates. Since ENOE started in 2005, and disaggregated PIBE data is available from 2003, I use data from its predecessor survey (*Encuesta Nacional de Empleo*, ENE) for 2003-2004. The concordance between both was done following INEGI's guideline, as described in Appendix A.

I consider real labor productivity (y) as either real value-added or GDP, divided by total employment or total hours, and real labor productivity growth ($\hat{y}$) as the corresponding compound annual growth rate between two periods. I deflate all nominal values using the Mexican Production Price Index (*Índice Nacional de Precios al Productor*, INPP). The baseline analysis considers only real labor productivity using total employment since the 1988-1993 censuses do not report total hours. Finally, I exclude Petroleum Products Manufacturing (324-326), as it is concentrated in a few states and has a strong government presence, which leaves me with 11 s3 manufacturing industries and 352 observations since Mexico has 32 States[3].

To get a sense of the recent history of the manufacturing sector, Figure 2 shows the nationwide evolution of manufacturing log labor-productivity (normalized to 2003) since 1990[4]. As can be seen, labor productivity growth has been relatively modest: around 40% in three decades. Moreover, this evolution can be characterized into three periods: expansion (1988-2002), stagnation (2003-2009), and moderate recovery (2010-2018). Interestingly, as shown later, these periods broadly coincide with different moments in the convergence process.

[3] In practice, I have fewer observations due to negative value-added or confidentiality missings.

[4] I employ INEGI's KLEMS dataset, which contains all the relevant information to reproduce the KLEMS methodology (Jorgenson and Sickles (2018)). This dataset, available from 1990 onwards, is disaggregated at 3-digit industries, although not by state. Hence, I only use it to make national comparisons.

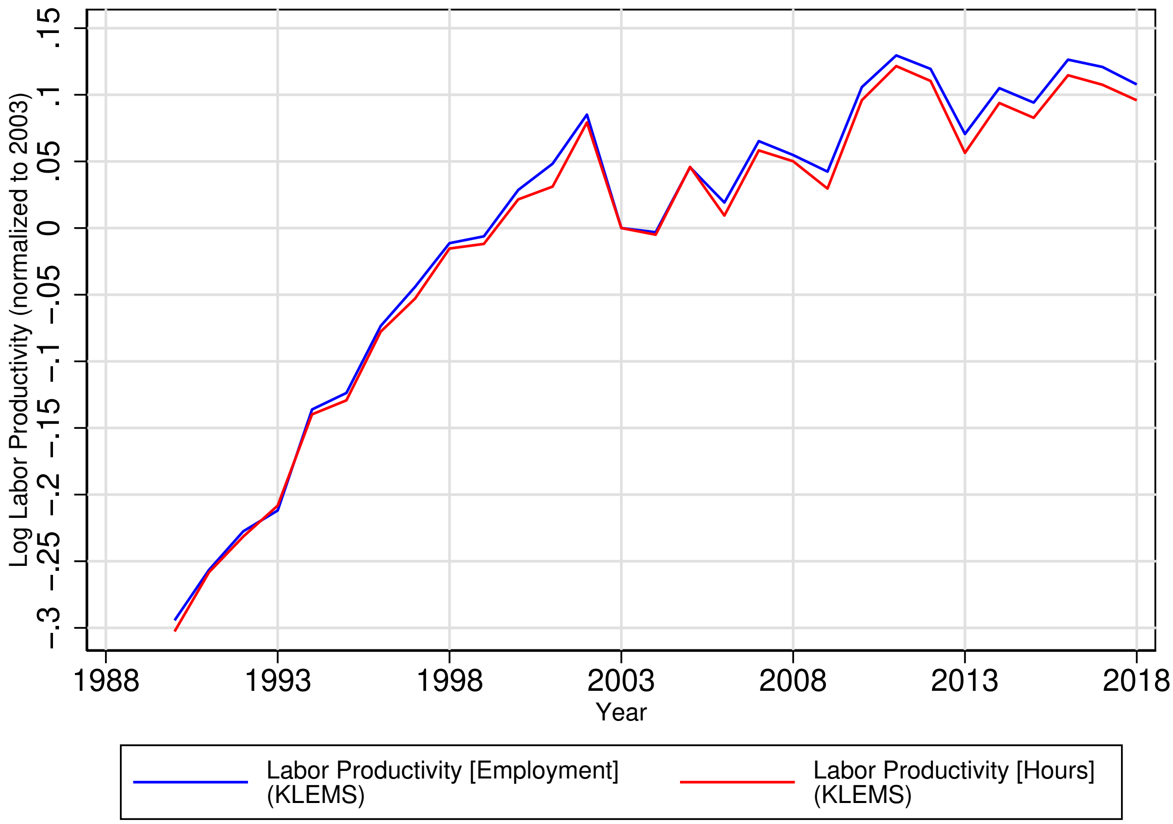


Figure 2: Evolution of manufacturing labor productivity

Notes: The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. Value-added is deflated using the sectoral GDP deflator. All series were normalized to their corresponding 2003 values. Data sources: KLEMS.

2.2.1 Measurement Issues

Both CE and PIBE+ENOE are natural data sources for studying productivity convergence since, in theory, GDP and Censal Aggregated Value Added aim to capture an equivalent concept. And in principle, aside from coverage, one could be indifferent to using one or the other. However, they differ in some significant aspects[5]. Precisely, as INEGI clearly explains it (INEGI, 2010, p. 7-8), methodological differences lead to discrepancies between the two. Among the most relevant to this study is that GDP is computed using market prices, while the Census reports production and intermediate consumption values using producer prices.

[5]Veleros et al. (2011) discuss in detail some of these differences for 2003-2008.

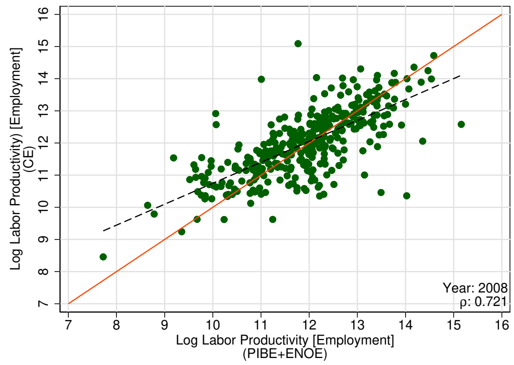
This may lead, for example, to observe negative values in the Censal Value Added, while GDP is always strictly positive. A second difference is how each source allocates regional production. While the main unit of observation in the Census is an establishment, in some cases, it may be a firm. Thus, a firm may report information in its headquarters location, even though production occurs in several regions. However, since most firms in the Census are single-establishment, this should not be a concern. Conversely, INEGI uses an algorithm to impute state GDP using different sources. Finally, employment data from ENOE is not necessarily representative at some levels of aggregation used in this paper[6].

To see in practice the magnitude of discrepancies between sources, Figures 3a - 3f show the correlation of log labor productivity and growth rates between CE and PIBE+ENOE for 2008-2018. The correlation at both s3-digit and 1-digit industries is high in terms of levels. However, the correlation in growth rates is 0.067 at the s3-digit, while at the 1-digit, although larger (0.354), it is still relatively low. There are two implications of these differences for the estimation of (2) or (3). As it is well-recognized by the literature, if initial labor productivity is measured with error, β, the convergence-coefficient will be *overestimated* (Temple (1998)). Instead, (classic) measurement error in growth rates will lead to larger standard errors for β (Cameron and Trivedi, 2005, p. 913). I consider the potential existence of measurement error and formally address this issue. However, to the extent that both CE and PIBE+ENOE provide relevant and, in a certain way, complementary information, whenever possible, I show every set of results for both datasets.

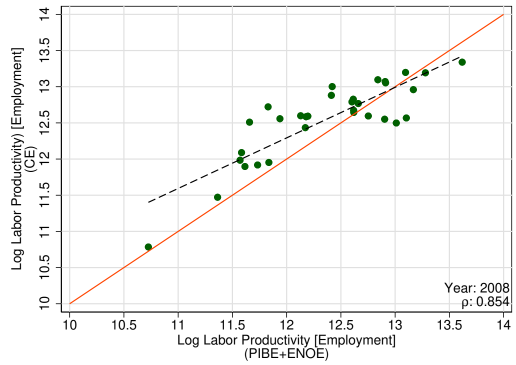
A final measurement concern is whether the transcription and homologation of the historical Census data (1988-1993) were done correctly. I validate the data in two ways to check for that. First, I compare aggregate s3-digit Censal Valued Added with GDP information from KLEMS. Figure B.1.1 in Appendix B plots the correlation of (log) labor productivity for both 1988 and 1993 with the corresponding KLEMS[7]. Finally, in Appendix B, I also show that results are similar if one estimates the convergence process from 1988 to 1998 using data in CMAP industrial classification instead of translating to SCIAN.

[6]Still, Table B.3.1 in Appendix B, I show both sources of employment are strongly correlated.

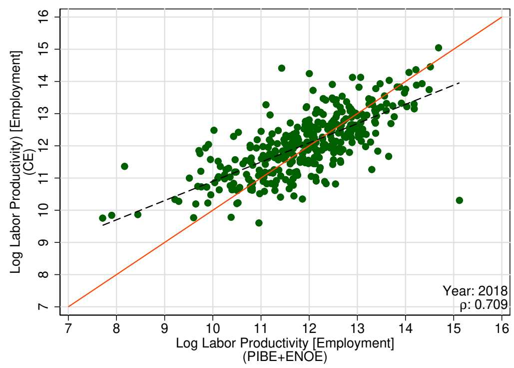
[7]Since the KLEMS dataset starts in 1990, I compare the 1988 values with those of 1990.



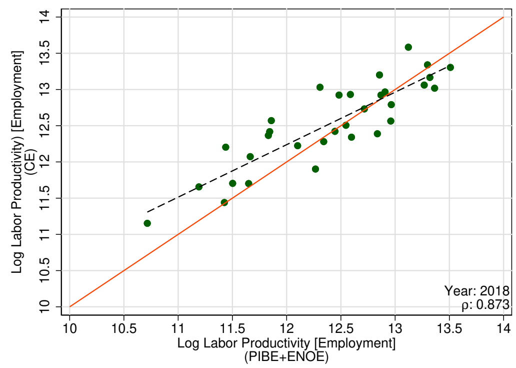
(a) Correlation Log Labor Productivity (2008), s3-digit



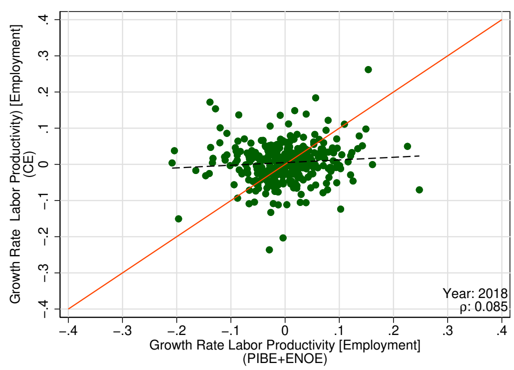
(b) Correlation Log Labor Productivity (2008), 1-digit



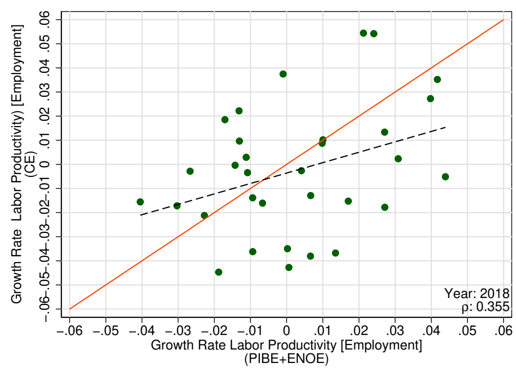
(c) Correlation Log Labor Productivity (2018), s3-digit



(d) Correlation Log Labor Productivity (2018), 1-digit



(e) Correlation Growth in Labor Productivity (2008-2018), s3-digit



(f) Correlation Growth in Labor Productivity (2008-2018), 1-digit

Figure 3: Correlation of Growth and Log Labor Productivity across datasets (2008-2018).

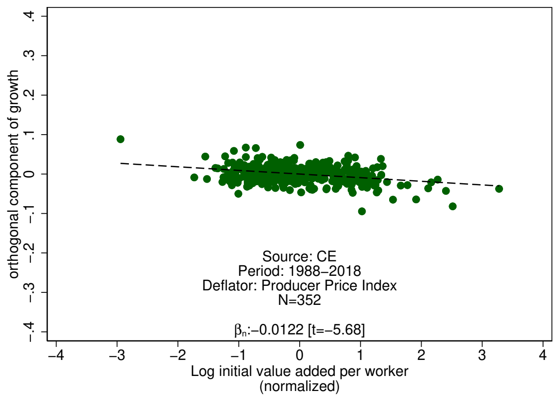
Notes: The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. Deflator: Producer Price Index. Data sources: CE; PIBE; ENOE.

3 Results

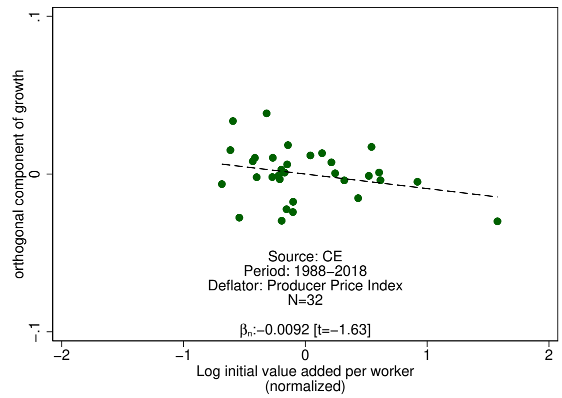
I start by reporting the results of estimating equation (3), the cross-sectional version of convergence, for both different levels of aggregation and periods. They are presented graphically to visually appreciate the presence of outliers or any non-linear relation. Standard errors are clustered at the state level. Figure 4a shows the existence of unconditional convergence at s3-digit manufacturing sectors for 1988-2018. The rate of convergence, strongly statistically significant, is 1.22% per year. Although quantitatively, the magnitude is relatively small, as it implies that the productivity gap between states at the bottom and top 10% of the distribution would close in 78 years $(\ln(0.9)/\ln(0.1) - 1)/0.0121)$. Moreover, Figure 4b shows that unconditional convergence does not exist in manufacture-wide labor productivity. The estimated coefficient, despite showing a tendency to convergence of 0.92% per year, is not statistically significant. In Section 3.3, I discuss why convergence fails at the aggregate level.

As seen earlier, the evolution of labor productivity has faced different stages. Hence, to understand its linkage to the convergence process, Figure 5 shows estimates by decade. Three facts can be noticed. First, manufacturing convergence at s3-digit industries has occurred in each decade, although at different paces, with the period 1988-1998 being the strongest (3.47%) followed by weaker convergences in 1998-2008 (1.44%) and 2008-2018 (2.49%). Second, manufacture-wide convergence has followed a similar convergence path, with the main difference that only for the period 1988-1998 β is statistically significant (albeit admittedly influenced by an outlier), while afterward, there is even a tendency towards divergence. Finally, both CE and PIBE+ENOE show similar results for 2008-2018, although the magnitude of convergence is smaller in the latter.

In Table 2, I present the results of stacking data for different decades, and thus, estimating (2). I do this exercise for different levels of aggregation, even for 3-digit industries. Recall these regressions control for time×industry fixed effects. Odd columns show that overall, there has been a tendency towards convergence in manufacturing labor productivity, although the convergence rate is faster for lower levels of aggregation. However, this effect is statistically significant only in s3-digit and 3-digit industries.



(a) s3-digit Manufacturing Sectors



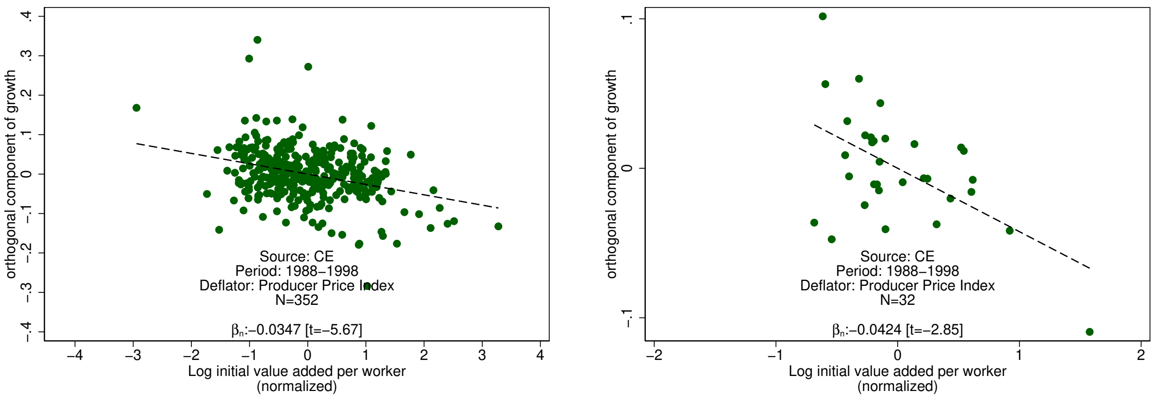
(b) 1-digit Manufacturing

Figure 4: Convergence in s3-digit Manufacturing Sectors and Manufacture-wide Labor Productivity

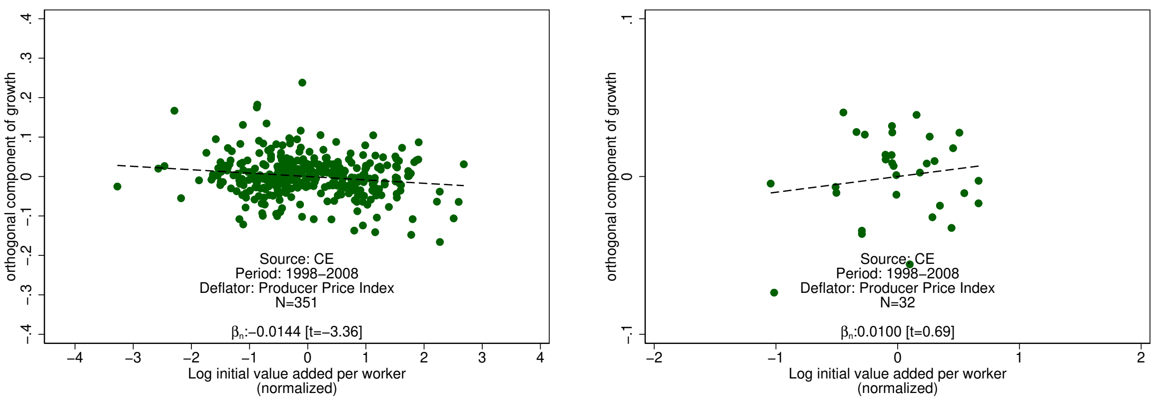
Notes: Estimates from (3). The sample includes all SCIAN s3-digit manufacturing industries except 324-326. t-statistic from clustered standard errors at the state level. Data sources: CE.

On the other hand, even columns formally test changes in convergence speed over time by interacting initial labor productivity with decade dummies. These results confirm the previous discussion: convergence was the strongest during 1988-1998, slowed in 1998-2008, and moderately recovered in 2008-2018. However, these changes are only statistically significant in s3-digit and 1-digit industries. More specifically, in Appendix B.4, I show that unconditional convergence existed at all levels of aggregation until 2003. Afterward, the convergence process broke down: it only kept occurring at s3-digit industries but at a slower pace.

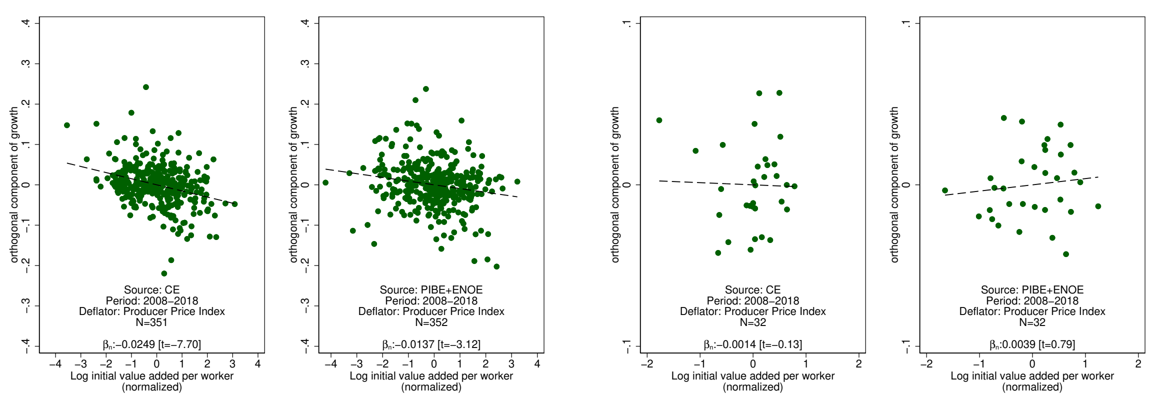
Do these results hold for alternative productivity measures, namely TFP (Total Factor Productivity)? While detailed TFP estimation involves a series of assumptions worth revisiting to assess its validity, some beyond the scope of this paper, in Appendix B.8, I show that the same patterns of convergence across periods and aggregate levels hold when considering TFP as a measure of productivity. Although, in general, the estimates are somewhat larger in magnitude. The main difference, however, lies in the fact that convergence for the aggregate manufacturing industry is, in general, statistically significant in every period except from 1998 to 2008, although mainly driven by the presence of outliers. As mentioned earlier, this potential overestimation of the convergence coefficient is consistent with measurement error in the TFP series. Details about the construction of TFP measures are in Appendix A.



(a) 1988-1998



(b) 1998-2008



(c) 2008-2018

Figure 5: Convergence in s3-digit Manufacturing Sectors and Manufacture-wide Labor Productivity by Decade

Notes: Estimates from (3). The sample includes all manufacturing SCIAN s3-digit industries except 324-326. t-statistic from clustered standard errors at the state level. Data sources: CE; PIBE; ENOE.

Table 2: Convergence in Manufacturing Sector by Decade (1988-2018)

	SCIAN 1-digit		SCIAN s3-digit		SCIAN 3-digit	
	(1)	(2)	(3)	(4)	(5)	(6)
Log initial productivity	-.0126	-.0424***	-.0242***	-.0347***	-.0382***	-.0359***
	(.0096)	(.015)	(.0021)	(.0061)	(.0038)	(.0082)
Log initial productivity, 1998		.0524***		.0203**		-.0032
		(.0168)		(.0076)		(.0111)
Log initial productivity, 2008		.041*		.0098		-.003
		(.0211)		(.008)		(.0088)
Observations	96	96	1054	1054	1641	1641
R-squared	.0852	.1993	.2069	.2172	.2246	.2249
State FE	No	No	No	No	No	No
Year FE	No	No	No	No	No	No
Industry FE	No	No	No	No	No	No
IndustryXYear FE	Yes	Yes	Yes	Yes	Yes	Yes

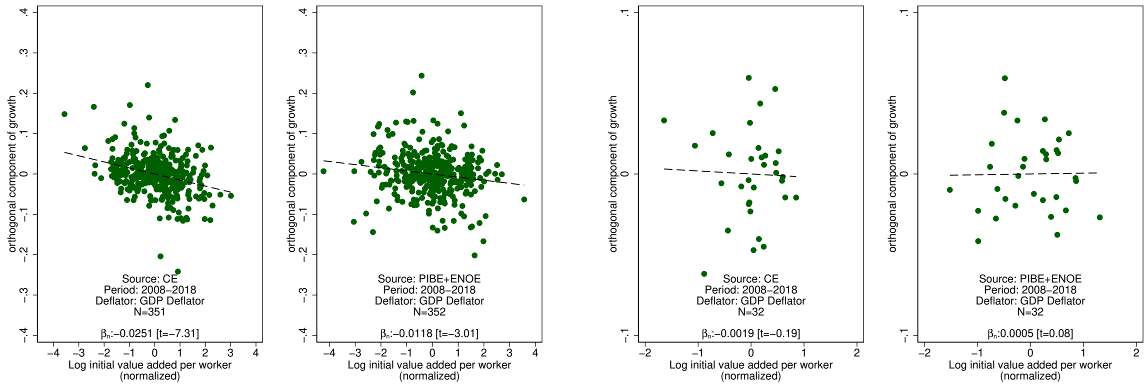
Notes: Estimates from (2). The sample includes all SCIAN s3-digit manufacturing industries except 324-326. Clustered standard errors at the state level in parenthesis. Data sources: CE.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

3.1 Robustness Checks

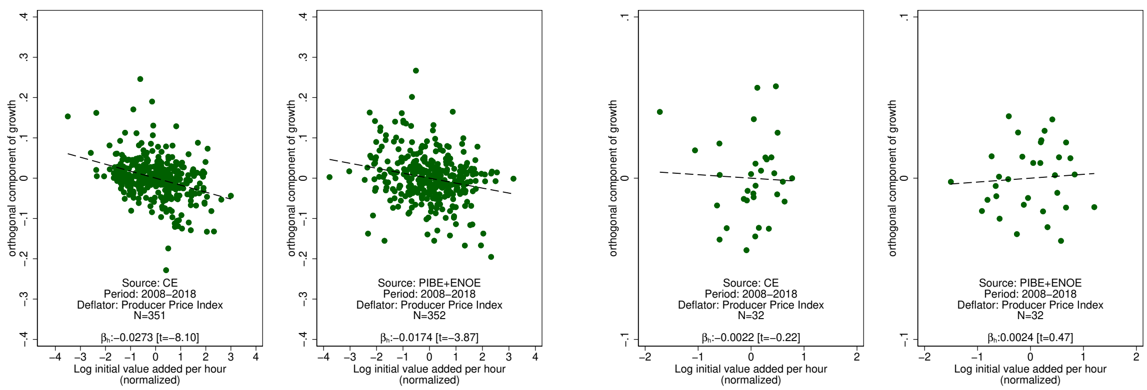
In this section, I consider alternative empirical decisions to those of the baseline analysis. First, I check if results change when measuring labor productivity as valued-added per hour worked. I also study how sensitive results are if I use the state-sectoral GDP deflator, which has the advantage of being specific for each industry and state, as opposed to the PPI. However, I only show these checks for 2008-2018 due to the data limitations described earlier. So, they can be directly compared to those of Figure 5c. Figure 6 shows the results[8].

Overall, the estimates from these robustness checks show no significant differences from the baseline ones. Using a different deflator slightly reduces the β coefficient, while employing valued-added per hour worked increases it. It is an open question whether these similarities hold for other periods, but, in principle, they do not seem quantitatively relevant. Instead, the differences in the estimated β coefficients between datasets remain important.

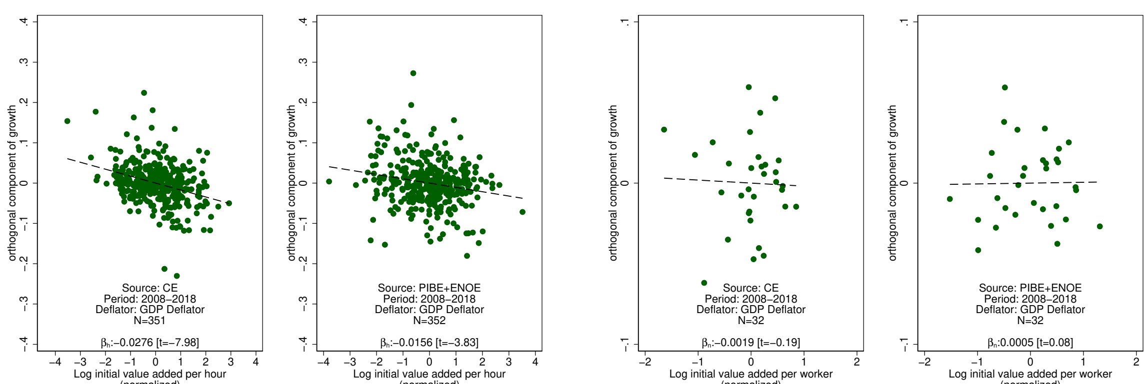
[8] In Appendix B.6 I show that including the oil industry (324-326) does not change the results, except for aggregate convergence (significant at the 10%), likely due to its overrepresentation in particular States.



(a) 2008-2018, Labor Productivity per Worker, GDP Deflator



(b) 2008-2018, Labor Productivity per Hour, INPP Deflator



(c) 2008-2018, Labor Productivity per Hour, GDP Deflator

Figure 6: Convergence in s3-digit Manufacturing Sectors and Manufacture-wide Labor Productivity (2008-2018). Robustness Checks.

Notes: Estimates from (3). The sample includes all SCIAN s3-digit manufacturing industries except 324-326. t-statistic from clustered standard errors at the state level. Data sources: CE; PIBE; ENOE.

To address this issue, I estimate (2), using two instruments for CE's $\ln(y_{ijt-s})$. The first is the 5-year CE's lagged labor productivity (IV1). The second one is labor productivity from PIBE+ENOE (IV2). The exclusion restriction assumption in the first case is that measurement error coming from different CE's is uncorrelated, while in the second case, the one from CE is uncorrelated from that of PIBE+ENOE. Although untestable, these are relatively weak assumptions, particularly for the second case, given the discussed methodological differences between sources. I once again present these estimates for different levels of aggregation for only the 2008-2018 period. Table 3 shows the results.

Table 3: Convergence in Manufacturing Sector (2008-2018): IV Approach

	SCIAN 1-digit			SCIAN s3-digit		
	(OLS)	(IV1)	(IV2)	(OLS)	(IV1)	(IV2)
	(1)	(2)	(3)	(4)	(5)	(6)
Log initial productivity	-.0014	.0047	.0067	-.0249***	-.0058	-.0153**
	(.0101)	(.0115)	(.0123)	(.0032)	(.0052)	(.0067)
Observations	32	32	32	351	351	351
R-squared	.0008	-.0145	-.0259	.2395	.1526	.2174
F statistic (First Stage)		44.3333	46.462		41.2374	156.094
State FE	No	No	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimates from (2). The sample includes all SCIAN s3-digit manufacturing industries except 324-326. Clustered standard errors at the state level in parenthesis. Data sources: CE; PIBE; ENOE.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

One can observe that β-convergence estimates reduce whenever instrumenting initial labor productivity. For the case of s3-digit industries, it is no longer statistically significant when the instrument is the 5-year lagged CE value, while it drops by more than half when using PIBE+ENOE metrics. This is consistent with the interpretation of measurement error in the CE dataset. Moreover, if the size of this bias holds for other periods, it implies that the β coefficients shown previously are an upper bound of the actual convergence process. Extrapolating these results would suggest that the convergence of the s3-digit industries for 1988-2018 will be less than 1% per year, while the implications for aggregate manufacturing would be even more pessimistic. Hence, opposite to what seems to occur at a cross-country level, unconditional manufacture convergence in Mexico is only mildly present[9].

[9]In Appendix B.7 I show that *conditional* convergence is present at all levels of aggregation and periods,

3.2 Convergence by Industry

Figures 7 and 8 show the 1988-2018 convergence of labor productivity for different s3-digit industries. As expected from the results of the previous section, unconditional convergence exists (statistically significant) in almost half of the industries (5/11). Despite not being statistically significant, the rest of them show a tendency towards convergence.

As Rodrik (2012) shows, in a cross-section, there is a relationship between the β estimate from (2), and those obtained from individual regressions, which can be written as

$$\beta = \sum_{i=1}^{I} \beta i \underbrace{\left(\frac{var(\ln y_{ij}|J = i)Pr(J = i)}{\sum_{l=i}^{I} var(\ln y_{lj}|J = l)Pr(J = l)} \right)}_{\text{Weight}_i} \tag{4}$$

So, regressing jointly all industries (with the corresponding fixed effects) yields the same β coefficient as the weighted sum of β coefficients estimated from individual regressions. Table 4 reports these coefficients, along with the corresponding weights, for each period. Although in 30 years, only 5 industries converged (column 1), at some point, each industry showed unconditional convergence. The industries with a stronger tendency towards it are Beverage and Tobacco Product Manufacturing (312), Textile Mills+Textile Product Mills (313-314), and Wood Product Manufacturing (321). Machinery *et al.* (333-336), which includes flagship Mexican industries like automobile production, only showed convergence for the 1988-1998 period.

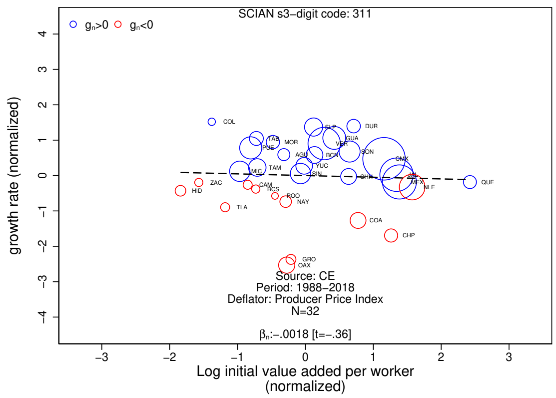
An important aspect of the Mexican convergence is that it does not exhibit a catching-up feature. Instead, it seems to happen downwards. This means that certain states that were industrial leaders in the past, particularly after 1998, have shown a decrease in labor productivity, which, to some extent, facilitated convergence. However, this raises concerns, as it suggests that some states are not reaching the technological frontier but are approaching a lower level of productivity than the former leaders. Moreover, in Appendix B.5, I also show that this phenomenon is not particular to the CE dataset.

consistent with the fact that region-specific conditions play a role in determining the speed of catch-up.

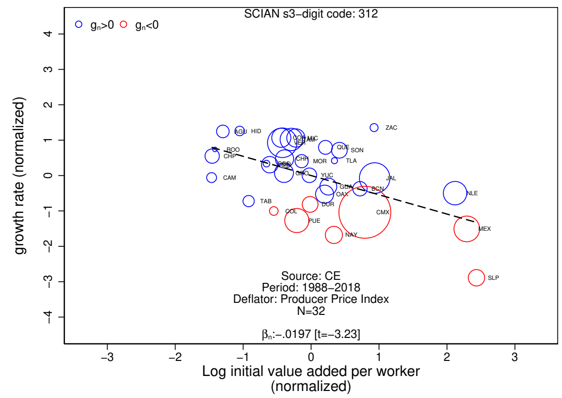
Table 4: Beta-Convergence Coefficients by Industry

	1988-2018		1988-1998		1998-2008		2008-2018			
	CE		CE		CE		CE		PIBE+ENOE	
SCIAN code	β	W	β	W	β	W	β	W	β	W
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
311	-.0018	.0317	-.0031	.0317	-.0123	.0498	-.0258**	.0496	-.0066	.0344
312	-.0197***	.1108	-.0485***	.1108	-.0221	.0473	-.0486**	.083	-.0216	.0996
313-314	-.0203***	.1867	-.0316*	.1867	-.0129*	.1972	-.023**	.1496	.0072	.1761
315-316	-.0108	.0287	-.0123	.0287	-.0444**	.048	-.0065	.0408	-.0035	.0632
321	-.0243***	.0508	-.0684***	.0508	-.0053	.0282	-.0009	.0308	-.0626***	.0682
322-323	-.0116*	.1047	-.0292**	.1047	-.0144	.0972	-.0114	.1096	-.021**	.0721
327	-.0159***	.1393	-.0239	.1393	-.0085	.1518	-.0233***	.1275	-.0166	.0551
331-332	-.003	.1136	.0027	.1136	.0208***	.1423	-.0335***	.1998	.0091	.115
333-336	-.0023	.1488	-.0649***	.1488	-.0601***	.1504	-.0043	.062	-.0135	.1243
337	-.0088	.0373	-.0282	.0373	-.01	.0467	-.0254***	.0424	-.0098	.0565
339	-.0029	.0476	-.0568***	.0476	.0326*	.0411	-.0344***	.1048	-.0329***	.1354

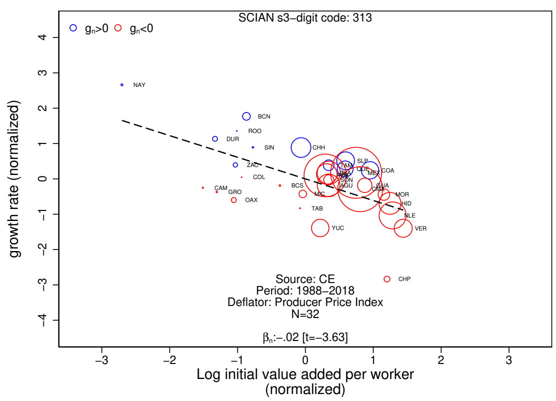
Notes: Estimates from $\hat{y}^i_j = -\beta^i \ln y_j + \epsilon_j, i \in \{311, 312, \ldots 339\}$. Weights from (4). The sample includes all SCIAN s3-digit manufacturing industries except 324-326. p-values from Robust standard errors. Data sources: CE; PIBE; ENOE.
*p < 0.1, **p < 0.05, ***p < 0.01



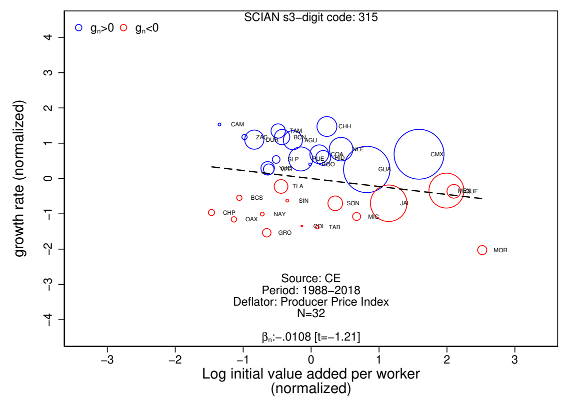
(a) 311: Food Manufacturing



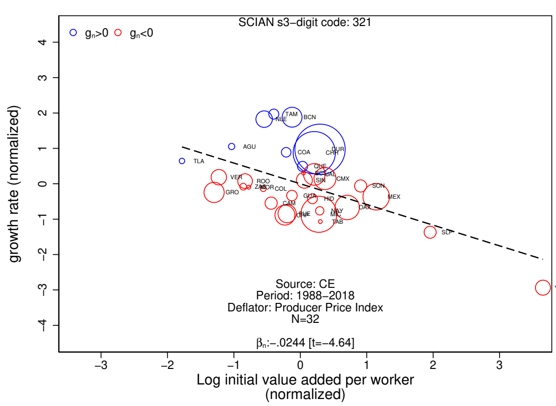
(b) 312: Beverage and Tobacco Product Manufacturing



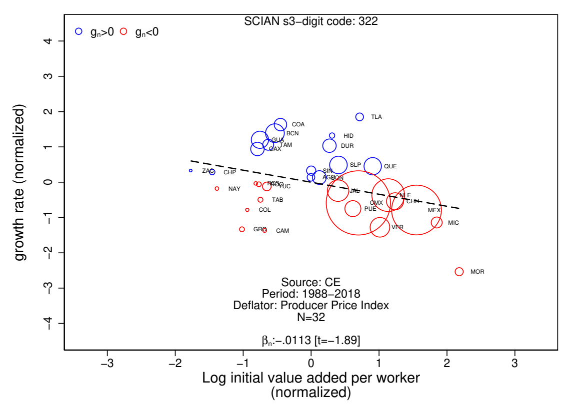
(c) 313-314: Textile Mills; Textile Product Mills



(d) 315-316: Apparel Manufacturing; Leather and Allied Product Manufacturing



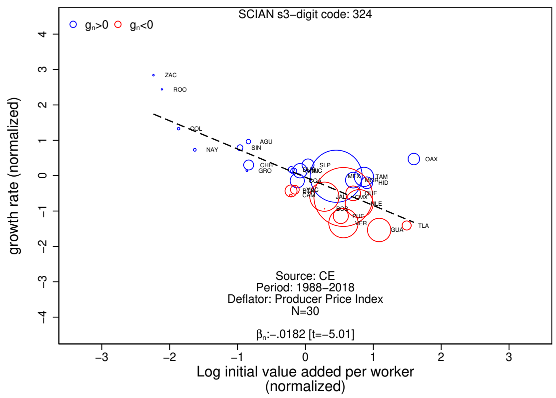
(e) 321: Wood Product Manufacturing



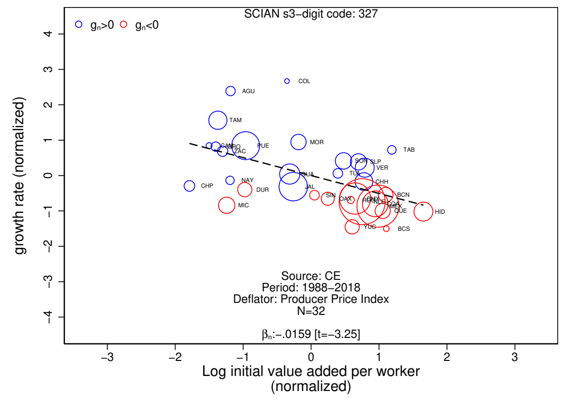
(f) 322-323: Paper Manufacturing; Printing and Related Support Activities

Figure 7: Beta-convergence by Industry (I) 1988-2018

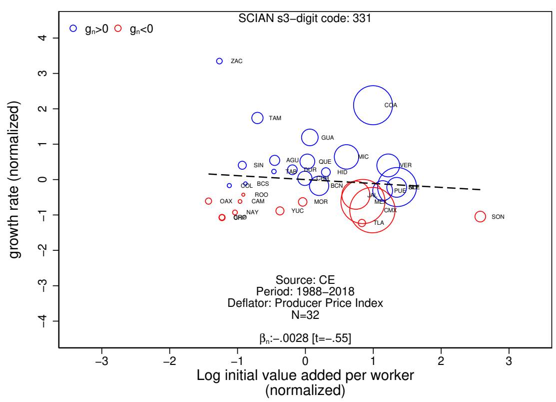
Notes: Estimates from $\hat{y}^i_j = -\beta^i \ln y_j + \epsilon_j$, $i \in \{311, 312, \dots 339\}$. t-statistic from robust standard errors. The size of markers correspond to the importance of employment at a national level in the initial period. Data sources: CE.



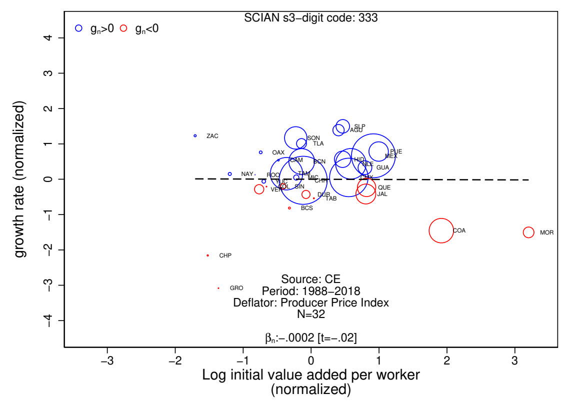
(a) 324-326: Petroleum and Coal Products Manufacturing; Chemical Manufacturing; Plastics and Rubber Products Manufacturing



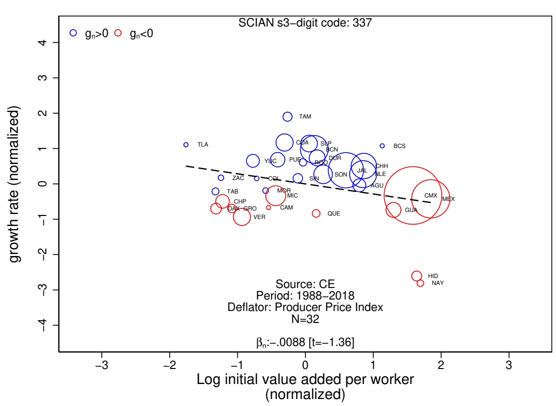
(b) 327: Nonmetallic Mineral Product Manufacturing



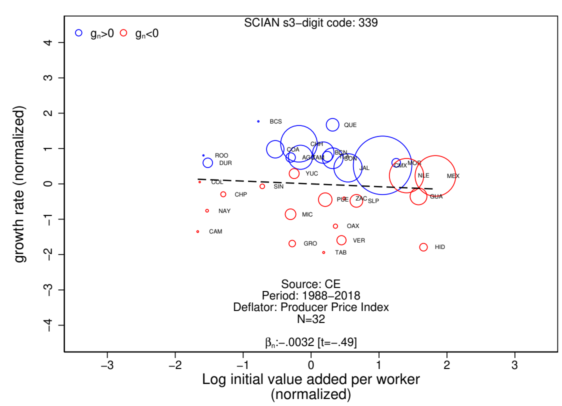
(c) 331-332: Primary Metal Manufacturing; Fabricated Metal Product Manufacturing



(d) 333-336: Machinery Manufacturing; Computer and Electronic Product Manufacturing; Electrical Equipment, Appliance, and Component Manufacturing; Transportation Equipment Manufacturing



(e) 337: Furniture and Related Product Manufacturing



(f) 339: Miscellaneous Manufacturing

Figure 8: Beta-convergence by Industry (II) 1988-2018

Notes: Estimates from $\hat{y}^i_j = -\beta^i \ln y_j + \epsilon_j$, $i \in \{311, 312, \dots 339\}$. t-statistic from robust standard errors. The size of markers corresponds to the importance of employment at a national level in the initial period. Data sources: CE.

Mechanically, this could simply result from a lack of historical quality-adjusted industry deflators by state, leading to underestimating real growth. However, if former, high-productive industry states faced more distortionary policies, like size-dependent ones (Guner et al. (2008)), it is natural that their productivity would be affected. For instance, from 1998 to 2013, Mexican small firms (sales below 2 million pesos≈200 thousand USD in 2006) were subject to a state-varying flat tax rate (REPECO), excepting them from other forms of taxation (VAT, payroll and income taxes), as opposed to large ones, which had to pay all the corresponding taxes. Thus, by distorting the firm's growth incentives (Sánchez-Vela and Valero-Gil (2011)), aggregate growth could have been compromised, facilitating convergence.

3.3 Convergence Decomposition

An open question from Section 3 is why convergence has not added up? To answer it, I follow Wong (2006), and notice that growth in labor-productivity (GLP) can be written as[10],

$$\frac{\Delta y_t}{y_{t-s}} = \underbrace{\sum_{i=1}^{I} \underbrace{\frac{Y_{it-s}}{Y_{t-s}}\left[\frac{\Delta y_{it}}{y_{it-s}}\right]}_{\text{Growth Effect Sector i (GE}_i\text{)}}}_{\text{Total Growth Effect (TGE)}} + \underbrace{\underbrace{\sum_{i=1}^{I}\left[\frac{y_{it-s}}{y_{t-s}}\right]\Delta s_{it}}_{\text{Total Shift Effect (TSE)}} + \underbrace{\sum_{i=1}^{I}\left[\frac{y_{it-s}}{y_{t-s}}\right]\left[\frac{\Delta y_{it}}{y_{it-s}}\right]\Delta s_{it}}_{\text{Total Interaction Effect (TIE)}}}_{\text{Total Reallocation Effect (TRE)}} \tag{5}$$

where Y_t is Value Added at period t; s_{jt} is the share of employment in industry j, at t; Δ_t is the change from $t-s$ to t and I is the total number of industries, which are 11 (s3) in our case. Hence, one can decompose β-convergence by estimating the following I+2 regressions,

$$\begin{aligned}
\text{GE}_{1jt} &= \beta^{\text{GE}_1} \ln(y_{jt-s}) + \epsilon_{\text{GE}_{1jt}} \\
&\vdots \\
\text{GE}_{Ijt} &= \beta^{\text{GE}_I} \ln(y_{jt-s}) + \epsilon_{\text{GE}_{Ijt}} \\
\text{TSE}_{jt} &= \beta^{TSE} \ln(y_{jt-s}) + \epsilon_{\text{TSE}_{jt}} \\
\text{TIE}_{jt} &= \beta^{TIE} \ln(y_{jt-s}) + \epsilon_{\text{TIE}_{jt}}
\end{aligned} \tag{6}$$

[10]There is a long tradition of studies using the so-called shift-share analysis (Timmer et al. (2010)). Recently, Dieppe and Matsuoka (2021) follow a similar approach to decompose convergence across countries.

So

$$\beta^{\text{1-digit}} = \sum_{k=1}^{K} \beta^{k} \quad k \in \text{GE}_1, \ldots \text{GE}_I, \text{TSE}, \text{TIE}$$

This decomposition has the advantage of showing how each industry and the reallocation between them contribute to the overall convergence process. Thus, it also considers how some sectors, despite not showing convergence, may free labor to others so they can grow faster. The results are presented in Table 5.

Table 5: Beta-Convergence Decomposition

	1988-2018		1988-1998		1998-2008		2008-2018			
	CE		CE		CE		CE		PIBE+ENOE	
Dependent Variable	β	%	β	%	β	%	β	%	β	%
GLP	-.3973*	100	-.4723***	100	.0668	100	-.0236	100	.0429	100
TRE	.0606	-15.25	-.0191	4.05	.0995**	148.97	-.0044	18.76	.0499	116.32
TSE	.0869	-21.88	-.0526	11.15	.1342*	200.95	.0138	-58.41	.0338	78.89
TIE	-.0263	6.63	.0335	-7.1	-.0347	-51.98	-.0182	77.17	.0161	37.43
TGE	-.4579**	115.25	-.4532**	95.95	-.0327	-48.97	-.0192	81.24	-.007	-16.32
GE_{311}	-.0207	5.22	-.0567	12	-.0442	-66.14	-.0043	18.01	-.0178	-41.39
GE_{312}	-.2097	52.78	-.0879***	18.61	.0216	32.34	.0073	-30.86	.0166	38.81
$\text{GE}_{313-314}$	-.0113	2.85	-.0108	2.29	-.0099*	-14.76	-.0167*	70.8	.0058*	13.55
$\text{GE}_{315-316}$	-.0112	2.82	-.0091*	1.92	-.0008	-1.26	-.0078	33.18	-.0108	-25.18
GE_{321}	.0043	-1.07	-.0009	.18	.0072***	10.76	.0021	-8.85	.0032	7.53
$\text{GE}_{322-323}$	-.013*	3.26	-.0043	.92	.0004	.53	-.0061	25.86	.0006	1.34
GE_{327}	-.1109	27.92	-.0915	19.38	.0175	26.24	-.0234	99.09	.0121	28.16
$\text{GE}_{331-332}$	.0503	-12.65	-.0062	1.32	.0245	36.75	-.013	54.84	.0075	17.56
$\text{GE}_{333-336}$	-.1334	33.58	-.1852**	39.22	-.0579	-86.72	.0524	-221.66	-.014	-32.56
GE_{337}	-.0028	.7	-.0003	.06	-.0014	-2.14	-.0059	24.83	.0003	.64
GE_{339}	.0006	-.15	-.0002	.05	.0103	15.43	-.0038	16	-.0106	-24.79

Notes: Estimates from (6). The sample includes all SCIAN s3-digit manufacturing industries except 324-326. p-values from Robust standard errors. Data sources: CE; PIBE; ENOE.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

From 1988 to 2018, the main force of aggregate convergence has been sectoral growth. No sector by itself has contributed significantly to this convergence process, although Beverage and Tobacco Product Manufacturing (312), Nonmetallic Mineral Product Manufacturing (327), and Machinery *et al.* (333-336) stand out despite not being individually statistically significant. Yet, for 1988-1998, these sectors show statistically significant effects, contributing to more than 70% of aggregate convergence. Afterward, with the convergence process broken down, some industries even pull towards divergence (e.g., 333-336 for 2008-2018).

Conversely, the Total Reallocation Effect (TSE+TIE) contributed -15.25% to the convergence process during 1988-2018, while only 4.05% during 1988-1998. However, notice that the effects are statistically significant in no period (except 1998-2008). In fact, from 1998 to 2008, it operated in the opposite direction, meaning that high-productivity states faced a substantial reallocation process, favoring the corresponding patterns toward divergence. Overall, these results suggest that low-productivity states have failed to properly move production toward their more productive sectors. Although, in general, this structural change within manufacturing, in which employment flows into relatively more productive sectors, seems to be elusive in Mexico.

Through the lens of this decomposition, it has been both the underperformance of certain important industries and the lack of reallocation that has prevented convergence in manufacture-wide productivity. Although certain industries have converged across states, their low employment (and value-added) participation has limited their influence towards convergence. In that sense, the challenge of the Mexican manufacturing industry is to promote upward convergence via productivity improvements and to overcome the widely documented misallocation (Levy (2018)) to free resources towards more productive sectors.

3.4 Sigma-Convergence

It can be said that behind the interest in seeing faster growth in followers is the desire for a reduction in productivity dispersion. However, beta-convergence is a necessary but not sufficient condition for sigma-convergence (Young et al. (2008)). Since the latter does not hold at an aggregate level, it is expected that sigma-convergence will also fail. Unsurprisingly, the evolution of the standard deviation of log-productivity, depicted in Figure 9, leads to the conclusion that there is no sigma-convergence in manufacturing-wide productivity for the 1988-2018 period. Only until 2003, when beta-convergence was strong, sigma-convergence occurred. Afterward, the standard deviation of labor productivity increased by 10 to 20 log points.

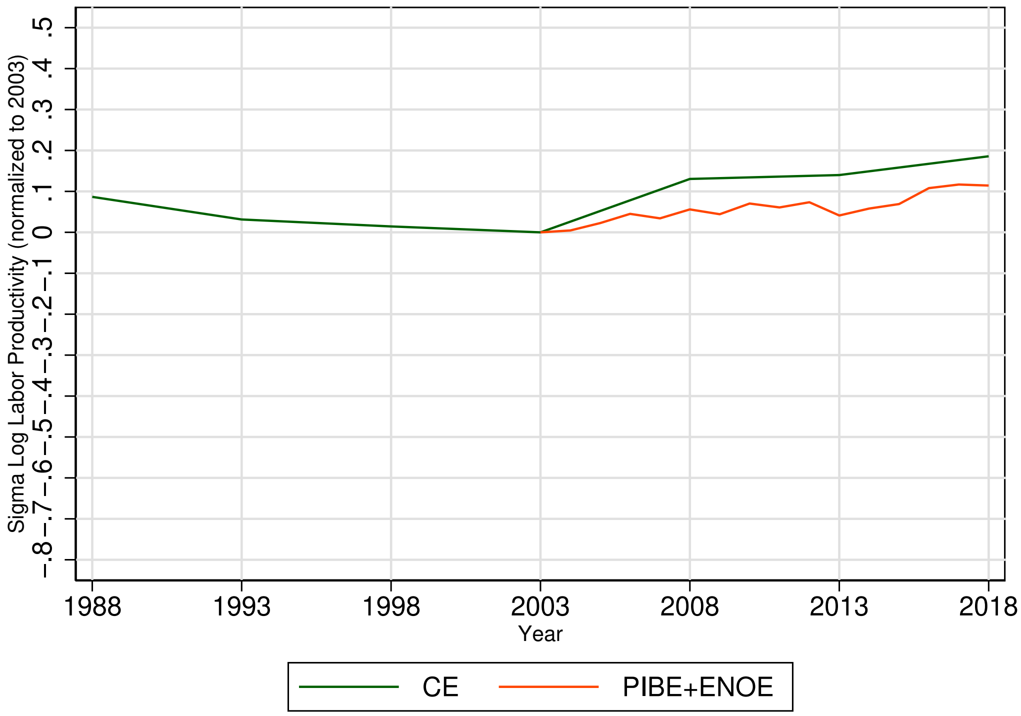
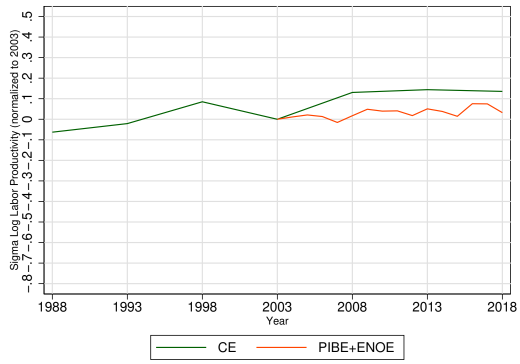


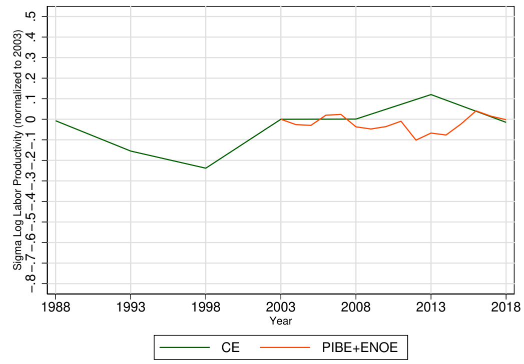
Figure 9: Sigma Manufacturing Log Labor Productivity

Notes: The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. All series were normalized to their corresponding 2003 value. Data sources: CE; PIBE; ENE-ENOE.

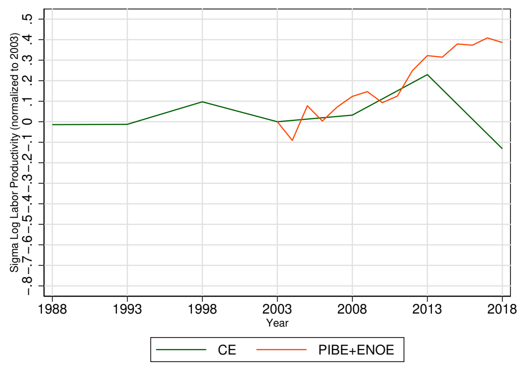
What about sigma-convergence by industry? Figures 10 - 11 show it for each s3-digit sub-sectors. Despite beta-convergence occurring in 5 out of 11 baseline industries for 1988-2018, almost none of them show sigma-convergence for the same period. Only Textile Mills+Textile Product Mills (313-314) displays it in a quantitatively significant way, with Beverage and Tobacco Manufacturing (312) and Nonmetallic Mineral Product Manufacturing (327) showing almost negligible changes. There are also certain discrepancies across datasets, particularly for 2013-2018. Nonetheless, they are consistent with the corresponding beta-convergence coefficients. One plausible explanation for these differences is that, as mentioned earlier, data from ENOE is not necessarily representative at certain industry-state levels, inducing to larger labor-productivity measurement error, and thus, more variation. This is noticeable for Machinery Manufacturing *et al.* (333-336), an industry that is scarce in the South, and for which the corresponding employment measures are not representative.



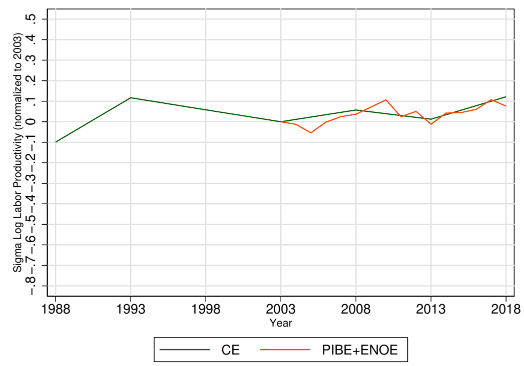
(a) 311: Food Manufacturing



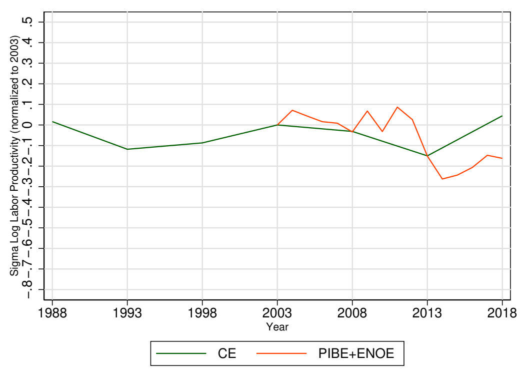
(b) 312: Beverage and Tobacco Product Manufacturing



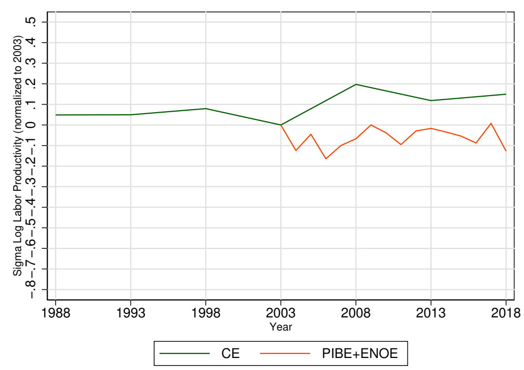
(c) 313-314: Textile Mills; Textile Product Mills



(d) 315-316: Apparel Manufacturing; Leather and Allied Product Manufacturing



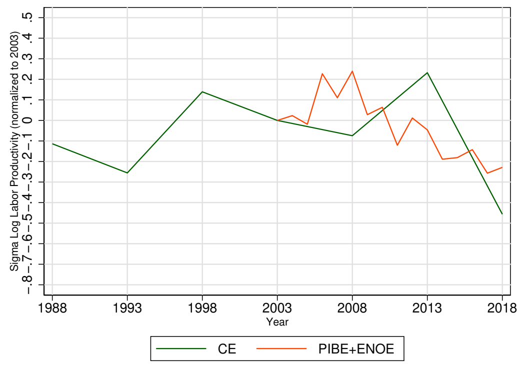
(e) 321: Wood Product Manufacturing



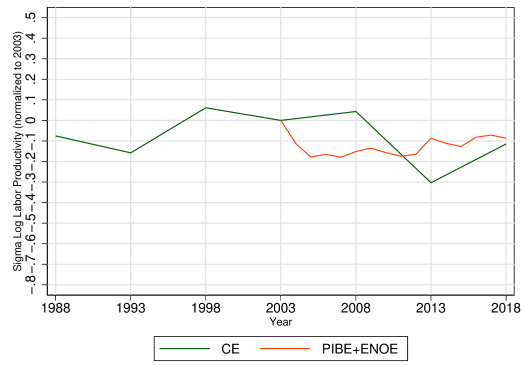
(f) 322-323: Paper Manufacturing; Printing and Related Support Activities

Figure 10: Sigma-convergence by Industry (I) 1998-2018

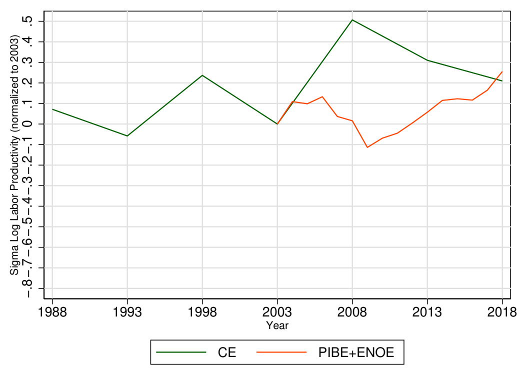
Notes: All series were normalized to their corresponding 2003 value. Data sources: CE; PIBE; ENE-ENOE.



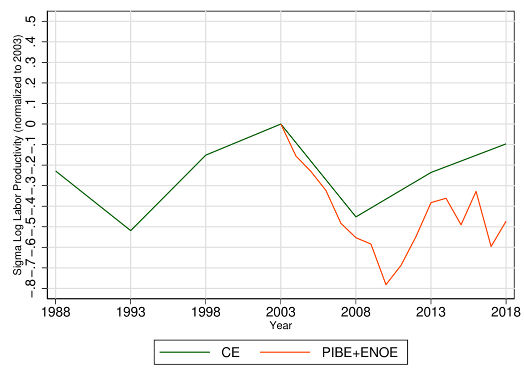
(a) 324-326: Petroleum and Coal Products Manufacturing; Chemical Manufacturing; Plastics and Rubber Products Manufacturing



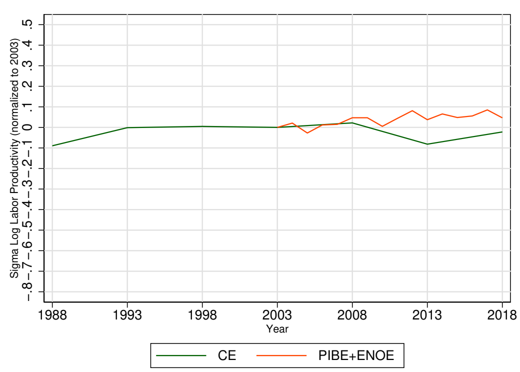
(b) 327: Nonmetallic Mineral Product Manufacturing



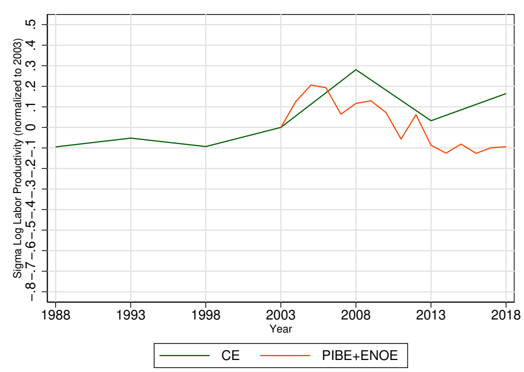
(c) 331-332: Primary Metal Manufacturing; Fabricated Metal Product Manufacturing



(d) 333-336: Machinery Manufacturing; Computer and Electronic Product Manufacturing; Electrical Equipment, Appliance, and Component Manufacturing; Transportation Equipment Manufacturing



(e) 337: Furniture and Related Product Manufacturing



(f) 339: Miscellaneous Manufacturing

Figure 11: Sigma-convergence by Industry (II) 1998-2018

Notes: All series were normalized to their corresponding 2003 value. Data sources: CE; PIBE; ENE-ENOE.

4 What forces account for convergence?

4.1 Regional differences

As Chiquiar (2005) suggests, Mexico's liberalization strengthened the ties between border states and the US. Moreover, it induced the reallocation of production from the center (Mexico City) to the north of the country (Hanson (1998)). Hence, manufacturing productivity growth in the north may have decoupled from the rest of the country, thus promoting convergence within rather than across regions. To see if convergence clubs exist, Table 6 shows the estimates of the cross-sectional specification (3) for different periods, but interacting both initial labor productivity and the set of industry fixed effects with four regional dummies (North, Center-North, Center, South), corresponding to Banxico's regional classification[11].

Two main observations arise regarding s3-digit industries (columns 5-8). First, from 1988 to 2018, the highest convergence rates were found within the Northern and Central regions, at 2.55% and 2.23% per year, respectively, followed by slower convergence rates of 1.5% in the Center and 1.25% in the South. Second, the convergence acceleration in the Northern region, likely due to Mexico's trade liberalization, was particularly notable from 1988 to 1998, at a rate of 5.8% per year. Afterward, convergence in each region continued, tracking a similar path as the national case: a slowdown from 1998 to 2008 and a resurgence from 2008 to 2018.

For aggregate manufacturing (columns 1-4), the highest convergence rate during 1988-2018 was found within the Central region, at a pace of 2.49% per year, followed by the Northern one at 0.78%. The North-Central and Southern regions do not show (statistically significant) convergence. Interestingly, the convergence process within the North and North-Central states also slowed or stopped at the end of the 1990s. Instead, there are signs of divergence in the Southern region during the same period, signaling the absence of a convergence club, plausibly due to the considerable presence of low-productivity States and the lack of a clear leader, although this phenomenon somehow reversed during 2008-2018.

[11] See the Regional Economic Reports: `https://www.banxico.org.mx/publicaciones-y-prensa/reportes-sobre-las-economias-regionales/reportes-economias-regionales.html`. This specification is equivalent to run separate regressions for each region, as assumes convergence occurs within them.

Table 6: Intra-regional Convergence by Decade

	SCIAN 1-digit				SCIAN s3-digit			
	1988-2018	1988-1998	1998-2008	2008-2018	1988-2018	1988-1998	1998-2008	2008-2018
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log initial productivity	-.0078***	-.0319***	-.0055	.0136	-.0255***	-.058***	-.027***	-.043***
XNorth	(.0026)	(.0087)	(.0095)	(.0087)	(.0015)	(.0086)	(.0089)	(.0081)
Log initial productivity	-.0137	-.0615**	-.0152	.0377	-.0152***	-.0331***	-.0137*	-.0273***
XCenter-North	(.0167)	(.0297)	(.0153)	(.036)	(.0025)	(.0085)	(.0079)	(.0093)
Log initial productivity	-.0248***	-.0701***	-.0467**	-.0741**	-.0223***	-.0386***	-.0446***	-.047***
XCenter	(.0026)	(.0111)	(.0203)	(.0298)	(.0028)	(.0059)	(.0102)	(.006)
Log initial productivity	.0139	.035*	.0465	-.0255**	-.0131***	-.0505***	-.0277	-.035***
XSouth	(.0188)	(.0175)	(.0299)	(.012)	(.0041)	(.0149)	(.0165)	(.0049)
Observations	32	32	32	32	352	352	351	351
R-squared	.4521	.6729	.3303	.3328	.4815	.4142	.2909	.3809
State FE	No	No	No	No	No	No	No	No
IndustryXRegion FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimates from (3), interacted with regional dummies. The sample includes all manufacturing SCIAN s3-digit industries except 324-326. Clustered standard errors at the state level in parenthesis. Data source: CE.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

In summary, the results in this section suggest that while all regions show convergence in s3-digit industries from 1988 to 2018, only the Northern and Central regions display convergence in both sub-sectors and the aggregate, forming somewhat convergence clubs. Following the discussion in Section 3.3, this suggests that in those cases either convergence occurred in large, representative industries or that a substantial reallocation happened. For instance, the regular convergence in the Central region might have been, as discussed above, the consequence of the reallocation of production from the center to the north, inducing simultaneously a reallocation of production and labor across industries in the Center States. While convergence should not necessarily occur within regions, as exemplified by the South, it is interesting to note that the post-1998 convergence deceleration documented above is more notable in the North and Central-North regions. In the next section, I discuss some likely factors behind it.

4.2 Some potential determinants of convergence

Since Barro (1991) and Mankiw et al. (1992), various papers in the literature have tried to assess the role of different economic factors on the convergence process. Aside that the inclusion of covariates may reflect some form of conditional convergence, there is a more critical argument against this practice related to endogeneity issues (Durlauf et al. (2005)).

Keeping these caveats in mind, I try to convey the role of specific economic forces that could also affect the convergence process. To do so, I follow a similar approach as Sever (2022) and estimate the following regression,

$$\hat{y_{ij}} = -\beta \ln y_{ij} + \gamma Determinant_{ij} + \lambda Determinant_{ij} \times \ln y_{ij} + D_i + \epsilon_{ij} \tag{7}$$

In this specification, the speed of convergence is also affected by a given determinant, $-\beta + \lambda Determinant_{ij}$. If λ is negative, then convergence occurs despite this force, although it could be accelerated by it. Instead, if λ is positive, then the considered determinant will slow or even revert productivity convergence. Given the potential endogeneity issues discussed above, I try to address them as best as possible. Still, one should see these results more as suggestive correlations rather than causal estimates. Table 7 shows the results.

Table 7: Determinants of Convergence (2008-2018)

	SCIAN 1-digit			SCIAN s3-digit		
	Informality	China Shock		Informality	China Shock	
	(OLS)	(OLS)	(IV)	(OLS)	(OLS)	(IV)
	(1)	(2)	(3)	(4)	(5)	(6)
Log initial productivity	.0127	-.1956	-.2304*	-.0288***	-.0802*	-.0671
	(.0211)	(.146)	(.129)	(.0057)	(.0436)	(.0456)
Log initial productivityXDeterminant	-.0493	.0186	.0219*	-.0017	.0029	.0022
	(.0375)	(.0147)	(.013)	(.0114)	(.0024)	(.0025)
Determinant	.5716	-.2213	-.2607	-.0233	-.0282	-.0198
	(.4754)	(.186)	(.1648)	(.1262)	(.0288)	(.0303)
Observations	32	32	32	351	351	351
R-squared	.1069	.1175	.1135	.2533	.2655	.265
F-statistic			94.1721			732.7787
State FE	No	No	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimates from (7). The sample includes all SCIAN s3-digit manufacturing industries except 324-326. Clustered standard errors at the state level in parenthesis. Data sources: CE; COMTRADE.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

The first force I focus on is informality, given its pervasive presence in the Mexican economy and its unproductive nature (Busso et al. (2012)). Moreover, this force takes particular importance since evidence of cross-country manufacturing convergence from Rodrik (2012) comes exclusively from data from the formal sector. Hence, it is likely that once the informal sector is considered, manufacturing convergence may not occur. To measure the size of the informal sector in each industry and state, I compute the corresponding share of informal employment using ENOE. In particular, I use the share of informal employment in the initial period ($t - s$). Additional details are provided in Appendix A.

The second force I focus on is the so-called China shock. As emphasized by recent literature, the entry of China into the WTO at the end of 2001 represented a negative shock to labor markets, both in the US (Autor et al. (2013)) and in Mexico (Chiquiar et al. (2017)). Moreover, the timing of the entrance coincides with the deceleration of manufacturing convergence documented earlier, as well as the slowdown in manufacturing labor productivity shown in Figure 2. In addition, as seen in Figure 12, it also coincides with a considerable deceleration in Mexico's manufacturing exports to the USA, which could have negatively impacted productivity and, thus, convergence.

To compute the magnitude of the shock, I follow the aforementioned literature and define import penetration in state j and industry i as $\frac{N_{ijt-s}}{N_{it-s}}\Delta M_{it}$, and the overall shock in state j as $\frac{1}{N_{jt-s}}\sum_{i=1}^{I}\frac{N_{ijt-s}}{N_{it-s}}\Delta M_{it}$. Where ΔM_{it} corresponds to the nominal change in dollars in the value of imports of the US from China in industry i, and N stands for the corresponding Mexican employment levels in the initial period. The intuition behind these measures is that increases in US imports of industry i from China, which could lead to a crowding-out of Mexican exports to the US, affect different states given their industry composition. Moreover, I follow Autor et al. (2013) and instrument these metrics using analogous penetration ones, but for changes in Chinese imports from other countries different than the US. To facilitate interpretation, I take the log of these measures. In Appendix A, I discuss additional details.

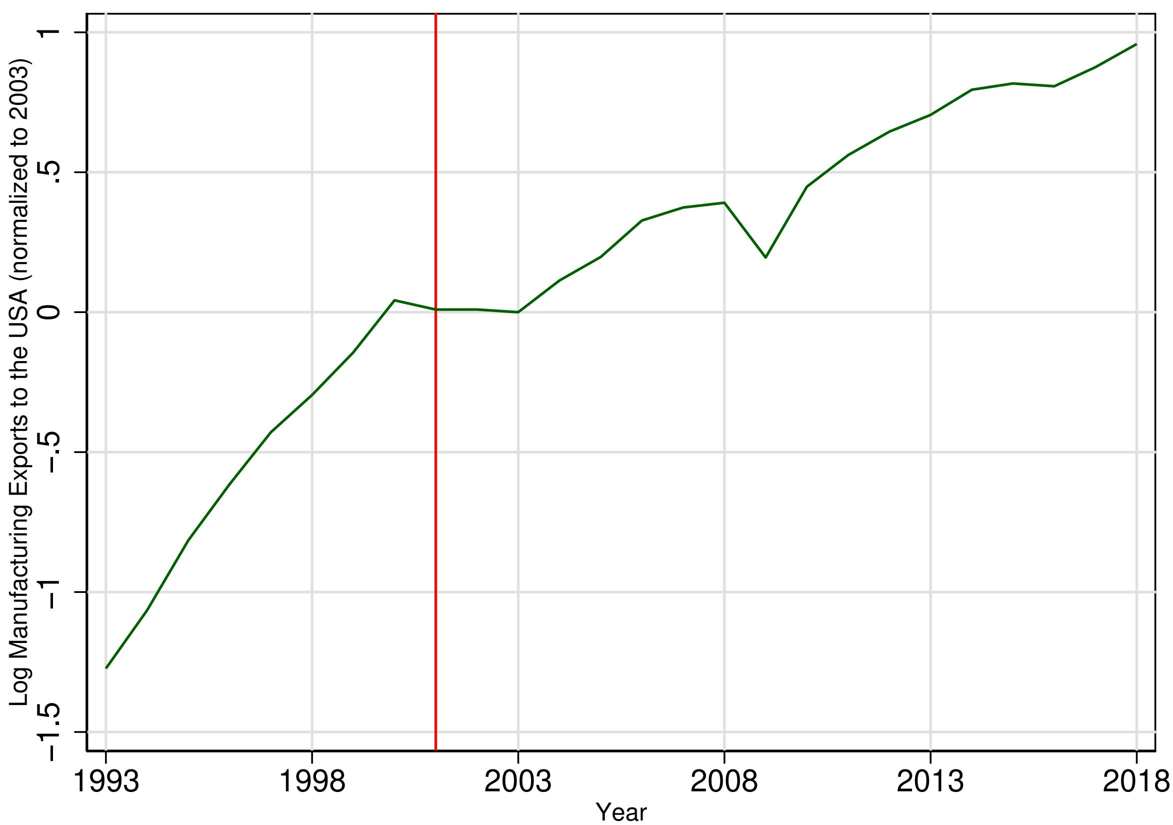


Figure 12: Evolution of manufacture exports to the USA

Notes: The sample includes all SCIAN s3-digit manufacturing industries. All series were normalized to their corresponding 2003 values. Data sources: SIE. Vertical red line: entry of China to the WTO (2001).

Overall, the results in Table 7 suggest that informality does not appear to significantly affect the convergence process in manufacturing, either at the sub-industry or aggregate level, over the past decade. In contrast, the China shock appears to hurt aggregate convergence, as indicated by the IV estimates (Column (3)), statistically significant at 10%. In that sense, Figure 13 shows the marginal effect of initial labor productivity for different shock magnitudes. As can be seen, had all states received the 10th percentile of the China Shock (9.26), convergence would have occurred at 2.7% per year ($-0.2371+0.0227\times9.26$). Note that for convergence to be affected, the China Shock must have differentially impacted the growth rates of low vis-a-vis high productivity states, which seems to be the case, as the partial effect of the China Shock is more pronounced for low-productivity ones: $-0.2607+0.0219\times$Log initial productivity. Thus, despite the China Shock concentrated in high-productivity states as the Northern ones (see Appendix A), the low-productivity ones are more sensitive to it. Moreover, these results also suggest that the underperformance of some key industries, which contributed to the failure of aggregate convergence after 2003, may be partially due to the disruption caused by China's penetration into the US market, Mexico's primary trade partner.

In fact, as seen in Figure B.2.1, the service sector did not exhibit any disruption in labor productivity after China entered the WTO, as manufacturing did. This additional observation strengthens the idea that the China Shock is a plausible candidate for understanding the 2000s convergence breakdown. Moreover, in Table 8, I present estimates of the convergence in the service sector by pooling different 1-digit service industries and controlling for industry fixed effects analogously to the s3-digit estimates for manufacturing, showing no reduction in labor productivity convergence for the service sector after 2003. Instead, opposite to what happened to the manufacturing sector, it has been increasing in the last decades at a notably faster pace. While the estimates themselves are interesting, the main point of this exercise is to demonstrate that manufacturing and services show contrarian experiences in the convergence process over time, as the latter does not show any particular breakdown around the timing of the China Shock[12].

[12] From the potential set of service industries, I exclude Finance and Insurance (52) and Management of Companies and Enterprises (55) because of their particular nature, as well as Educational Services (61) and Health Care and Social Assistance (62) due to the large government presence in them. Hence, the analysis

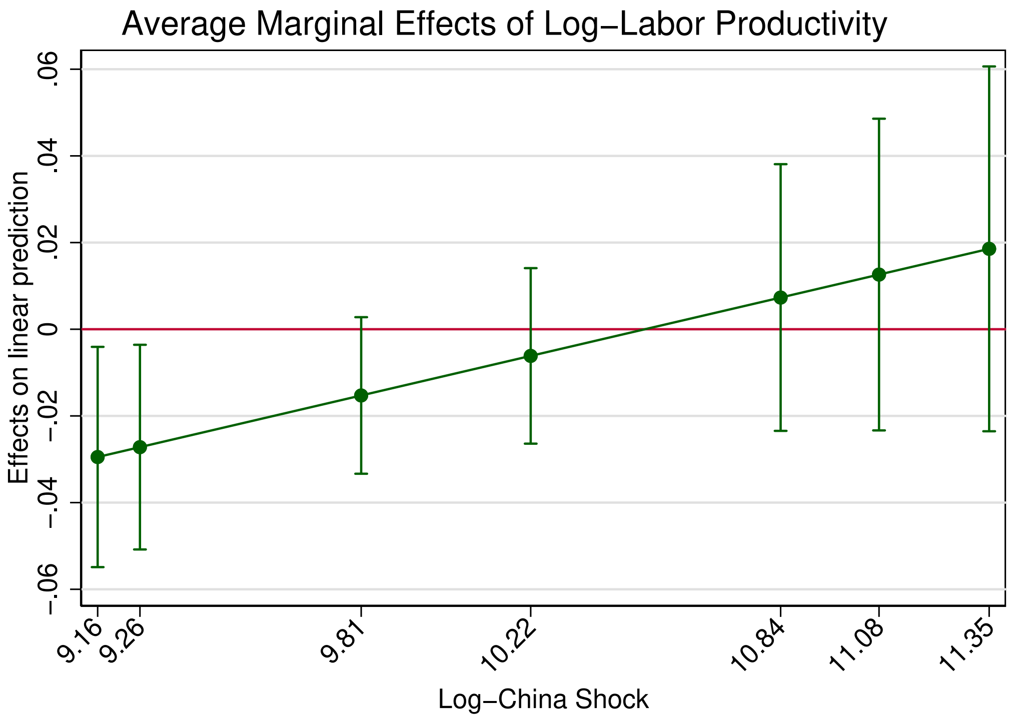


Figure 13: Interaction between convergence and the China shock

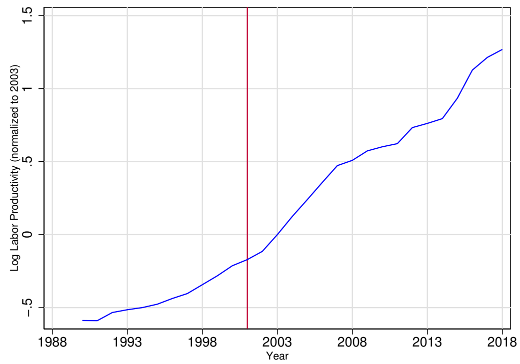
Notes: Estimates from Column (3) in Table 7. The sample includes all SCIAN s3-digit manufacturing industries except 324-326. 95% confidence intervals constructed from robust standard errors. Data sources: CE; COMTRADE.

Table 8: Unconditional Convergence in the Service Sector

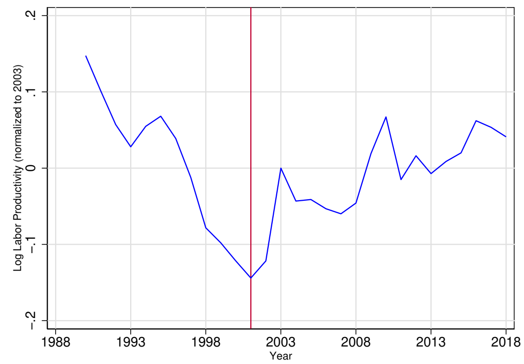
	SCIAN 1-digit			
	1988-2018	1988-1998	1998-2008	2008-2018
	(1)	(2)	(3)	(4)
Log initial productivity	-.0179***	-.0278	-.047***	-.0571***
	(.0039)	(.0192)	(.0073)	(.0105)
Observations	186	190	184	181
R-squared	.4019	.1643	.6674	.6608
State FE	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes

Notes: Estimates from (3). The sample includes 6 SCIAN 1-digit services sectors (51,53,54,56,71,72). Clustered standard errors at the state level in parenthesis. Data sources: CE.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

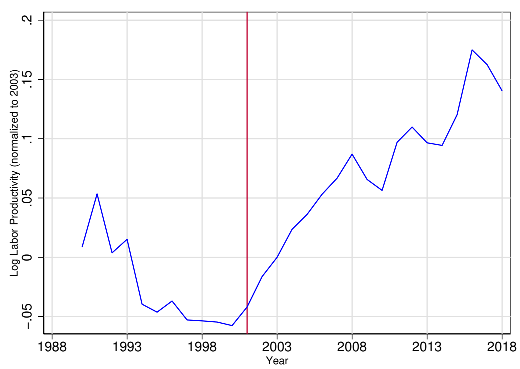
includes the following 6 sectors: Information (51), Real Estate and Rental and Leasing (53), Professional, Scientific, and Technical Services (54), Administrative and Support and Waste Management and Remediation Services (56), Arts, Entertainment, and Recreation (71), and Accommodation and Food Services (72).



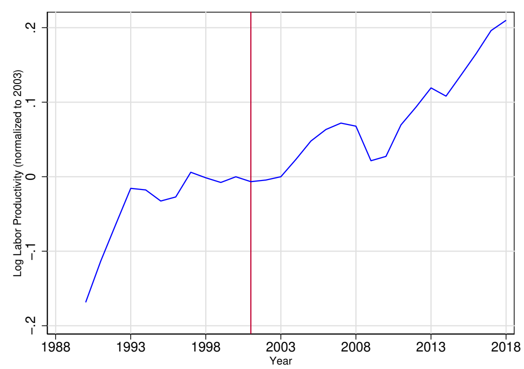
(a) 51: Information



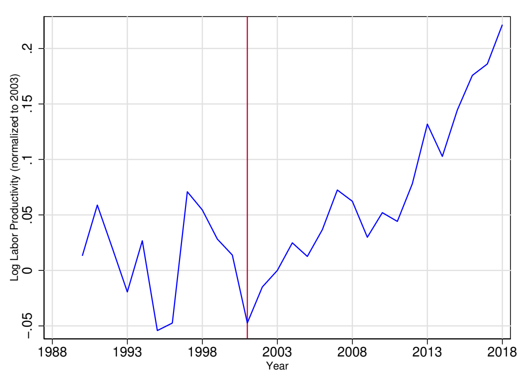
(b) 53: Real Estate and Rental and Leasing



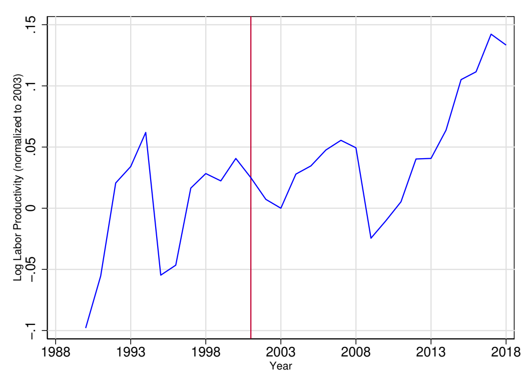
(c) 54: Professional, Scientific, and Technical Services



(d) 56: Administrative and Support and Waste Management and Remediation Services



(e) 71: Arts, Entertainment, and Recreation



(f) 72: Accommodation and Food Services

Figure 14: Evolution of service labor productivity, different industries.

Notes: All series were normalized to their corresponding 2003 value. Data sources: CE; PIBE; ENE-ENOE. Vertical red line: entry of China to the WTO (2001).

5 Conclusion

In this paper, I document that, unlike the international experience, unconditional convergence in the Mexican manufacturing sector is only slightly present. This convergence process has been heterogeneous across industries, aggregation levels, and periods. From 1988 to 2018, unconditional convergence was observed only at the s3-digit industry level, with a convergence rate of 1.22% per year. However, this convergence is not solely characterized by an increase in followers' labor productivity but also by a decrease in that of leaders.

Convergence was present at all levels of aggregation until 1998, with the 1988-1998 period being the strongest. During this period, the convergence rate in manufacturing productivity was 4.24%, accompanied by sigma-convergence as well. Shift-sharing analysis suggests that the aggregate convergence process stopped due to the underperformance of several key industries and the failure to reallocate employment toward more productive sectors.

Robustness checks indicate that the results do not vary significantly when using different price indexes or measures of employment. However, they change to some extent when using metrics of labor productivity from other datasets. Therefore, if we assume that there is measurement error, as hinted by the data, the results imply that the coefficients mentioned above are an upper bound of the actual convergence process. An IV strategy, in which one dataset's measure is used as an instrument for the other, supports this conclusion.

It is an open question why the results of manufacturing convergence across Mexico differ from cross-country ones. One reason could be the fact that Rodrik (2012) uses data mainly from the *formal* sector. Nonetheless, despite the large presence of the informal sector in the Mexican economy and its unproductive nature (Busso et al. (2012)), I show that it does not seem to play a significant role. Another reason could be that, as Chiquiar (2005) suggests, Mexico's liberalization strengthened the ties between border states and the U.S. So, it is likely that manufacturing convergence occurred more rapidly among regions connected by trade. Accordingly, I show that convergence has occurred at all levels in the Northern Region, although perhaps surprisingly, the Central Region shows higher convergence rates in the aggregate.

Future research may consider the results in this paper as a motivation to understand further why convergence changed in the early 2000s. While this study suggests that the underperformance of critical industries and a lack of reallocation played a significant role, it is unclear *why* these trends began during this period. One potential explanation is China's inclusion in the WTO in 2001, which hurt Mexican labor markets (Chiquiar et al. (2017)). In addition, the timing coincides with both the deceleration of manufacturing exports to the USA as well as a reduced growth of labor productivity, which notably contrasts with what was observed during the 1990s. Thus, following Autor et al. (2013), I construct Mexican states' exposure to the USA's China shock, showing it had a negative effect on manufacturing convergence in the past decade. In that sense, the penetration of China's exports to the USA, which crowded out Mexican ones, would have also affected Mexico's labor productivity. To further strengthen the idea that the China shock is a plausible explanation for the 2000s deceleration in manufacturing convergence, I also show that neither the service's labor productivity dynamics nor the service's convergence exhibited any breakdown during that time.

Still, there are other channels to explore to better understand the recent failure in aggregate manufacturing convergence. For instance, the role of automation in convergence is an interesting venue, as its effect may be ambiguous in principle. On one side, large automation processes make it less attractive to off-shore production to relatively cheap and labor-abundant countries like Mexico (Rodrik (2018)), hurting productivity. On the other hand, a greater demand for intermediates from those automated industries could boost it. Due to current data limitations on Mexican sectoral automation, I leave this mechanism for future exploration.

Lastly, the widespread barriers to resource reallocation documented in the literature (Busso and Madrigal (2013), Hsieh and Klenow (2014)) suggest that a promising area for future research is the joint study of misallocation and convergence. For instance, it will be interesting to study how managerial practices shape misallocation (Bloom et al. (2022)) and convergence. Moreover, going forward, expanding this class of empirical investigations to other countries and regions is important. The richness of the experiences will help us understand under what conditions and contexts we can expect to observe convergence in manufacturing industries and how generalizable the previous cross-country evidence is.

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A Data Appendix

Census

As mentioned in the text, I obtained 1998, 2003, 2008, 2013, and 2018 census data from INEGI's webpage. In particular, I downloaded the tabulates reported in their Censal Information System (Sistema Automatizado de Información Censal, SAIC). Although all this information uses SCIAN nomenclature, they differ in their version. Tabulates for 2003-2013 use SCIAN 2013 codes, while tabulates for 1998 and 2018 use SCIAN 2007 and 2018 codes, respectively. However, as the 2019 SAIC manual reports (pp. 48-54, `https://www.inegi.org.mx/contenidos/app/saic/saic_historico_metodologico_ce2019_23_10.pdf`), there has been no changes in the SCIAN coding system that could alter the mapping at 3-digit industries for the manufacturing sector. Hence, I do not homologate the different censal versions as they are all comparable at the level of analysis.

For the 1988 and 1993 censuses, data was digitized from INEGI's physical records.[13]. Since this data is reported in CMAP industry codes, I map them into SCIAN 2002 using INEGI's conversion tables[14]. When a CMAP code is mapped to several SCIAN ones, I use equal weights to distribute the corresponding value of that industry. For example, the CMAP code 311901 maps to both 311320 and 311330 SCIAN ones, so I split production of the former 50/50 in the latter two. The following Table summarizes the sources and characteristics of each dataset.

[13] Juan Carmona, Ruben Perez, Ezequiel Piedras, and Gerardo Sanchez digitized data for 1988, while data for 1993 was digitized by UNAM's library and facilitated by Omar Contreras.

[14] SCIAN Mexico 2002-CMAP 1994 from `https://www.inegi.org.mx/app/scian/`. I do not homologate the 2002 SCIAN version to other years either, as the changes between it and the 2007 one are almost negligible.

Year	Link	Industry Codes
1988	https://www.inegi.org.mx/programas/ce/1989/	CMAP 1994 (mapped to SCIAN 2002)
1993	https://www.inegi.org.mx/programas/ce/1994/	CMAP 1994 (mapped to SCIAN 2002)
1998	https://www.inegi.org.mx/app/saich/v1/?evt=1999	SCIAN 2007
2003-2013	https://www.inegi.org.mx/app/saich/v2/	SCIAN 2013
2018	https://www.inegi.org.mx/app/saic/default.html	SCIAN 2018

ENE-ENOE

I downloaded ENE and ENOE micro-data from `https://www.inegi.org.mx/programas/ene/2004/#Microdatos` and `https://www.inegi.org.mx/programas/enoe/15ymas/#Microdatos`, respectively. To clean them, I follow INEGI's standard procedure described in *Conociendo la base de datos de la ENOE*: `https://www.inegi.org.mx/contenidos/productos/prod_serv/contenidos/espanol/bvinegi/productos/metodologias/est/702825001357.pdf`). The correspondence between sources follows INEGI's methodology (*Conociendo la base de datos de la ENE con criterio ENOE*: `https://www.inegi.org.mx/contenidos/productos/prod_serv/contenidos/espanol/bvinegi/productos/metodologias/est/Conociendo_bd_ENE.pdf`).

GDP

State GDP data for 2003-2018, disaggregated at s3-digit industries, comes from INEGI's *Producto Interno Bruto por entidad federativa. Serie detallada*. While aggregated for 1980-2018 from *Producto Interno Bruto por entidad federativa. Serie retropolada reducida.* Both can be downloaded from `https://www.inegi.org.mx/programas/pibent/2013/#Datos_abiertos`.

KLEMS

I downloaded KLEMS data from INEGI's open-source: https://www.inegi.org.mx/programas/ptf/2013/#Datos_abiertos. The main series used in the analysis are,

1. Nominal value-added (ptf150_293_ptf_165)
2. Total employment (ptf150_293_ptf_244)
3. Total hours worked (ptf150_293_ptf_172)

Population

Population data comes from the National Council of Population (Consejo Nacional de Población, CONAPO) webpage: https://datos.gob.mx/busca/dataset/proyecciones-de-la-poblacion-de-mexico-y-de-las-entidades-federativas-2016-2050.

Prices

1. Producer Price Index (1981-2018): Organization for Economic Co-operation and Development, Domestic Producer Prices Index: Manufacturing for Mexico [MEXPPDMAINMEI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/MEXPPDMAINMEI, January 24, 2022.

2. GDP deflator (2003-2018): the corresponding GDP deflator by state and industry (s3-digit) from States National Accounts (see above).

Informality

I compute the share of informality in each industry and state from the ENOE micro-data. Specifically, I consider the pre-codified variable by INEGI that accounts for the informal sector[15].

[15] That is, TUE2=5. See https://www.inegi.org.mx/contenidos/productos/prod_serv/contenidos/espanol/bvinegi/productos/metodologias/est/702825001357.pdf

COMTRADE

I obtained import data from China for different countries from the UN COMTRADE webpage: `https://comtrade.un.org/data`. I downloaded imports data, as opposed to exports data from China, since the former are better recorded[16]. I also downloaded the data in its Harmonized System (HS) classification version, under the option "as reported". Subsequently, I converted the different HS versions of the data to NAICS using the R package 'concordance' (Liao et al. (2020)). Note that, at 3 digits of aggregation, the correspondence between NAICS (USA) and SCIAN (Mexico) are equivalent (`https://biblioteca.semarnat.gob.mx/janium/Documentos/Ciga/libros2018/CD003192.pdf`).

Due to the construction of the China shock instrument (see below), in addition to the US data, I also obtained imports data from China for the following countries: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. For each country, I downloaded separately annual data from 2003 to 2018.

Manufacturing Exports (SIE)

Exports to the USA (Serie: CE171) from `https://www.banxico.org.mx/SieInternet/`.

China Shock

To instrument the China shock to the US, I follow Autor et al. (2013) and use import data from China for the set of countries mentioned above but use employment weights from previous periods. So the instruments at sub-industry and the aggregate are defined as $\frac{N_{ijt-s-k}}{N_{it-s-k}}\Delta M_{it}^{other}$ and $\frac{1}{N_{jt-s-k}}\sum_{i=1}^{I}\frac{N_{ijt-s-p}}{N_{it-s-p}}\Delta M_{it}^{other}$, respectively. Where ΔM_{it}^{other} is the nominal change in dollars in the value of imports from China of all these countries in the industry i, and N stands for the corresponding Mexican employment levels in p years before the initial period. More specifically, given that I study the role of this force on the convergence between 2008 and 2018, the employment shares are built using 2003 data.

[16] See for example `https://wits.worldbank.org/wits/wits/witshelp/content/data_retrieval/T/Intro/B2.Imports_Exports_and_Mirror.htm`.

Geographical Distribution of the China shock

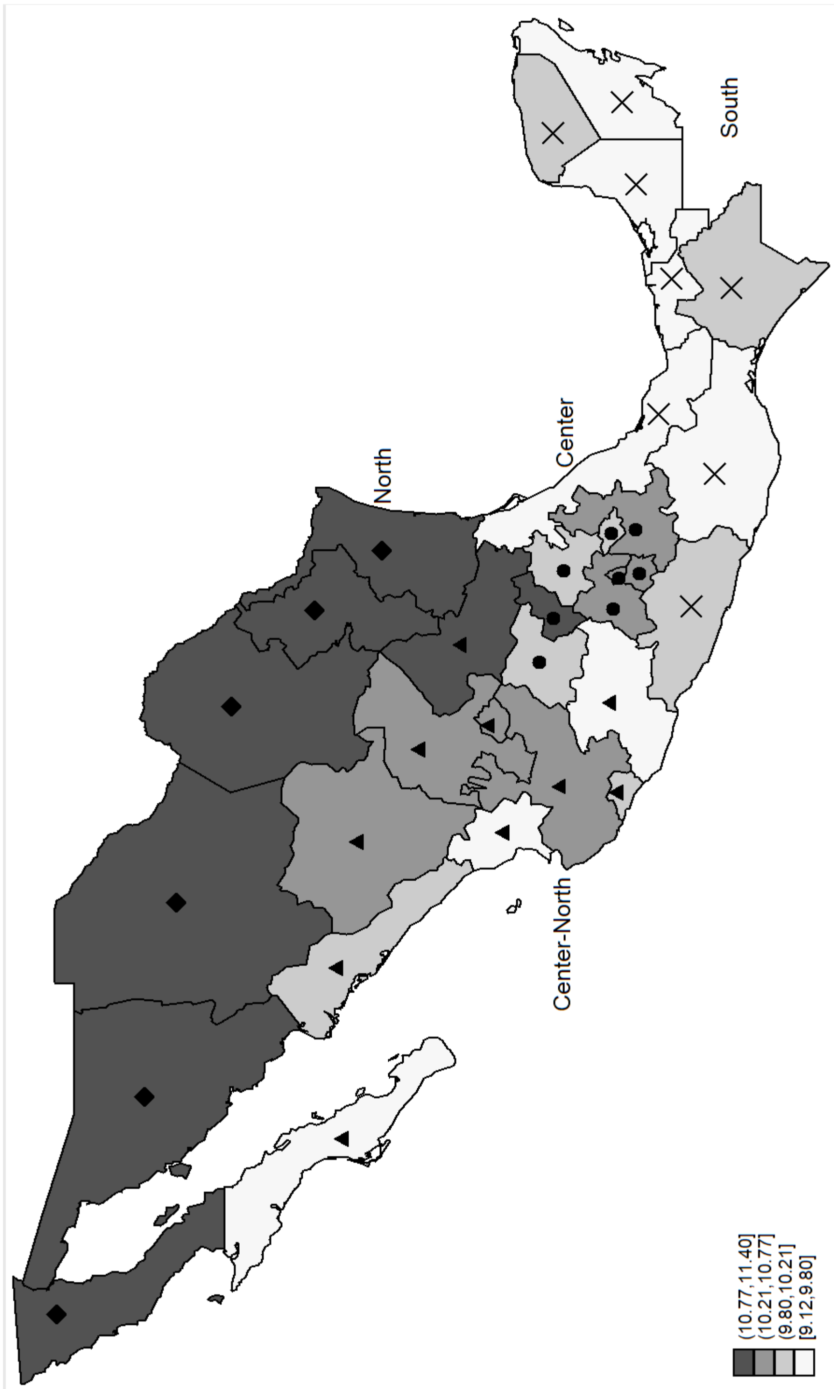


Figure A.1: Regional distribution of the China shock

Notes: The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. Data sources: CE; COMTRADE.

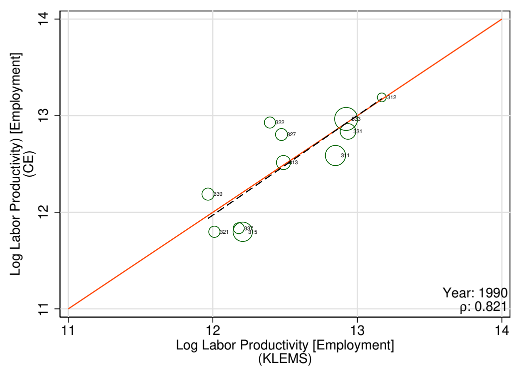
TFP

I compute TFP for each s3-digit industry as follows. First, I assume that for each industry i in State j production exhibits constant returns to scale in the form of a Cobb-Douglas production function: $Y_{ij} = A_{ik} K_{ij}^{\alpha_i} N_{ij}^{1-\alpha_i}$. However, I assume that the capital share, α, only varies across industries, but not across States. To recover these shares, I follow the misallocation literature (Hsieh and Klenow (2009)) and obtain them using data from the USA, implicitly assuming that those computed with Mexican data may include wedges that reflect distortions. I obtain the corresponding data from the Bureau of Labor Statistics (BLS): `https://www.bls.gov/productivity/tables/`[17]. To account for potential technological changes in the intensity of capital usage over time, I compute these shares annually and then average them over a 5-year period (e.g., the 1998 share is the average of those from 1994 to 1998). Finally, I recover TFP as a residual from the production function by mapping the censal variable Gross Fixed Assets (*Activos Fijos Brutos*) to K. Moreover, I note as Bernard and Jones (1996), that $TFP_j \approx \sum_i TFP_{ij}\omega_{ij}$, so TFP of a State j is approximately a weighted average of the sectoral TFPs, where the weights (ω_{ij}) are given by the corresponding share of each industry i in the State's manufacture-wide value-added. By doing so, I somehow incorporate into aggregate TFP the heterogeneity of each state's industry composition instead of recovering it using aggregate shares. I deflate these TFP measures using the price indexes mentioned in the text.

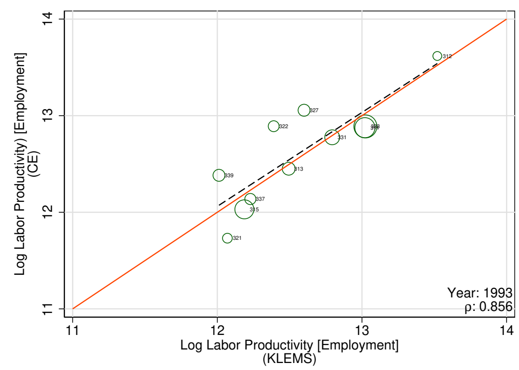
[17] Specifically, from the section: TOTAL FACTOR PRODUCTIVITY AND RELATED MEASURES: Major industries – March 21, 2024.

B Additional Results

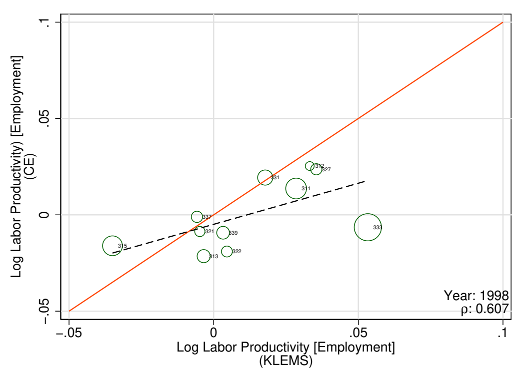
B.1 Validation of Digitized Data



(a) Correlation Log Labor Productivity (1988), s3-digit



(b) Correlation Log Labor Productivity (1993), s3-digit

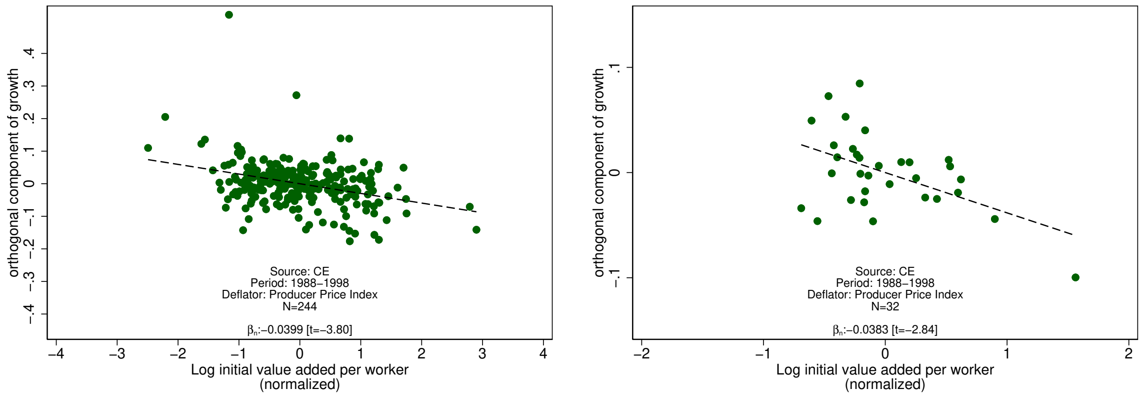


(c) Correlation Growth in Labor Productivity (1988/1990-1998), s3-digit

Figure B.1.1: Correlation Growth and Log Labor Productivity across datasets (1988/1990-1993).

Notes: The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. 1990 KLEMS data is considered as of 1988. Deflator: Producer Price Index. Data sources: CE; KLEMS.

B.2 Unconditional Convergence (CMAP Nomenclature)



(a) 2-digit Manufacturing Sectors

(b) 1-digit Manufacturing

Figure B.2.1: Convergence in 2-digit Manufacturing Sectors and Manufacture-wide Labor Productivity (CMAP)

Notes: Estimates from (3). The sample includes all CMAP 2-digit manufacturing industries except 35 (Chemicals, oil, coal products, rubber, and plastic). t-statistic from clustered standard errors at the state level. Data sources: CE.

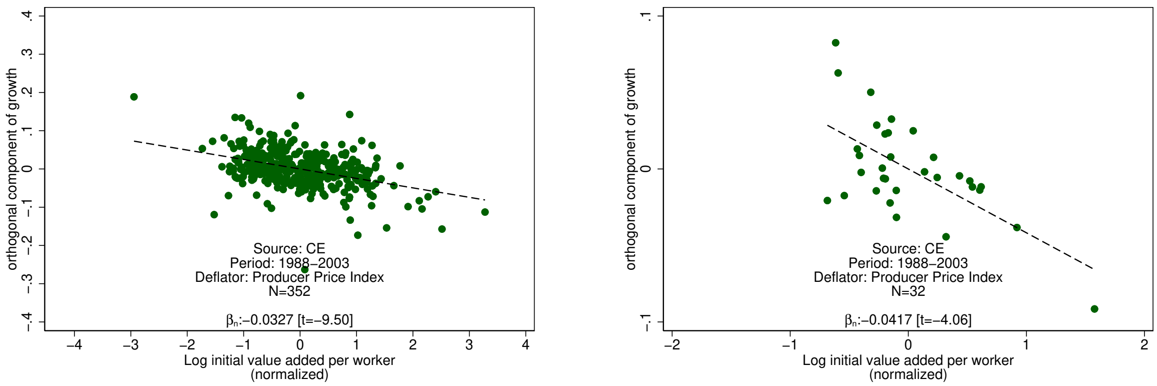
B.3 Correlation between CE and PIBE+ENOE measures

Table B.3.1: Correlation Growth and Levels, across datasets (2008-2018)

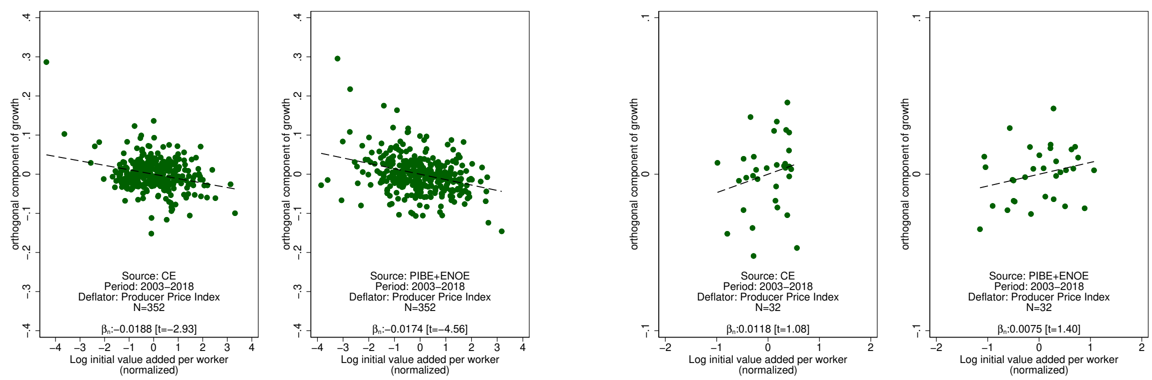
	SCIAN 1-digit			SCIAN s3-digit		
	Value-Added	Employment	Labor Productivity	Value Added	Employment	Labor Productivity
	(1)	(2)	(3)	(4)	(5)	(6)
Levels: 2008	.987	.959	.854	.939	.917	.721
Levels: 2018	.984	.968	.873	.931	.925	.709
Growth: 2008-2018	.644	.682	.355	.363	.389	.085

Notes: The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. Data sources: CE; PIBE; ENOE.

B.4 Convergence by Period: 1988-2003, 2003-2018



(a) 1988-2003

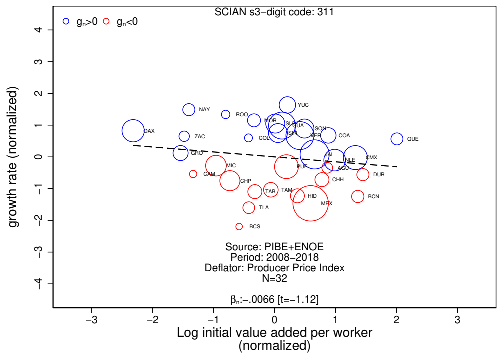


(b) 2003-2018

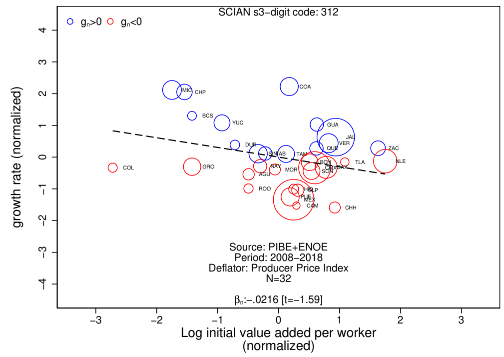
Figure B.4.1: Convergence in Manufacturing Sector (1988-2003), (2003-2018)

Notes: Estimates from (3). The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. t-statistic from clustered standard errors at the state level. Data sources: CE; PIBE; ENE-ENOE.

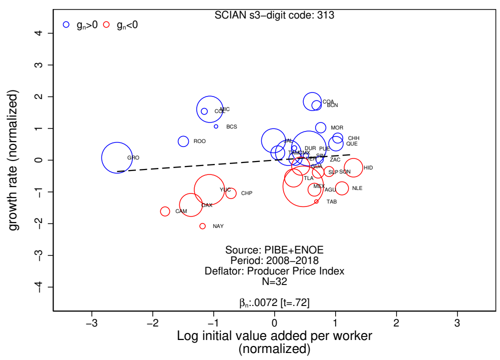
B.5 Convergence by Industry: PIBE+ENOE (2008-2018)



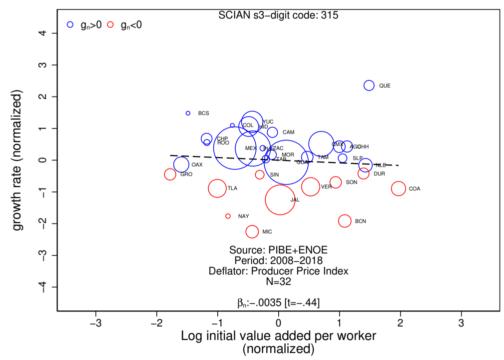
(a) 311: Food Manufacturing



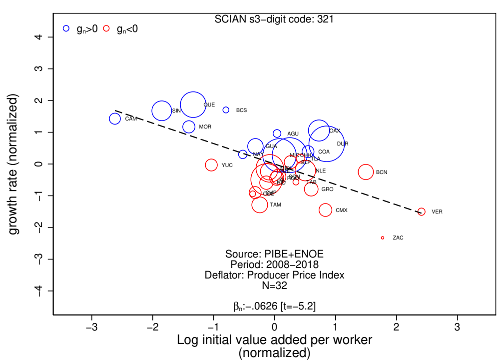
(b) 312: Beverage and Tobacco Product Manufacturing



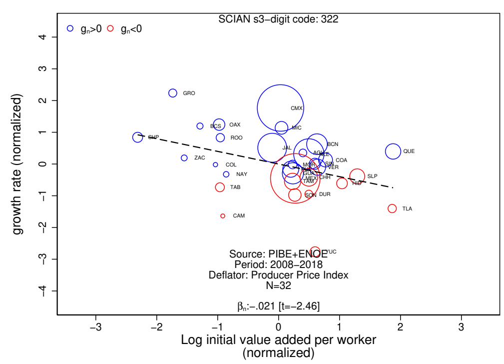
(c) 313-314: Textile Mills; Textile Product Mills



(d) 315-316: Apparel Manufacturing; Leather and Allied Product Manufacturing



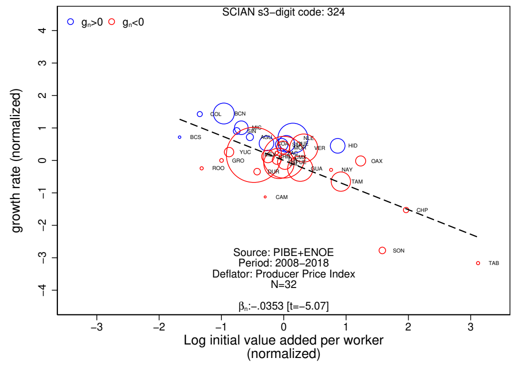
(e) 321: Wood Product Manufacturing



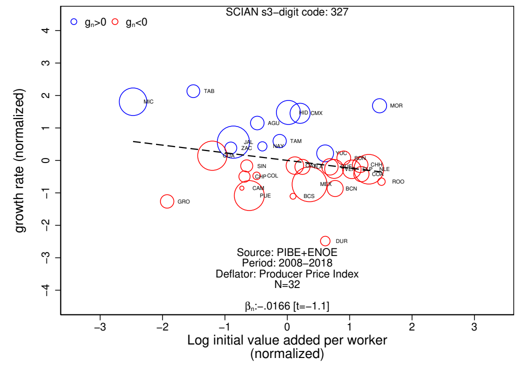
(f) 322-323: Paper Manufacturing; Printing and Related Support Activities

Figure B.5.1: Convergence by Industry (I) 2008-2018

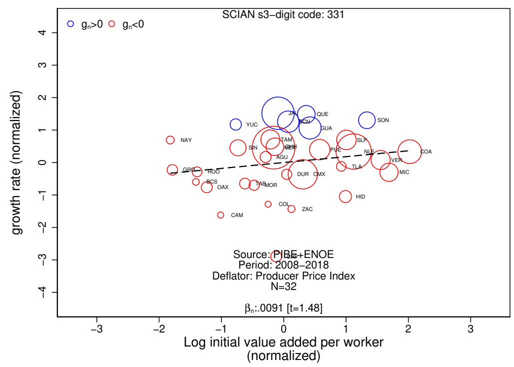
Notes: Estimates from $\hat{y_j^i} = -\beta^i \ln y_j + \epsilon_j,\ i \in \{311, 312, \dots 339\}$. t-statistic from robust standard errors. The size of markers correspond to the importance of employment at a national level in the initial period. Data sources: PIBE; ENOE.



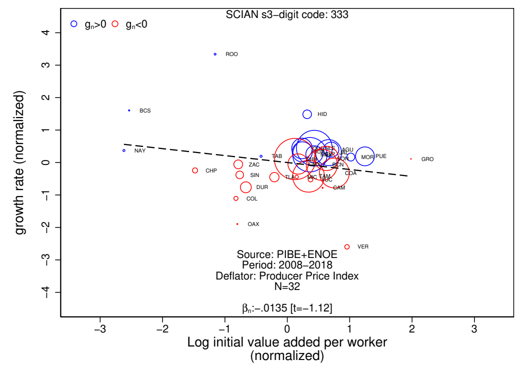
(a) 324-326: Petroleum and Coal Products Manufacturing; Chemical Manufacturing; Plastics and Rubber Products Manufacturing



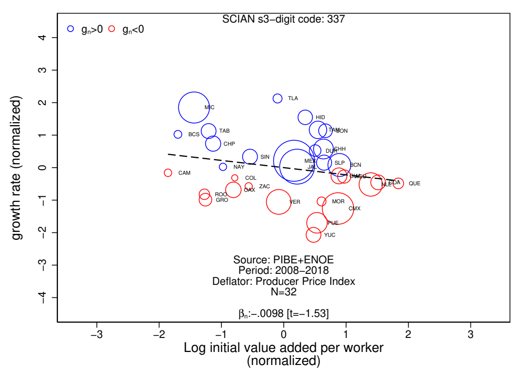
(b) 327: Nonmetallic Mineral Product Manufacturing



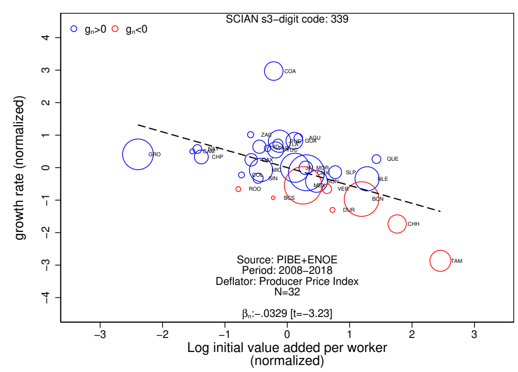
(c) 331-332: Primary Metal Manufacturing; Fabricated Metal Product Manufacturing



(d) 333-336: Machinery Manufacturing; Computer and Electronic Product Manufacturing; Electrical Equipment, Appliance, and Component Manufacturing; Transportation Equipment Manufacturing



(e) 337: Furniture and Related Product Manufacturing



(f) 339: Miscellaneous Manufacturing

Figure B.5.2: Convergence by Industry (II) 2008-2018

Notes: Estimates from $\hat{y^i_j} = -\beta^i \ln y_j + \epsilon_j$, $i \in \{311, 312, \ldots 339\}$. t-statistic from robust standard errors. The size of markers corresponds to the importance of employment at a national level in the initial period. Data sources: PIBE; ENOE.

B.6 Include Petroleum Products Manufacturing (324-326)

Table B.6.1: Convergence in Manufacturing Sector by Decade. All Sub-sectors

	SCIAN 1-digit		SCIAN s3-digit		SCIAN 3-digit	
	(1)	(2)	(3)	(4)	(5)	(6)
Log initial productivity	-.0185*	-.0304*	-.0281***	-.0335***	-.039***	-.0388***
	(.01)	(.0153)	(.0026)	(.006)	(.0032)	(.0066)
Log initial productivity, 1998		.0331*		.009		.0004
		(.0171)		(.0101)		(.0096)
Log initial productivity, 2008		.0051		.006		-.0009
		(.0222)		(.0078)		(.0064)
Observations	95	95	1140	1140	1868	1868
R-squared	.1193	.1429	.2297	.2317	.2549	.2549
State FE	No	No	No	No	No	No
Year FE	No	No	No	No	No	No
Industry FE	No	No	No	No	No	No
Year-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The sample includes all SCIAN s3-digit manufacturing industries. Clustered standard errors at the state level in parenthesis. Data sources: CE.
*p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01

B.7 Conditional Convergence

Table B.7.1: Conditional Convergence in Manufacturing Sector by Decade

	SCIAN 1-digit		SCIAN s3-digit		SCIAN 3-digit	
	(1)	(2)	(3)	(4)	(5)	(6)
Log initial productivity	-.088***	-.0976***	-.0418***	-.0506***	-.0586***	-.0566***
	(.0126)	(.0119)	(.0041)	(.0078)	(.0051)	(.0089)
Log initial productivity, 1998		.0117		.0188**		-.0015
		(.0175)		(.0082)		(.0108)
Log initial productivity, 2008		.0177		.0065		-.0038
		(.0122)		(.0073)		(.0078)
Observations	96	96	1054	1054	1641	1641
R-squared	.7152	.7268	.3169	.326	.3304	.3306
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
Industry FE	No	No	No	No	No	No
IndustryXYear FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. Clustered standard errors at the state level in parenthesis. Data sources: CE.
*p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01

B.8 TFP convergence

Table B.8.1: TFP Convergence by Decade

	SCIAN 1-digit				SCIAN s3-digit			
	1988-2018	1988-1998	1998-2008	2008-2018	1988-2018	1988-1998	1998-2008	2008-2018
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All								
Log initial productivity	-.0161**	-.0346**	-.0394	-.0264**	-.0191***	-.0531***	-.0227***	-.0449***
	(.0068)	(.0132)	(.0349)	(.012)	(.0017)	(.0058)	(.0047)	(.0037)
Observations	32	32	32	32	352	352	351	351
R-squared	.2592	.2184	.1338	.1954	.6879	.374	.5927	.5872
Panel B: Without Outliers								
Log initial productivity	-.0098	-.0203	.0006	-.0171**	-.0188***	-.0523***	-.0221***	-.0444***
	(.0084)	(.0144)	(.0111)	(.008)	(.0018)	(.0062)	(.005)	(.0038)
Observations	31	31	31	31	341	341	340	340
R-squared	.0804	.0612	.0001	.1167	.682	.3598	.5959	.5893
State FE	No	No	No	No	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimates from (3). The sample includes all manufacturing SCIAN s3-digit industries except 324-326. Clustered standard errors at the state level in parenthesis. Data source: CE. Omitted States in Panel B: Morelos (1988), Campeche (1998), Baja California Sur (2008).
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

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