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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.

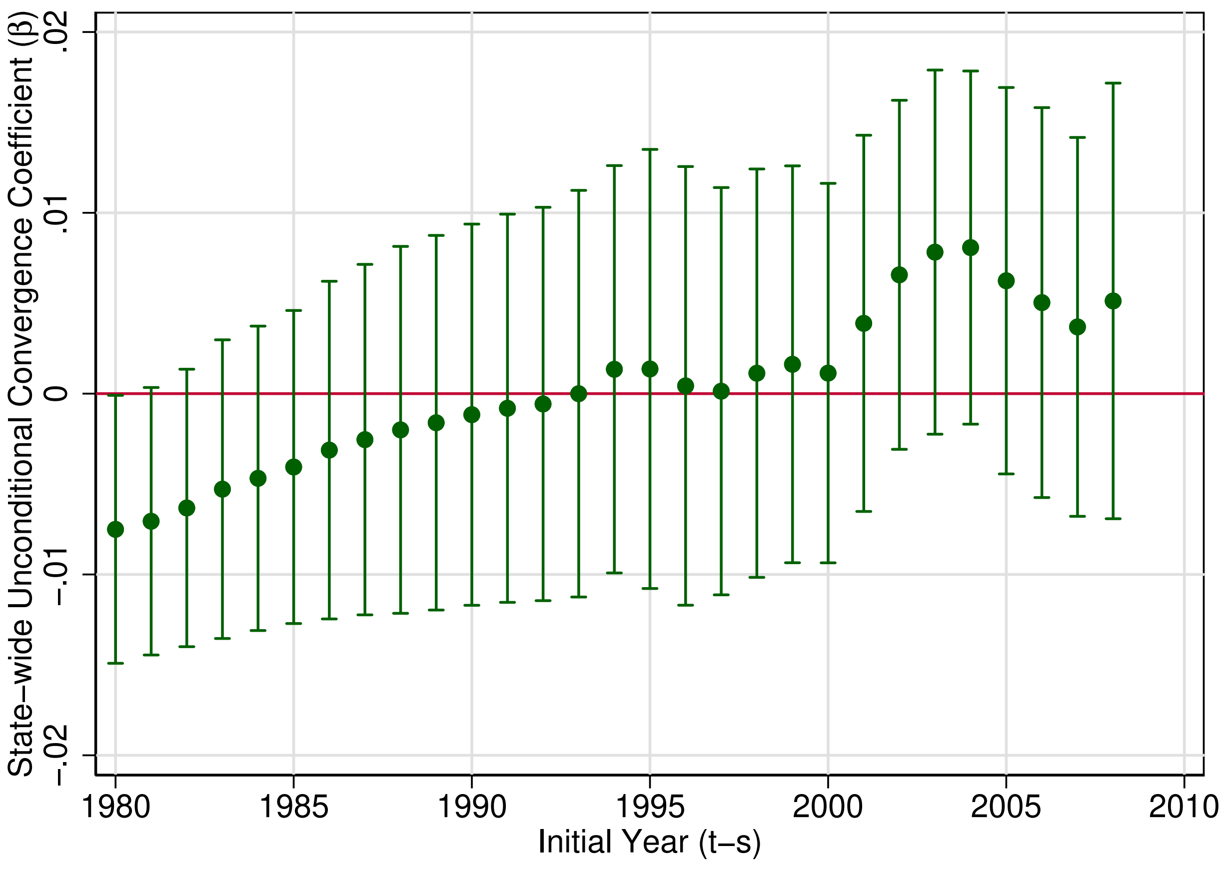


Figure 1: Convergence State-wide GDP per capita

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.

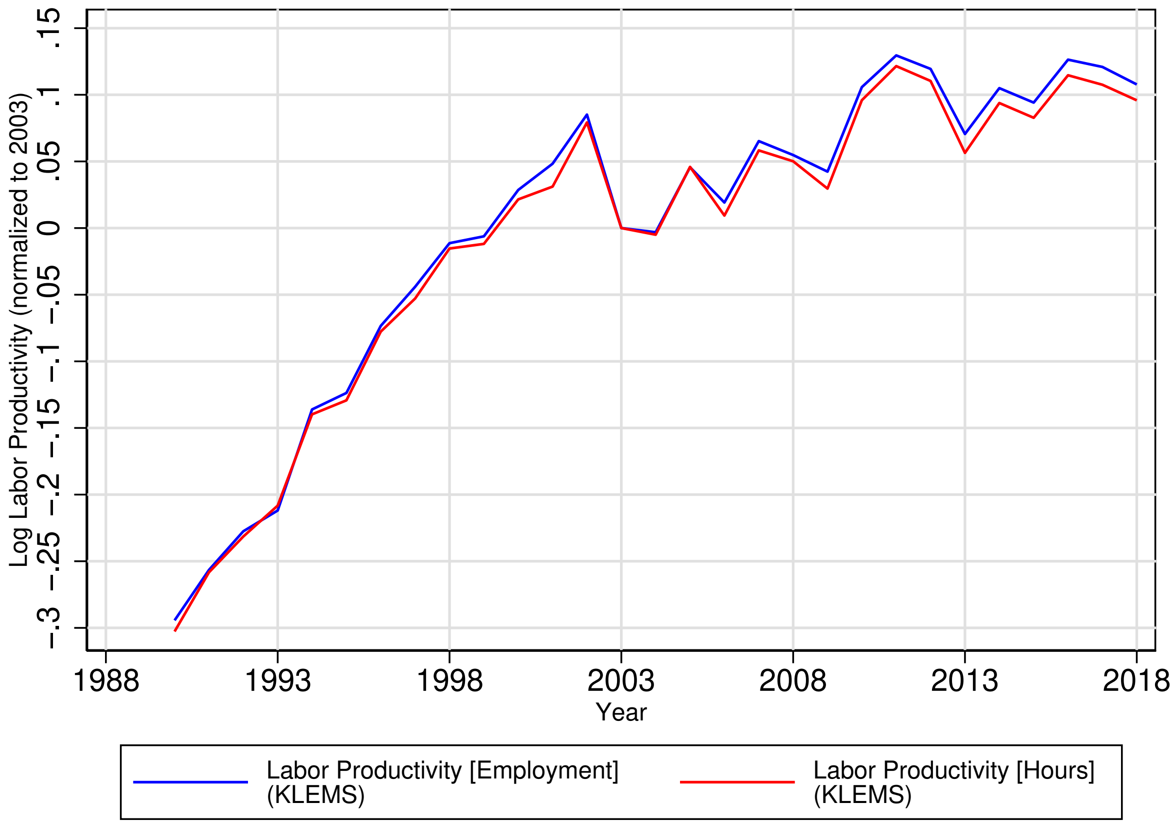


Figure 2: Evolution of manufacturing labor productivity

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.

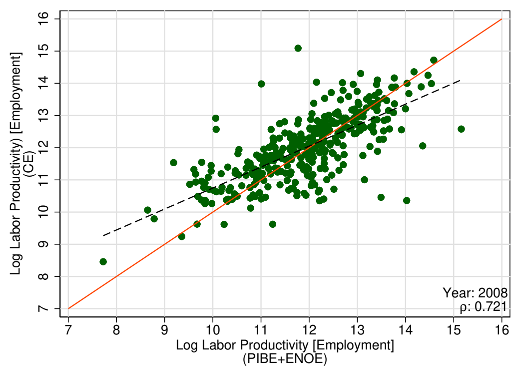
This may lead, for example, to observe negative values in the Censal Value Added, while GDP is always strictly positive. A second difference is how each source allocates regional production. While the main unit of observation in the Census is an establishment, in some cases, it may be a firm. Thus, a 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.

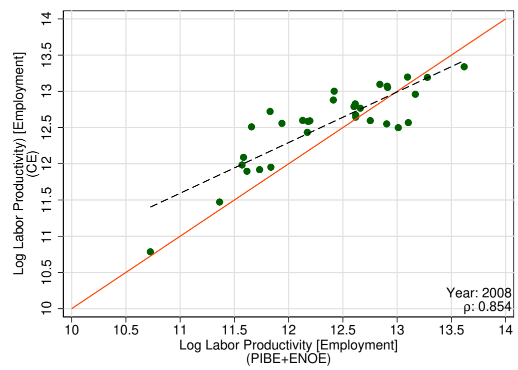
A final measurement concern is whether the transcription and homologation of the historical Census data (1988-1993) were done correctly. I validate the data in two ways to check for that. First, I compare aggregate s3-digit Censal Valued Added with GDP information from KLEMS. Figure B.1.1 in Appendix 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.

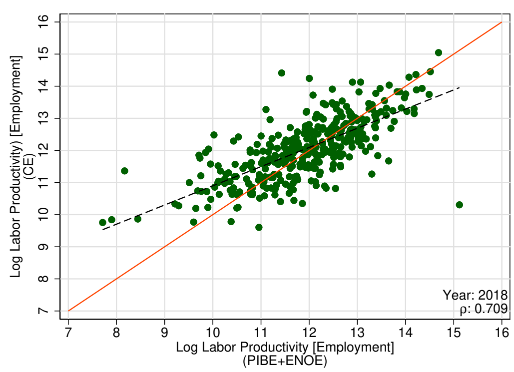
[7]Since the KLEMS dataset starts in 1990, I compare the 1988 values with those of 1990.



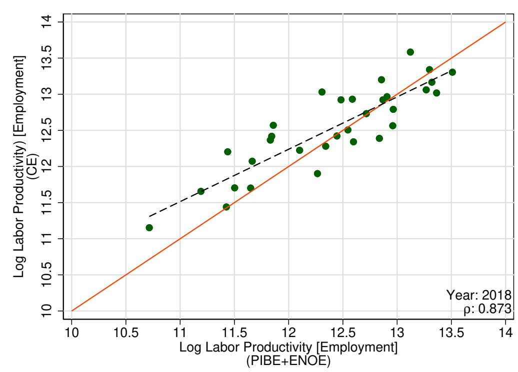
(a) Correlation Log Labor Productivity (2008), s3-digit



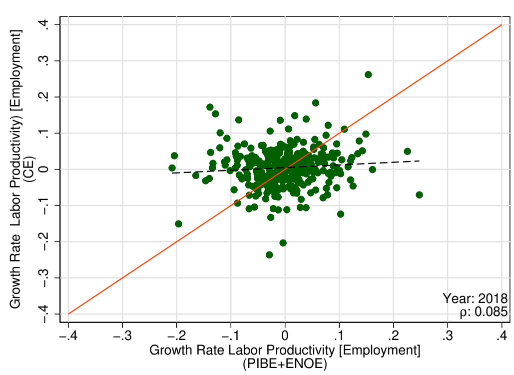
(b) Correlation Log Labor Productivity (2008), 1-digit



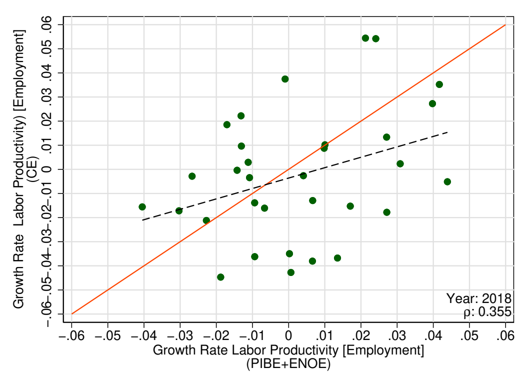
(c) Correlation Log Labor Productivity (2018), s3-digit



(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).

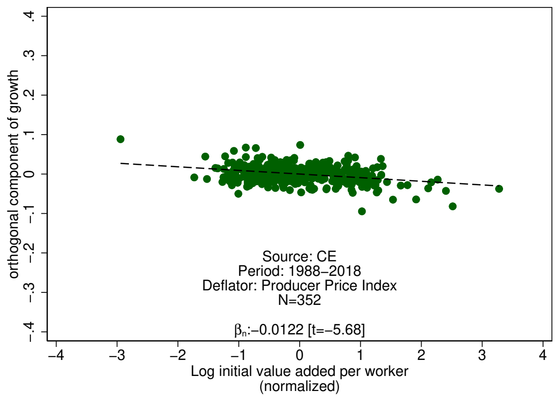
Notes: The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. Deflator: Producer Price Index. Data sources: CE; PIBE; ENOE.

3 Results

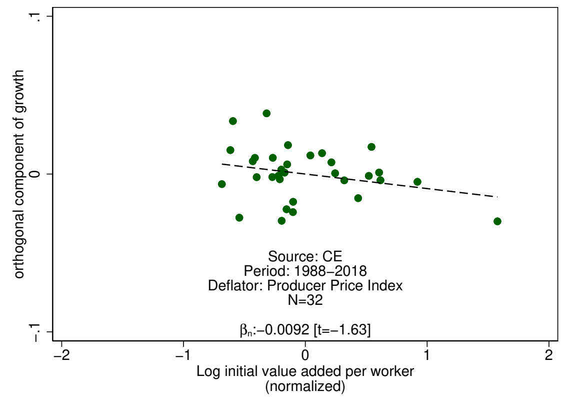
I start by reporting the results of estimating equation (3), the cross-sectional version of convergence, for both different levels of aggregation and periods. They are presented graphically to visually appreciate the presence of outliers or any non-linear relation. Standard errors are clustered at the 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



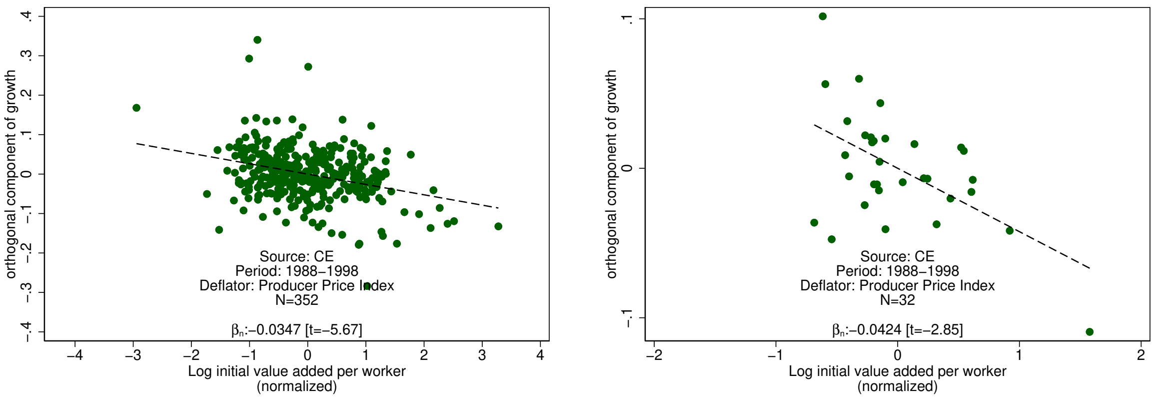
(b) 1-digit Manufacturing

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

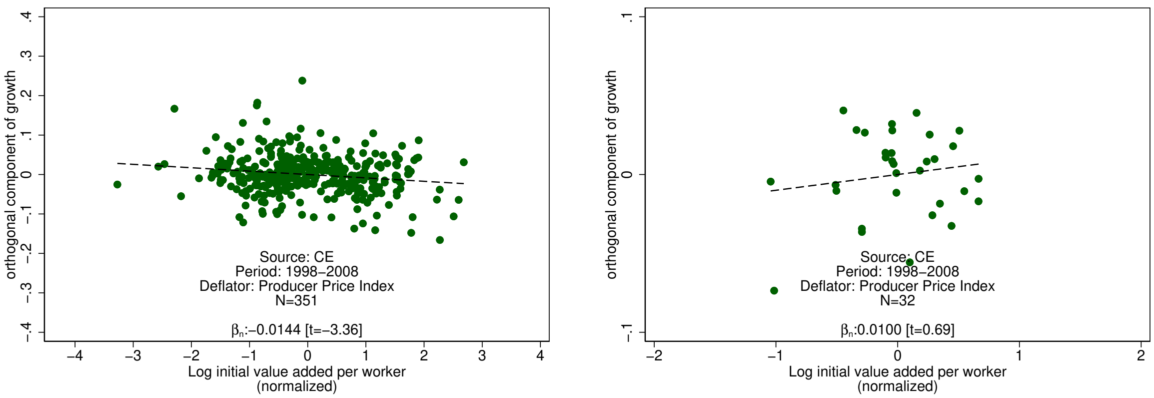
Notes: Estimates from (3). The sample includes all SCIAN s3-digit manufacturing industries except 324-326. t-statistic from clustered standard errors at the state level. Data sources: CE.

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.

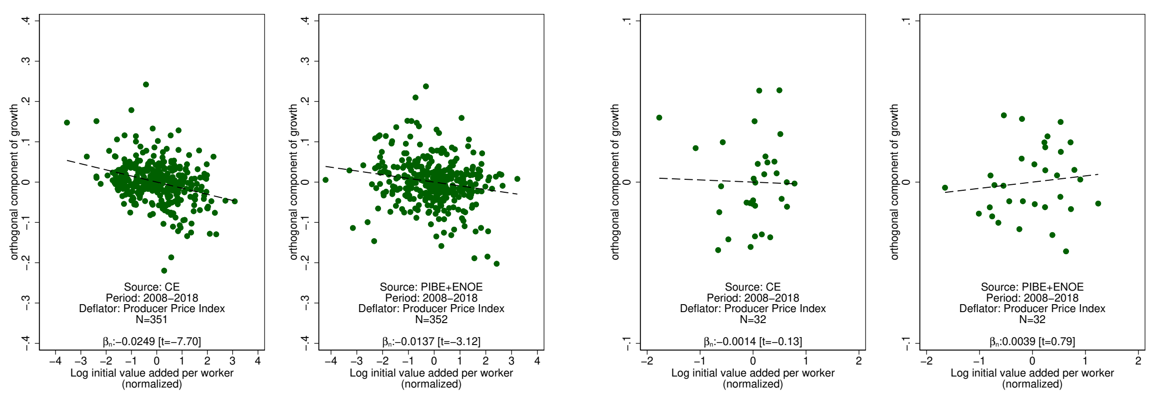
Do these results hold for alternative productivity measures, namely TFP (Total Factor Productivity)? While detailed TFP estimation involves a series of assumptions worth revisiting to assess its validity, some beyond the scope of this paper, in Appendix B.8, I show that the same patterns of convergence 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

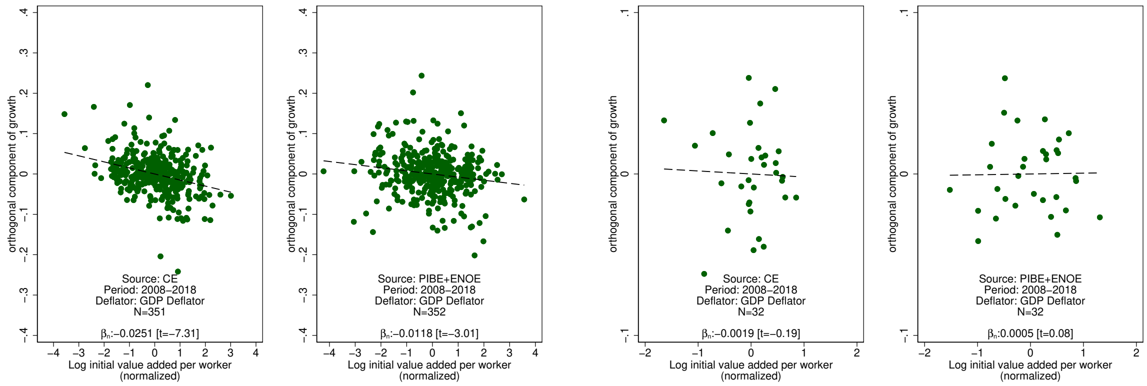
Notes: Estimates from (2). The sample includes all SCIAN s3-digit manufacturing industries except 324-326. Clustered standard errors at the state level in parenthesis. Data sources: CE.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

3.1 Robustness Checks

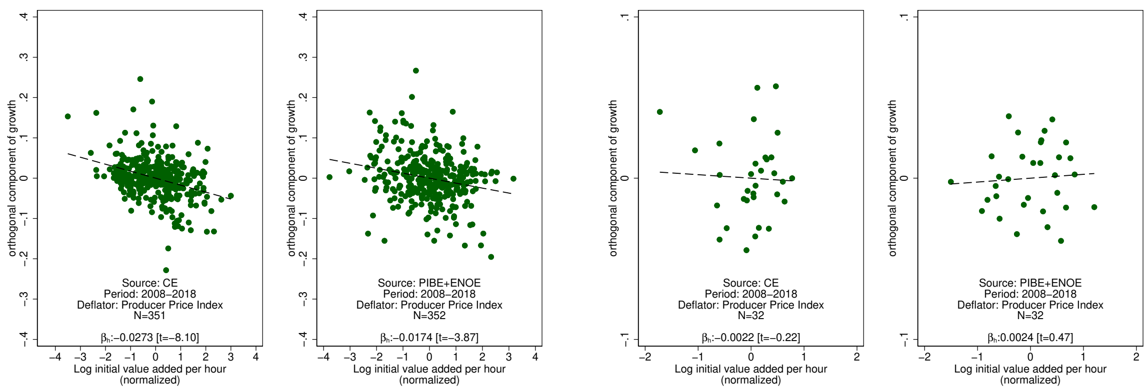
In this section, I consider alternative empirical decisions to those of the baseline analysis. First, I check if results change when measuring labor productivity as valued-added per hour worked. I also study how sensitive results are if I use the state-sectoral GDP deflator, which has the advantage of 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.

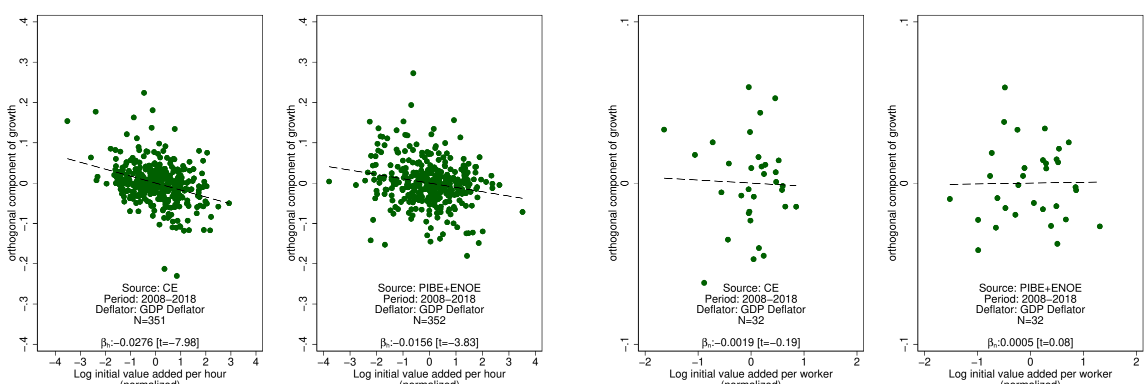
[8] In Appendix B.6 I show that including the oil industry (324-326) does not change the results, except for aggregate convergence (significant at the 10%), likely due to its overrepresentation in particular States.



(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.

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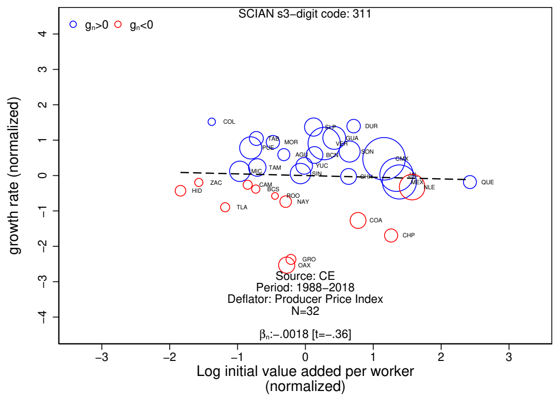
consistent with the fact that region-specific conditions play a role in determining the speed of catch-up.

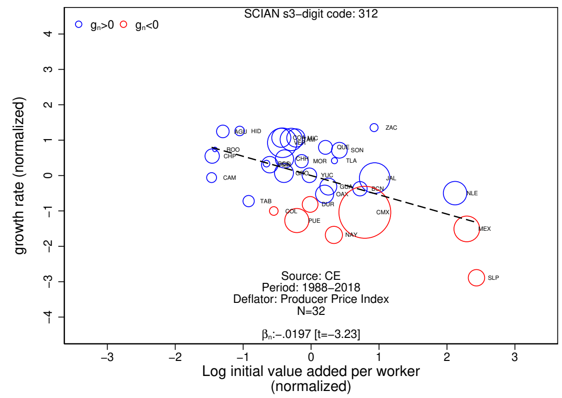
Table 4: Beta-Convergence Coefficients by Industry

	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

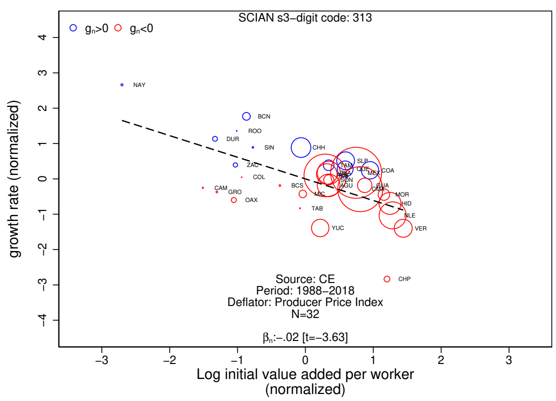
Notes: Estimates from $\hat{y_j^i} = -\beta^i \ln y_j + \epsilon_j, i \in \{311, 312, \ldots 339\}$. Weights from (4). The sample includes all SCIAN s3-digit manufacturing industries except 324-326. p-values from Robust standard errors. Data sources: CE; PIBE; ENOE.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p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



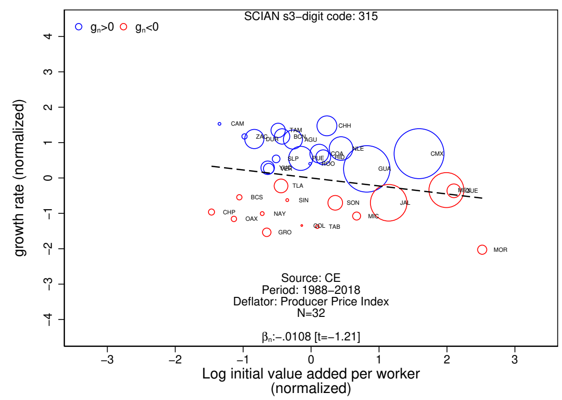
(a) 311: Food Manufacturing



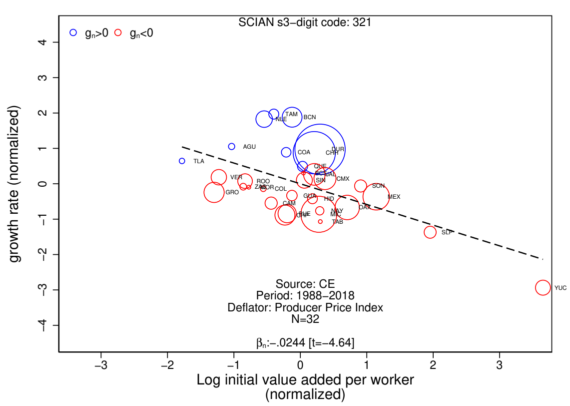
(b) 312: Beverage and Tobacco Product Manufacturing



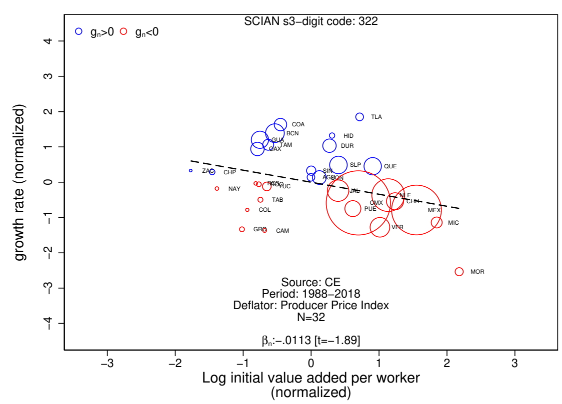
(c) 313-314: Textile Mills; Textile Product Mills



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



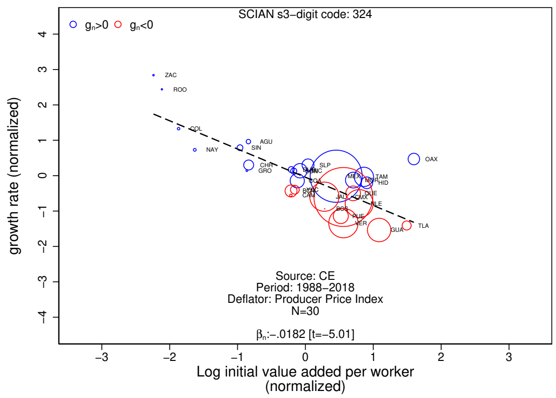
(e) 321: Wood Product Manufacturing



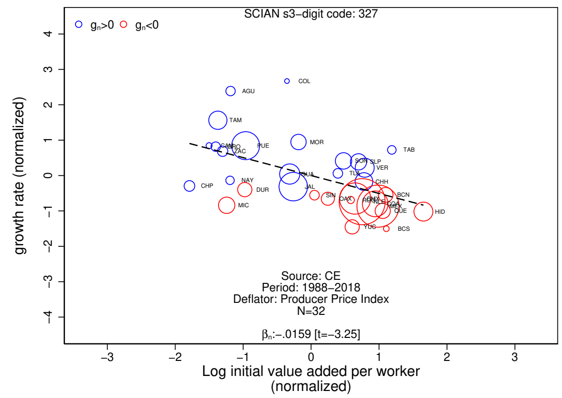
(f) 322-323: Paper Manufacturing; Printing and Related Support Activities

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

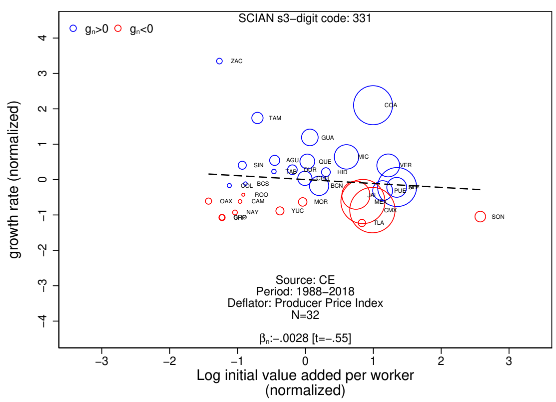
Notes: Estimates from $\hat{y}^i_j = -\beta^i \ln y_j + \epsilon_j$, $i \in \{311, 312, \ldots 339\}$. t-statistic from robust standard errors. The size of markers correspond to the importance of employment at a national level in the initial period. Data sources: CE.



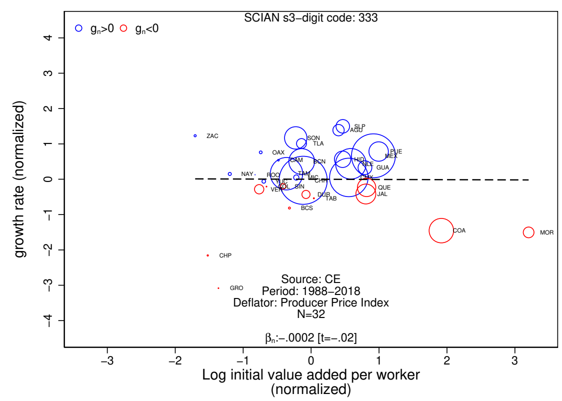
(a) 324-326: Petroleum and Coal Products Manufacturing; Chemical Manufacturing; Plastics and Rubber Products Manufacturing



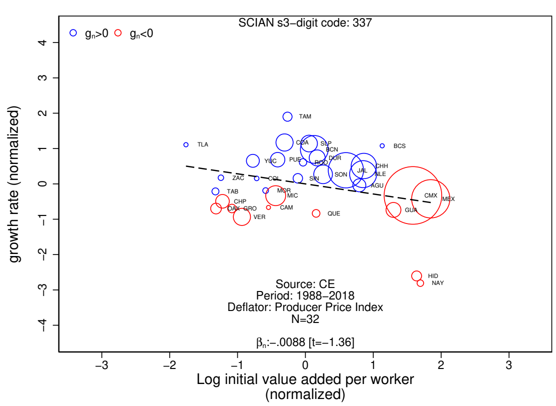
(b) 327: Nonmetallic Mineral Product Manufacturing



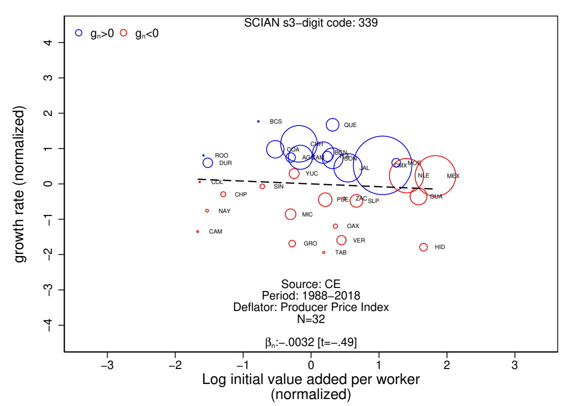
(c) 331-332: Primary Metal Manufacturing; Fabricated Metal Product Manufacturing



(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 $\hat{y_j^i} = -\beta^i \ln y_j + \epsilon_j$, $i \in \{311, 312, \ldots 339\}$. 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: 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.

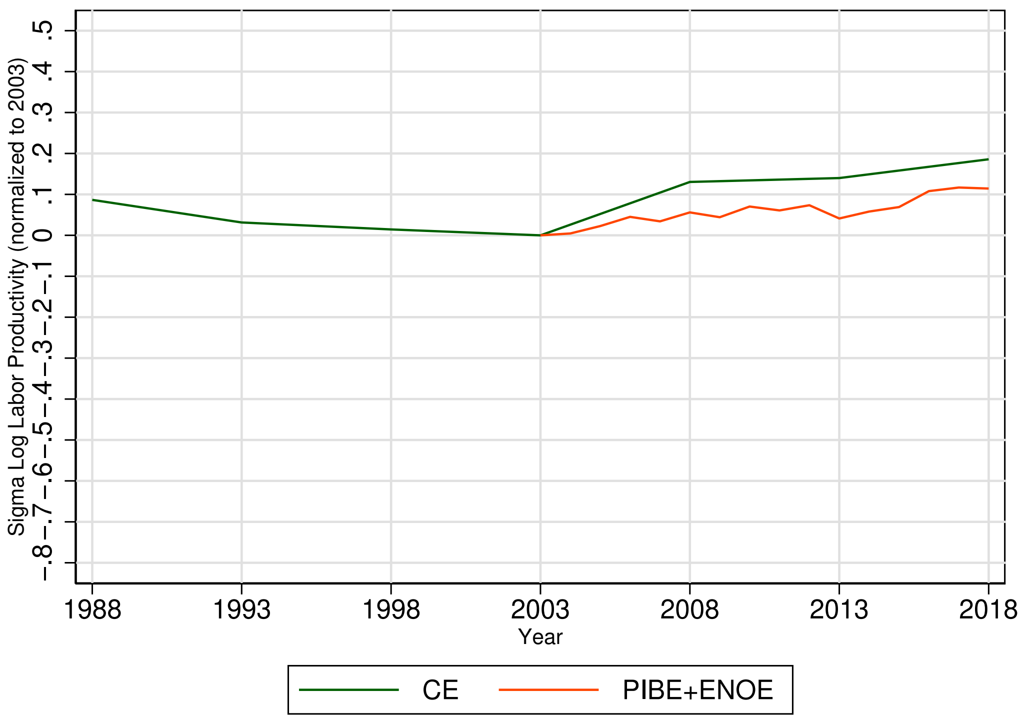
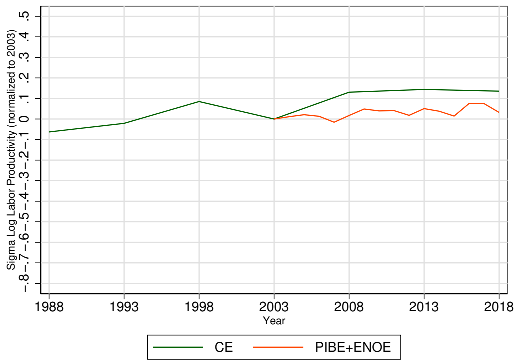


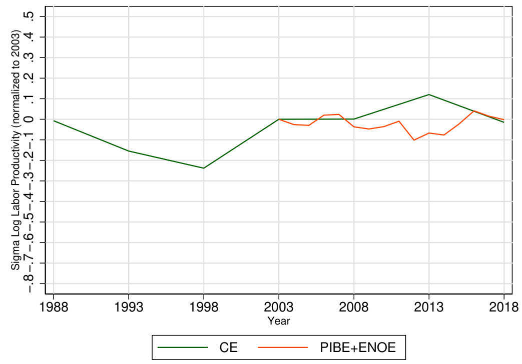
Figure 9: Sigma Manufacturing Log Labor Productivity

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.

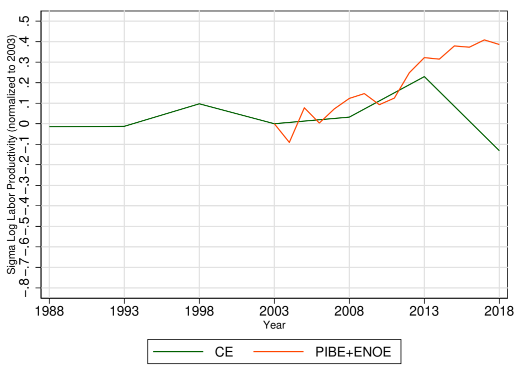
What about sigma-convergence by industry? Figures 10 - 11 show it for each s3-digit sub-sectors. Despite beta-convergence occurring in 5 out of 11 baseline industries for 1988-2018, almost none of them show sigma-convergence for the same period. Only Textile Mills+Textile Product Mills (313-314) displays 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.



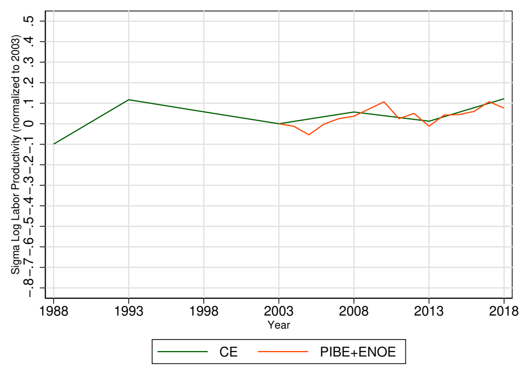
(a) 311: Food Manufacturing



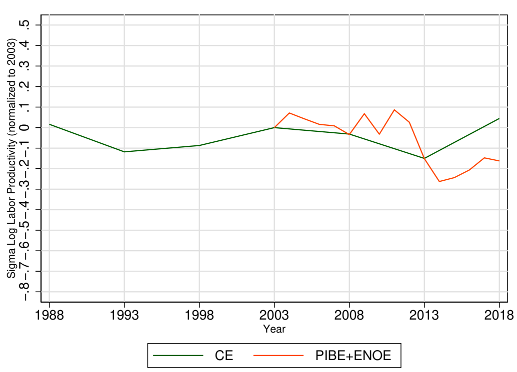
(b) 312: Beverage and Tobacco Product Manufacturing



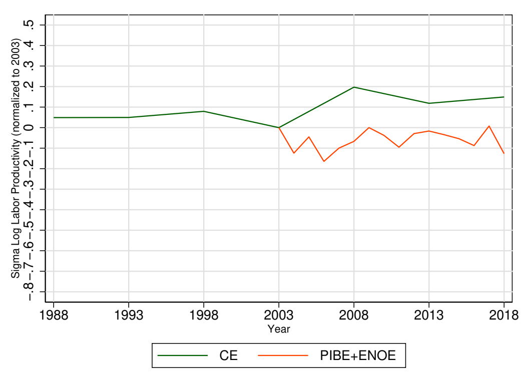
(c) 313-314: Textile Mills; Textile Product Mills



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



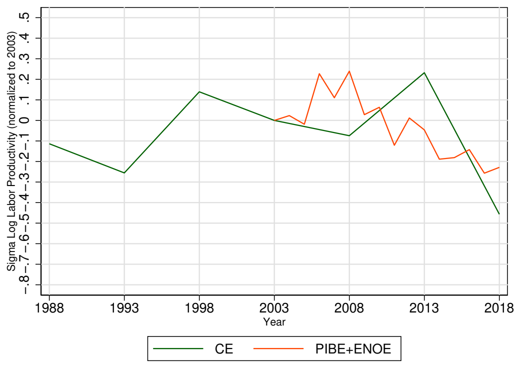
(e) 321: Wood Product Manufacturing



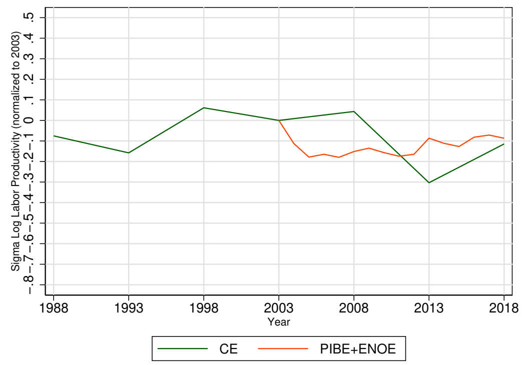
(f) 322-323: Paper Manufacturing; Printing and Related Support Activities

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

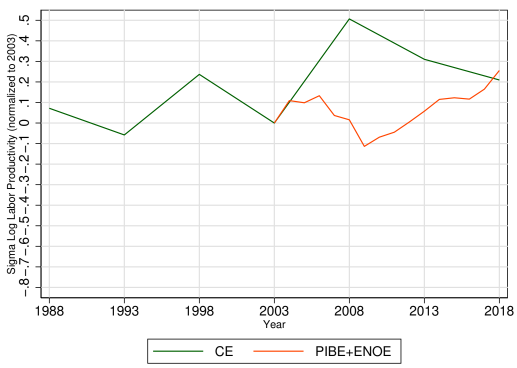
Notes: All series were normalized to their corresponding 2003 value. Data sources: CE; PIBE; ENE-ENOE.



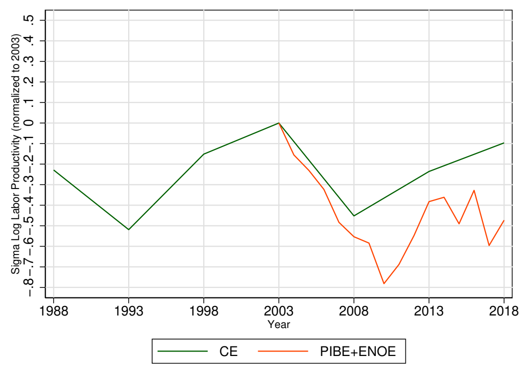
(a) 324-326: Petroleum and Coal Products Manufacturing; Chemical Manufacturing; Plastics and Rubber Products Manufacturing



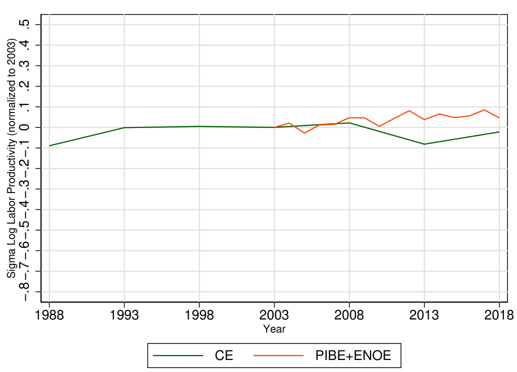
(b) 327: Nonmetallic Mineral Product Manufacturing



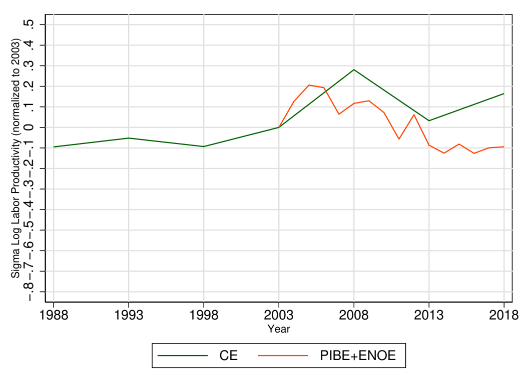
(c) 331-332: Primary Metal Manufacturing; Fabricated Metal Product Manufacturing



(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.