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

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Abstract: In this paper, I document the existence of unconditional convergence in labor productivity across Mexican states in three-digit manufacturing industries. The rate of convergence for the period 1988-2018 is 1.18% 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 for this 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, has tended to exhibit a catching-down feature, where past-leaders have seen their labor productivity decline.
Keywords: Growth; Convergence; Manufacturing; Mexico
JEL Classification: O40, O14, O54

Resumen: Este trabajo muestra la existencia de convergencia incondicional entre estados mexicanos en la productividad laboral de los subsectores manufactureros. La tasa de convergencia para el periodo 1988-2018 es de 1.18% anual. Sin embargo, este resultado no se ve a nivel agregado: no se halla evidencia de convergencia incondicional entre estados en la productividad laboral del sector manufacturero agregado. Un análisis de cambio y descomposición revela que la principal razón es la falta de redistribución de recursos hacia las industrias más productivas, así como el bajo rendimiento de muchas de las más grandes. La convergencia incondicional a todos los niveles solo ocurrió durante 1988-1998. Posteriormente, el proceso se detuvo y solo fue observado a niveles desagregados. Se provee evidencia de que una posible causa de esta ruptura es la abrupta irrupción de China al comercio internacional. También se muestra que el proceso de convergencia, cuando ha ocurrido, se ha caracterizado por un declive de la productividad laboral de los sectores líderes del pasado.
Palabras Clave: Crecimiento; Convergencia; Manufacturas; México

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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.

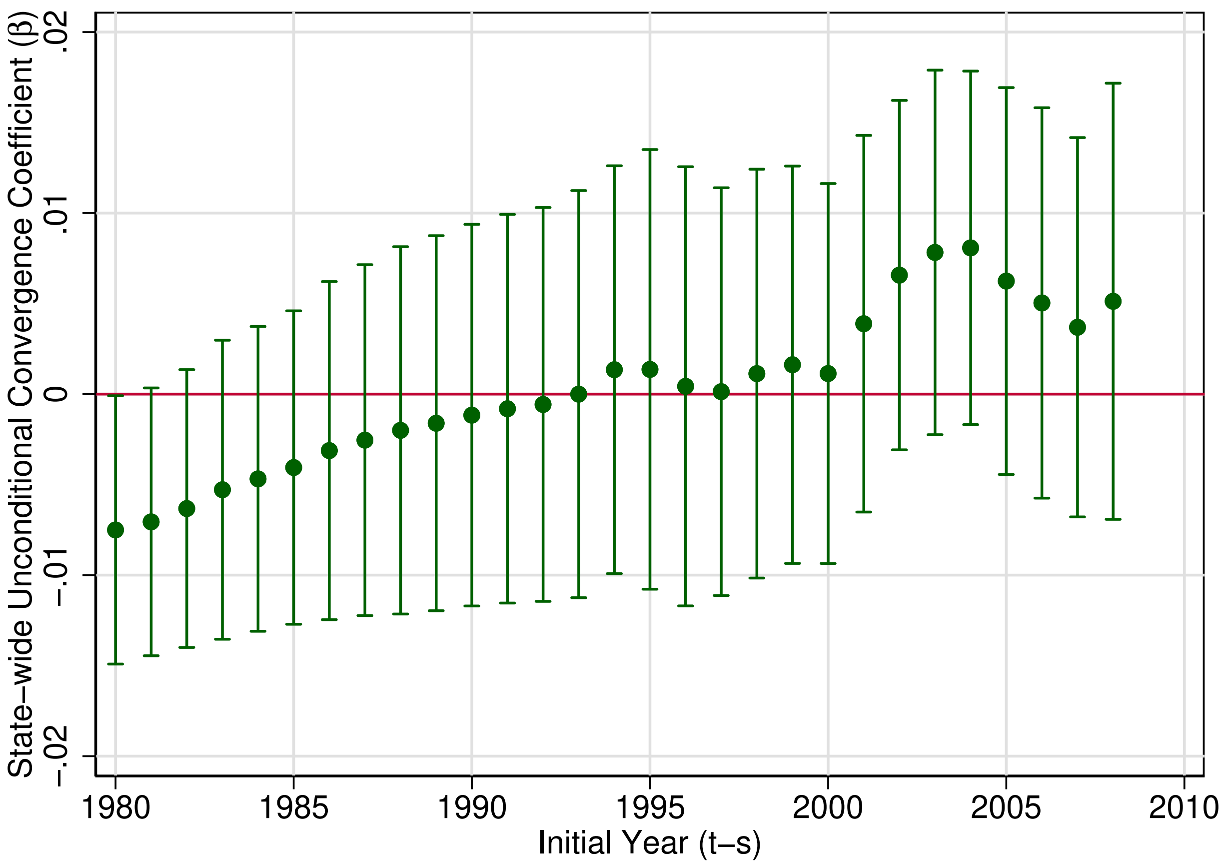


Figure 1: Convergence State-wide GDP per capita

Notes: The sample excludes 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, $\ln(y_{t-s})$, $s \in \{10, 11, \dots, 38\}$, 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 rate of convergence at the sub-sectorial level was 1.18% per year. Furthermore, similar to what is observed for GDP per-capita, 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 sub-sectors. For instance, during 1988-2018, only 5 out of 11 industries displayed unconditional convergence, despite that at some point during the three decades of analysis, each industry showed signs of it. However, this convergence tends to exhibit a downward feature. That is, former leaders have underperformed in terms of labor productivity growth, exhibiting in some cases even negative growth rates, which has contributed to the convergence process.

The main sources for this analysis are 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 for recent periods only. 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 the focus of this paper is 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 only during 1988-2003 sigma-convergence did occur, while afterward, the standard deviation of the log of labor productivity across states has increased.

To the best of my knowledge, this is the first paper that documents unconditional convergence in manufacture labor productivity for Mexico. Regional studies in the past like Mallick and Carayannis (1994) have documented some degree of aggregate convergence for short periods of time, 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 period of study is not only longer, but 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 large periods of time are, in general, scarce. Thus, this work also stands out as one of the few papers that has 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, the results of this paper highlight the fact that convergence could be elusive even in this promising sector. Particularly if both external shocks hit star industries, as well as the reallocation process is limited, as it seems to be the case in Mexico.

In that respect, I also examine the impact of various economic forces and shocks on the convergence process in manufacturing, with a focus 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 down the convergence process during the period from 2008 to 2018. Specifically, instrumental variable estimates indicate that when values of the shock exceed the 25th percentile of the distribution, manufacture-wide convergence starts to be compromised.

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, as opposed to 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, for the years 2003-2004 I use data from its predecessor survey (*Encuesta Nacional de Empleo*, ENE). The concordance between both was done following INEGI's guideline and is described in Appendix A.

I consider real labor productivity (y) as either real value-added, or GDP, divided by total employment, or total hours, while real labor productivity growth ($\hat{y}$) is 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 few States and has a strong government presence.

To get a sense of the recent history of the manufacture sector, Figure 2 shows the nationwide evolution of manufacture log labor-productivity (normalized to 2003) since 1990[3]. As it can be seen, the evolution of labor-productivity has been quite modest: it has grown 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]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.

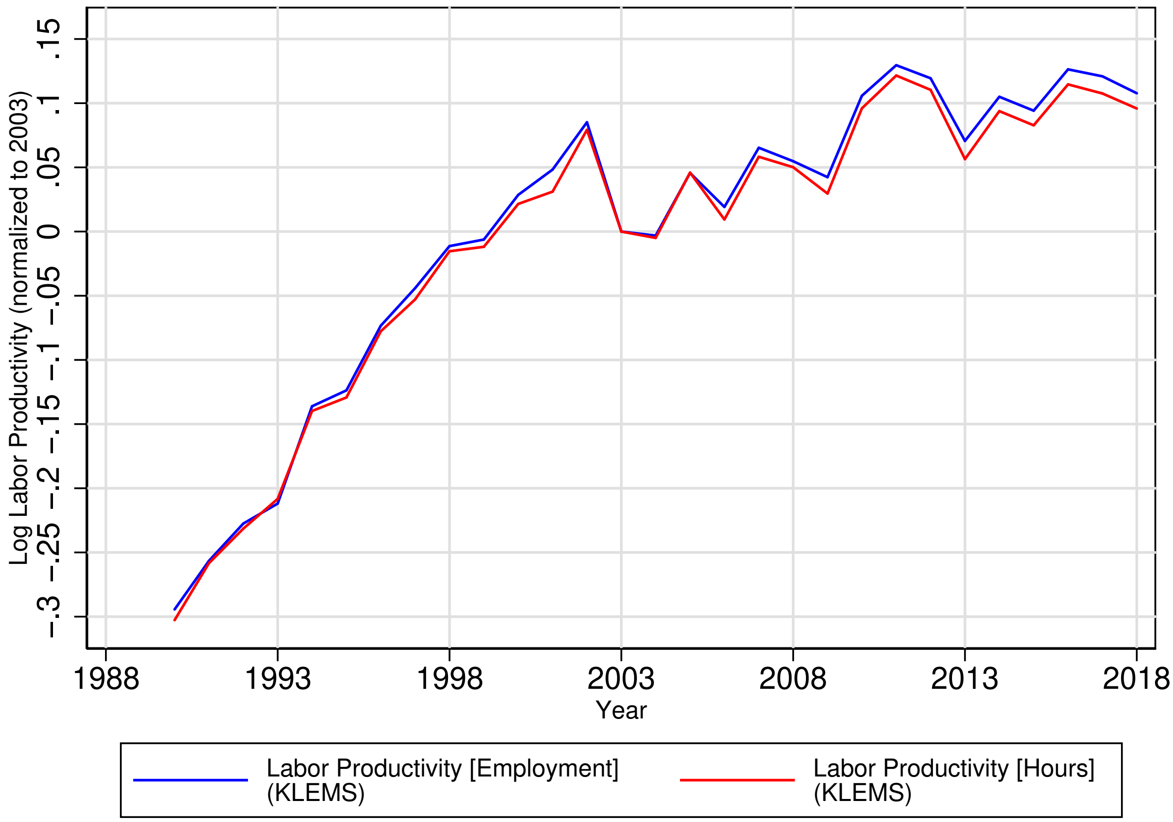


Figure 2: Evolution of manufacture labor productivity

Notes: The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. Value-added is deflated using the Producers Price Index (INPP). All series were normalized to their corresponding 2003 values. Data sources: KLEMS.

2.2.1 Measurement Issues

Both CE and PIBE+ENOE are the natural data sources to study productivity convergence. And in principle, aside from coverage, one could be indifferent to using one or the other. However, they differ in some significant aspects[4]. Note for instance that, in theory, GDP and Censal Aggregated Value Added should be similar since they aim at capturing an equivalent concept. Nonetheless, as INEGI clearly explains it (INEGI, 2010, p. 7-8), there are methodological differences that lead to discrepancies between the two. Among the most relevant to this study is the fact that GDP is computed using market prices, while the Census

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

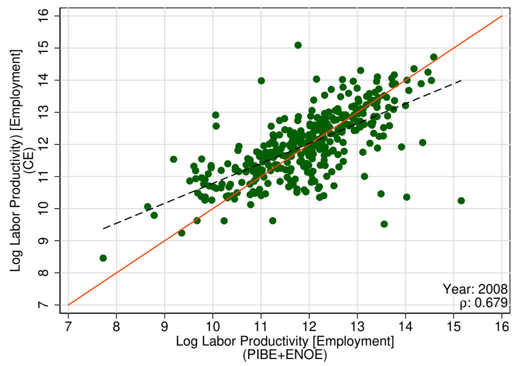
reports values of production and intermediate consumption using producer prices. This may lead, for example, to observing negative values in the Censal Value Added, while GDP is always strictly positive. A second difference is how each source allocates regional production. While the main unit of observation in the Census is an establishment, in some cases it may be a firm. Thus, a firm may report information in their headquarter's location, even though production took place in several regions. However, since the majority of firms in the Census are single-establishment ones, 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[5].

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. In terms of levels, the correlation at both s3-digit and 1-digit industries is high. However, the correlation in growth rates is 0.067 at s3-digit, while at 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 take into consideration 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.

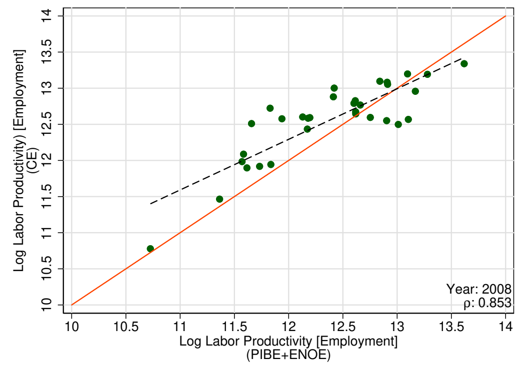
A final measurement concern is if the transcription and homologation of the historical Census data (1988-1993) was done properly. To check if that is the case, I validate the data in two ways. First, I compare aggregate s3-digit Censal Valued Added with GDP information from KLEMS. Figure 13 in Appendix B plots the correlation of (log) labor productivity for both 1988 and 1993 with the corresponding KLEMS[6]. Finally, in Appendix B I also show that results are similar if one estimates the convergence process from 1988 to 1998 using data

[5] Still, Table 8 in Appendix B, I show both sources of employment are strongly correlated.
[6] Since KLEMS dataset starts in 1990, I compare the 1988 values with those of 1990.

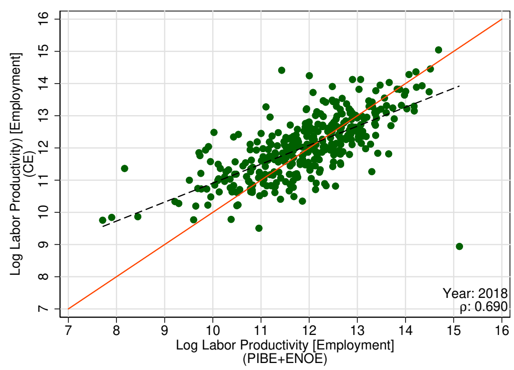
in CMAP industrial classification, instead of translating to SCIAN.



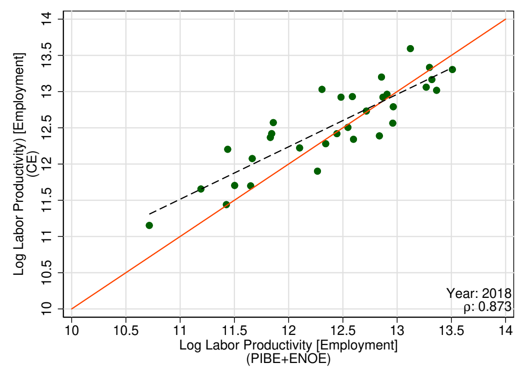
(a) Correlation Log Labor Productivity (2008), s3-digit



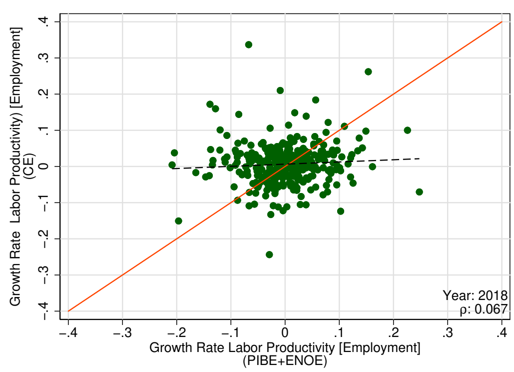
(b) Correlation Log Labor Productivity (2008), 1-digit



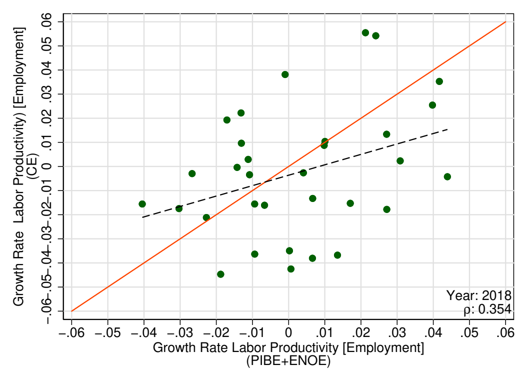
(c) Correlation Log Labor Productivity (2018), s3-digit



(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).

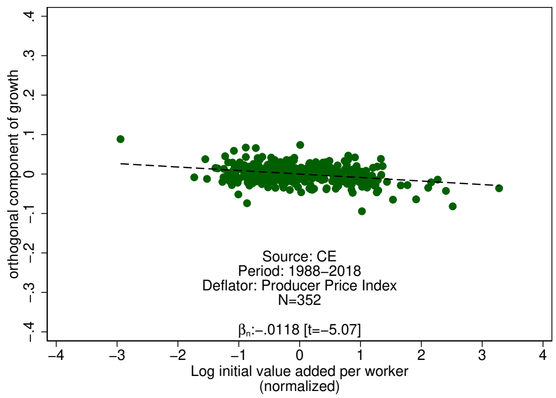
Notes: The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. Data sources: CE; PIBE; ENOE.

3 Results

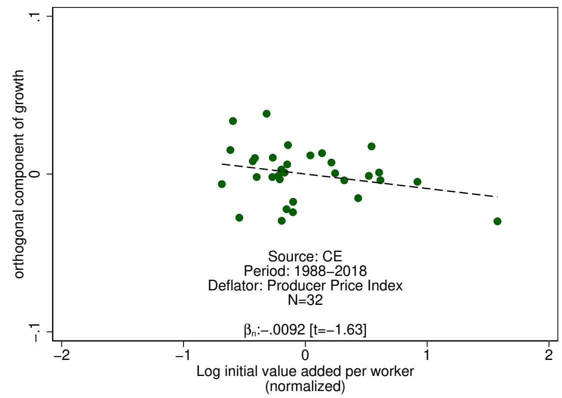
I start by reporting the results of estimating equation (3), the cross-sectional version of convergence, for both different levels of aggregation and periods. They are presented graphically to visually appreciate the presence of outliers or any non-linear relation. Standard errors are clustered at the 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 1.18% per year. Although quantitatively, the magnitude is relatively small, as it implies that productivity gap between states at the bottom and top 10% of the distribution would close in 81 years $(\ln(0.9)/\ln(0.1) - 1)/0.0118)$. Moreover, Figure 4b shows that there does not exist unconditional convergence 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 (1.36%) and 2008-2018 (2.7%). 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, while afterwards 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 manufacture labor productivity, although the rate of convergence is faster for lower levels of aggregation. But this effect is statistically significant only at s3-digit and 3-digit industries.



(a) s3-digit Manufacturing Sectors

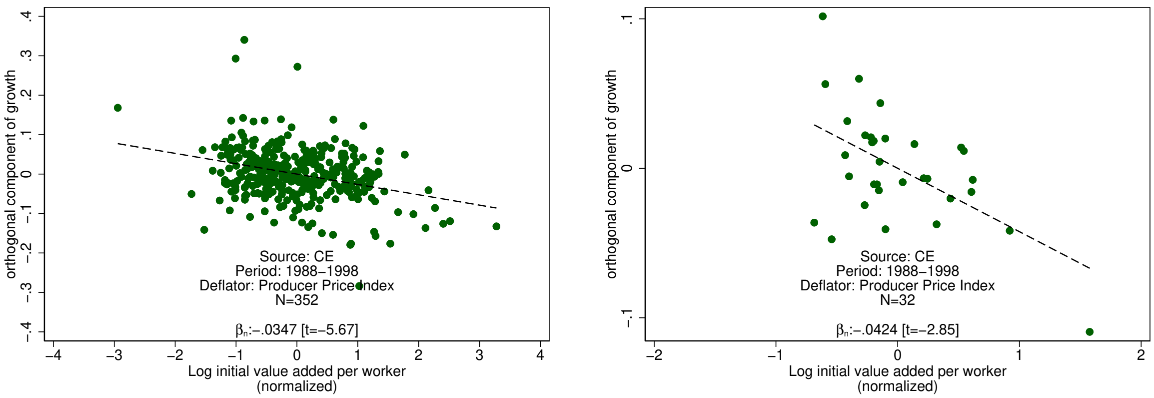


(b) 1-digit Manufacturing

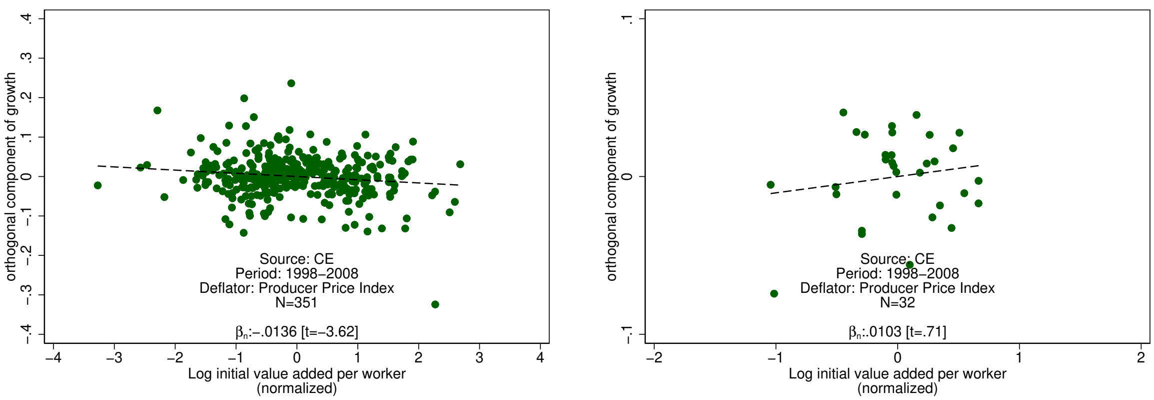
Figure 4: Convergence in s3-digit Manufacturing Sectors and Manufacture-wide Labor Productivity

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.

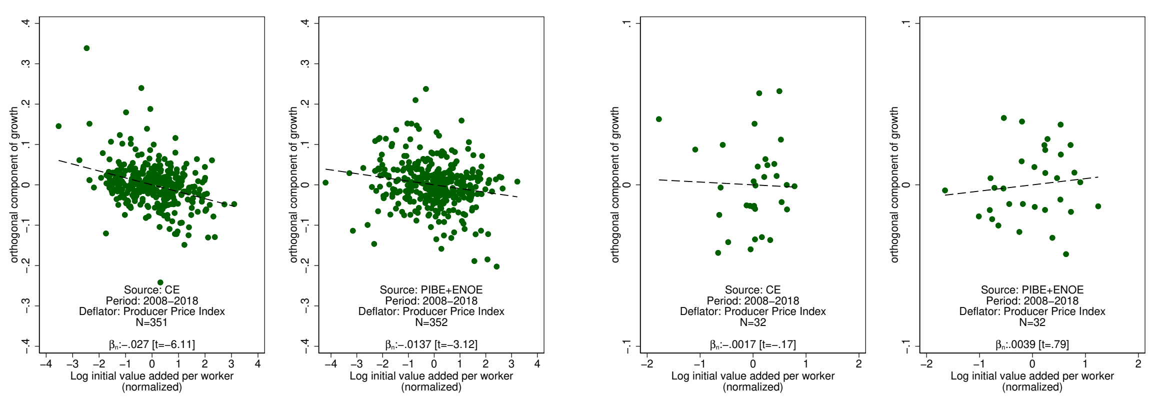
On the other side, even columns formally test changes in the speed of convergence over time, by interacting initial labor productivity with decade dummies. These results confirm what was already discussed: convergence was the strongest during 1988-1998, it slowed in 1998-2008, and moderately recovered in 2008-2018. However, these changes are only statistically significant at 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. Afterwards, the convergence process broke down: it only kept occurring at s3-digit industries, but at a slower pace.



(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 manufacture 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***	-.0248***	-.0347***	-.0343***	-.0359***
	(.0095)	(.015)	(.0021)	(.0061)	(.0047)	(.0082)
Log initial productivity, 1998		.0527***		.0211***		.0013
		(.0169)		(.0064)		(.0119)
Log initial productivity, 2008		.0407*		.0077		.003
		(.021)		(.0094)		(.0087)
Observations	96	96	1054	1054	1598	1598
R-squared	.0853	.1991	.2022	.2131	.2074	.2076
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

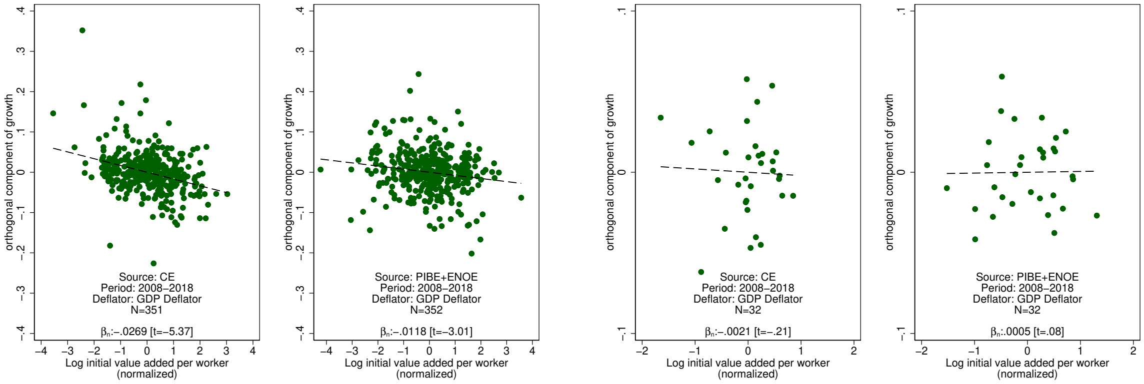
Notes: Estimates from (2). The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. Clustered standard errors at the state level in parenthesis. Data sources: CE.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

3.1 Robustness Checks

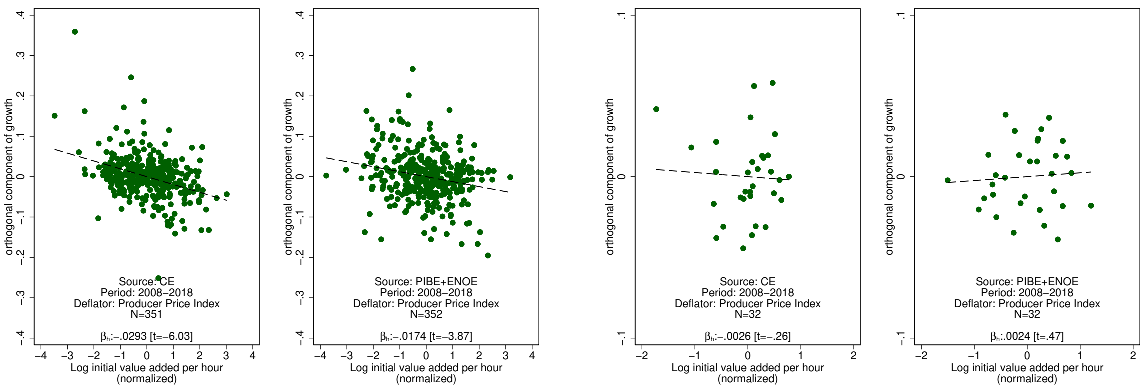
In this section, I consider alternative empirical decisions to those of the baseline analysis. To start, I check if results change when I measure labor productivity as valued-added per hour worked. I also check how sensitive results are if I use the state-sectoral GDP deflator, which has the advantage to be specific for each industry and state, as opposed to the PPI. However, due to data limitations described earlier, I only show these checks for 2008-2018. So, they can be directly compared to those of Figure 5c. Figure 6 shows the results[7].

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

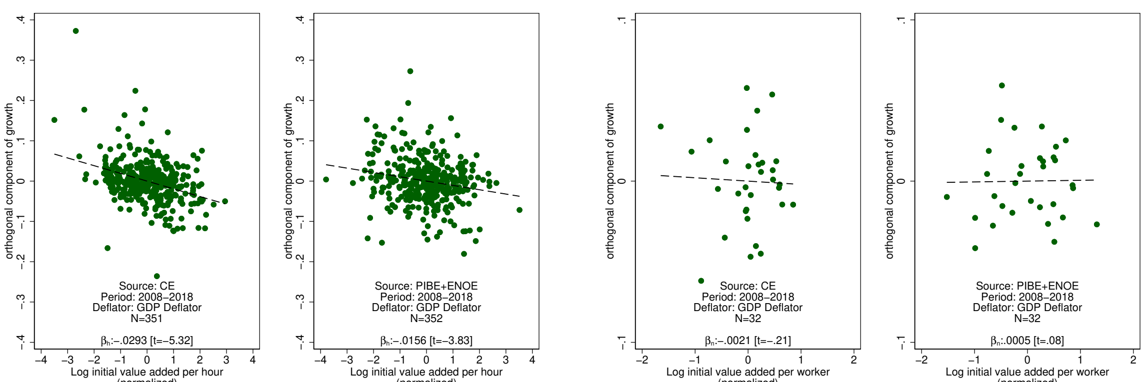
[7] In Appendix B.7 I show that including oil industry (324-326) do not change the results, except for aggregate convergence (significant at the 10%), likely due to its overrepresentation in particular States.



(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 one 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 is that 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, only for 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	-.0017	.0034	.0064	-.027***	-.0076*	-.0128*
	(.0101)	(.0113)	(.0123)	(.0044)	(.004)	(.0072)
Observations	32	32	32	351	350	351
R-squared	.0012	-.0098	-.0262	.2371	.1612	.1914
F statistic (First Stage)		43.6259	45.9434		100.3927	157.9369
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, whenever an instrument for initial labor productivity is used, β-convergence estimates reduce. For the case of s3-digit industries, it drops by approximately 70 and 50% when using as instruments 5-year lagged CE values and measures from PIBE+ENOE, respectively. This is consistent with the interpretation of the existence 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 real convergence process. Extrapolating these results, they would imply that the s3-digit industries convergence for 1988-2018 will be less than 1% per year. The results for aggregate manufacture will even lead to a much more pessimistic result. Hence, opposite to what seems to occur at a cross-country level, unconditional manufacture convergence in Mexico is only mildly present[8].

[8] In Appendix C 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 can be expected from the results in the previous section, there exists unconditional convergence (statistically significant) in almost half of the industries (5/11). The rest of them, despite not being statistically significant, 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 2) at some point each industry showed unconditional convergence. The industries with 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 include flagship Mexican industries like automobile production, only showed convergence for the 1988-1998 period.

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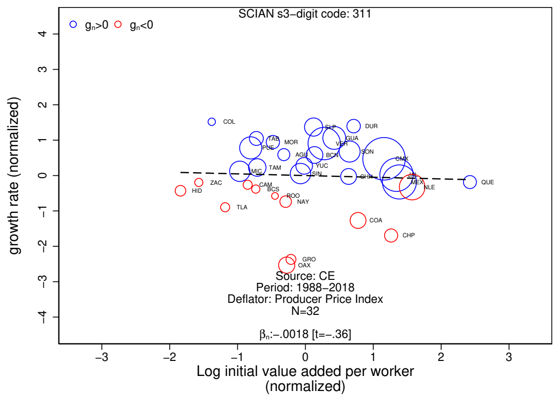
consistent with the fact that region-specific conditions play a role in determining the speed of catch-up.

Table 4: Beta-Convergence Coefficients by Industry

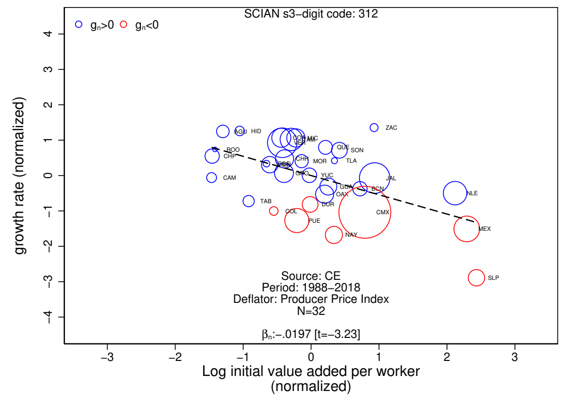
	1988-2018			1988-1998			1998-2008			2008-2018					
	CE			CE			CE			CE			PIBE+ENOE		
SCIAN code	N	β	W	N	β	W	N	β	W	N	β	W	N	β	W
311	32	-.0018	.03	32	-.0031	.03	32	-.0123	.05	32	-.0258**	.05	32	-.0066	.03
312	32	-.0197***	.11	32	-.0485***	.11	32	-.0239	.05	32	-.0539***	.08	32	-.0216	.1
313-314	32	-.02***	.19	32	-.0316*	.19	32	-.0151*	.2	32	-.0212**	.13	32	.0072	.18
315-316	32	-.0108	.03	32	-.0123	.03	32	-.0421*	.05	32	-.0091	.04	32	-.0035	.06
321	32	-.0244***	.05	32	-.0684***	.05	32	-.0053	.03	32	-.0011	.03	32	-.0626***	.07
322-323	32	-.0113*	.1	32	-.0292**	.1	32	-.0153	.1	32	-.0091	.1	32	-.021**	.07
327	32	-.0159***	.14	32	-.0239	.14	31	-.0085	.15	31	-.0233***	.12	32	-.0166	.06
331-332	32	-.0028	.11	32	.0027	.11	32	.0207***	.14	32	-.0334***	.19	32	.0091	.12
333-336	32	-.0002	.15	32	-.0649***	.15	32	-.0516**	.15	32	-.0316	.13	32	-.0135	.12
337	32	-.0088	.04	32	-.0282	.04	32	-.01	.05	32	-.0254***	.04	32	-.0098	.06
339	32	-.0032	.05	32	-.0568***	.05	32	.0326*	.04	32	-.0329***	.1	32	-.0329***	.14

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.

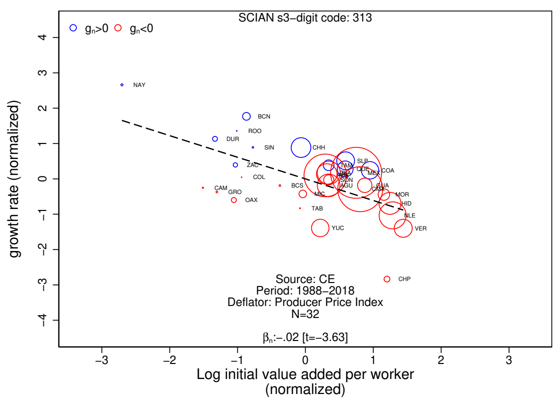
*p < 0.1, **p < 0.05, ***p < 0.01



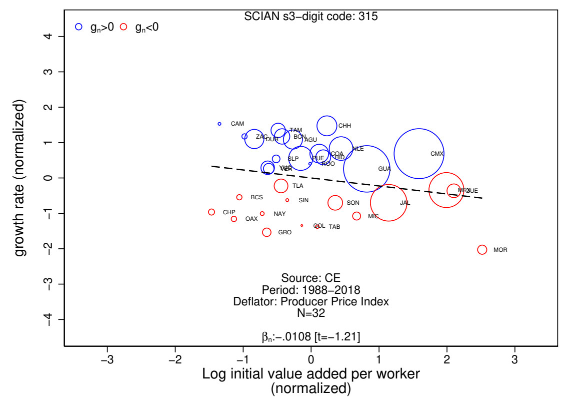
(a) 311: Food Manufacturing



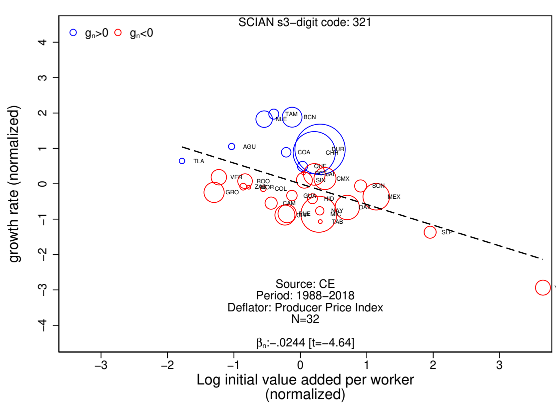
(b) 312: Beverage and Tobacco Product Manufacturing



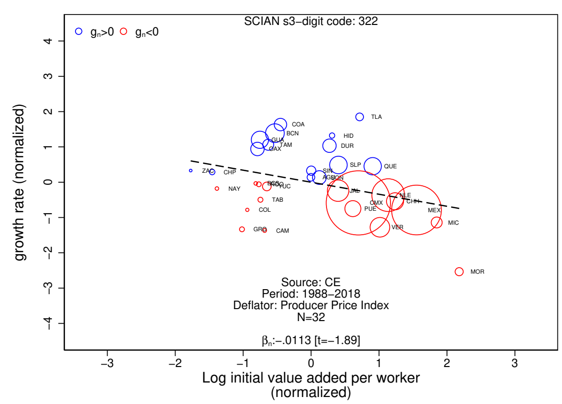
(c) 313-314: Textile Mills; Textile Product Mills



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



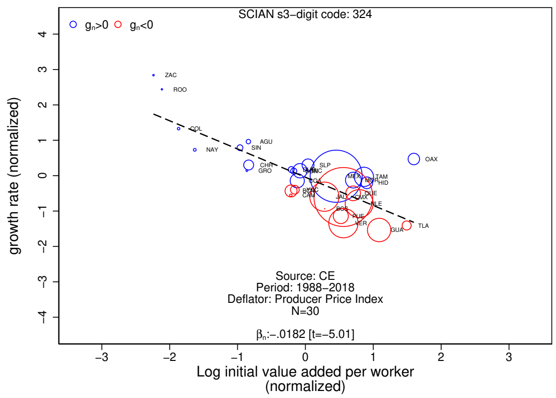
(e) 321: Wood Product Manufacturing



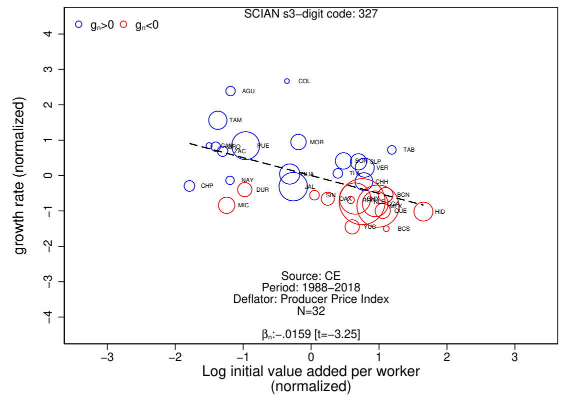
(f) 322-323: Paper Manufacturing; Printing and Related Support Activities

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

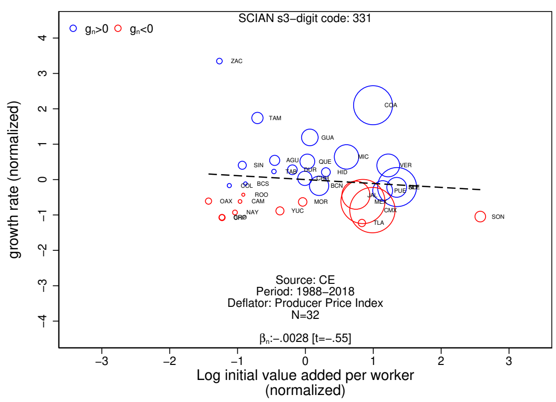
Notes: Estimates from $\hat{y}^i_j = -\beta^i \ln y_j + \epsilon_j$, $i \in \{311, 312, \ldots 339\}$. t-statistic from robust standard errors. The size of markers correspond to the importance of employment at a national level in the initial period. Data sources: CE.



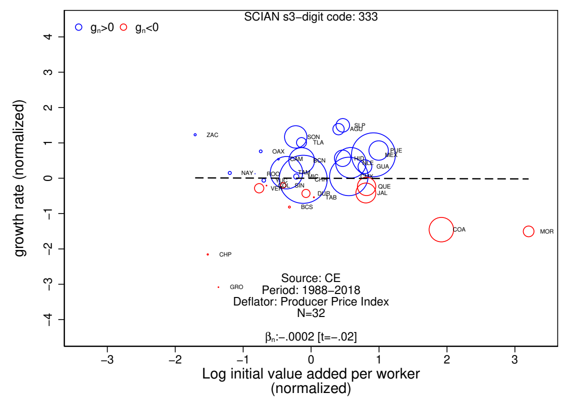
(a) 324-326: Petroleum and Coal Products Manufacturing; Chemical Manufacturing; Plastics and Rubber Products Manufacturing



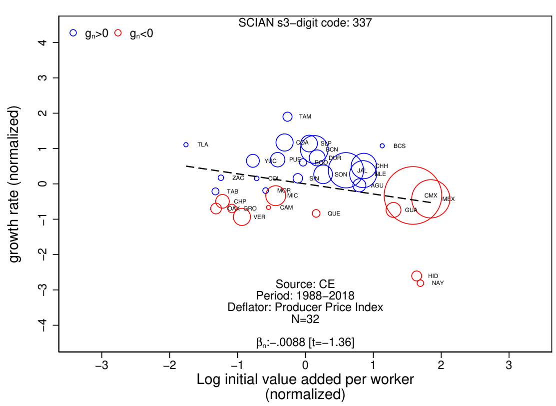
(b) 327: Nonmetallic Mineral Product Manufacturing



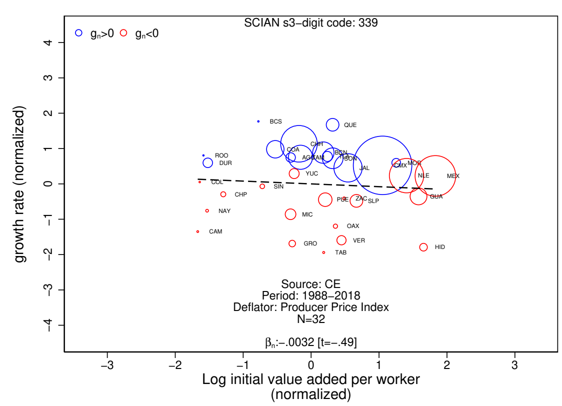
(c) 331-332: Primary Metal Manufacturing; Fabricated Metal Product Manufacturing



(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 correspond to the importance of employment at a national level in the initial period. Data sources: CE.

An important aspect of the Mexican convergence is that it does not exhibit a catching-up feature. Instead, it seems to happen downwards. That is, 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 raise concerns, as suggests that some states are not actually reaching the technological frontier, but instead approaching to a lower level of productivity of the former leaders. In Appendix B.5 I show this feature is present in every decade as well. Moreover, in Appendix B.6 I also show that is phenomenon is not particular to the CE dataset.

3.3 Convergence Decomposition

An open question from Section 3 was why has convergence not added-up? To answer it, I follow Wong (2006), and notice that growth in labor-productivity (GLP) can be written as[9],

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

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,

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

[9] 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 both showing how each industry, as well as the reallocation between them, contribute to the overall convergence process. That is, 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	-.3953*	100	-.4723***	100	.07	100	-.0279	100	.0429	100
TRE	.0611	-15.46	-.0191	4.05	.0908*	129.7	.0005	-1.67	.0499	116.32
TSE	.087	-22.02	-.0526	11.15	.1307*	186.72	.0286	-102.66	.0338	78.89
TIE	-.0259	6.56	.0335	-7.1	-.0399	-57.02	-.0281	100.98	.0161	37.43
TGE	-.4564**	115.46	-.4532**	95.95	-.0208	-29.7	-.0283	101.67	-.007	-16.32
GE_{311}	-.0207	5.25	-.0567	12	-.0442	-63.08	-.0048	17.32	-.0178	-41.39
GE_{312}	-.2097	53.04	-.0879***	18.61	.0217	30.95	.0071	-25.48	.0166	38.81
$\text{GE}_{313-314}$	-.0113	2.85	-.0108	2.29	-.0101*	-14.44	-.0167	59.98	.0058*	13.55
$\text{GE}_{315-316}$	-.0112	2.83	-.0091*	1.92	-.0009	-1.25	-.008	28.58	-.0108	-25.18
GE_{321}	.0041	-1.04	-.0009	.18	.0072***	10.26	.0018	-6.35	.0032	7.53
$\text{GE}_{322-323}$	-.0129*	3.26	-.0043	.92	.0003	.48	-.0061	21.87	.0006	1.34
GE_{327}	-.1109	28.06	-.0915	19.38	.0175	25.03	-.023	82.73	.0121	28.16
$\text{GE}_{331-332}$	.051	-12.9	-.0062	1.32	.0245	35.06	-.013	46.54	.0075	17.56
$\text{GE}_{333-336}$	-.1326	33.55	-.1852**	39.21	-.0458	-65.39	.044	-158.12	-.014	-32.56
GE_{337}	-.0028	.7	-.0003	.06	-.0014	-2.04	-.0059	21.03	.0003	.64
GE_{339}	.0006	-.14	-.0002	.05	.0103	14.72	-.0038	13.58	-.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 convergence has been growth within sectors. No sector has contributed by itself significantly to the convergence process. However, Beverage and Tobacco Product Manufacturing (312), Nonmetallic Mineral Product Manufacturing (327) and Machinery *et al.* (333-336) accounted for more than 100% of it, despite not being individually statistically significant. While for 1988-1998, they not only contributed to 65% of it, but also showed statistically significant effects. Afterwards, with the convergence process broken down, some industries have even shown divergence (e.g 333-336 for 2008-2018).

On the other side, the Total Reallocation Effect (TSE+TIE) contributed -15.5% to the convergence process during 1988-2018, while only 4% during 1988-1998. Moreover, from 1998 it continued to operate in the opposite direction. Although notice that in no period (except 1998-2008), the effects are statistically significant. So this structural change within manufacturing, in which employment flows into relatively more productive sectors, has not occurred in Mexico.

Through the lens of this decomposition, it has been both the underperformance of certain important industries, as well as the lack of reallocation, what has prevented convergence in manufacture-wide productivity. Although certain industries have converged across states, their low employment (and value-added) participation have limited their influence towards convergence. In that sense, the challenge of the Mexican manufacturing industry is not only to promote upward convergence via productivity improvements, but 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 of seeing faster growth in followers is the desire of a reduction in productivity's dispersion. However, beta-convergence is a necessary, but not sufficient condition to 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 conclude 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. Afterwards, the standard deviation of labor productivity has increased 10 to 20 log-points.

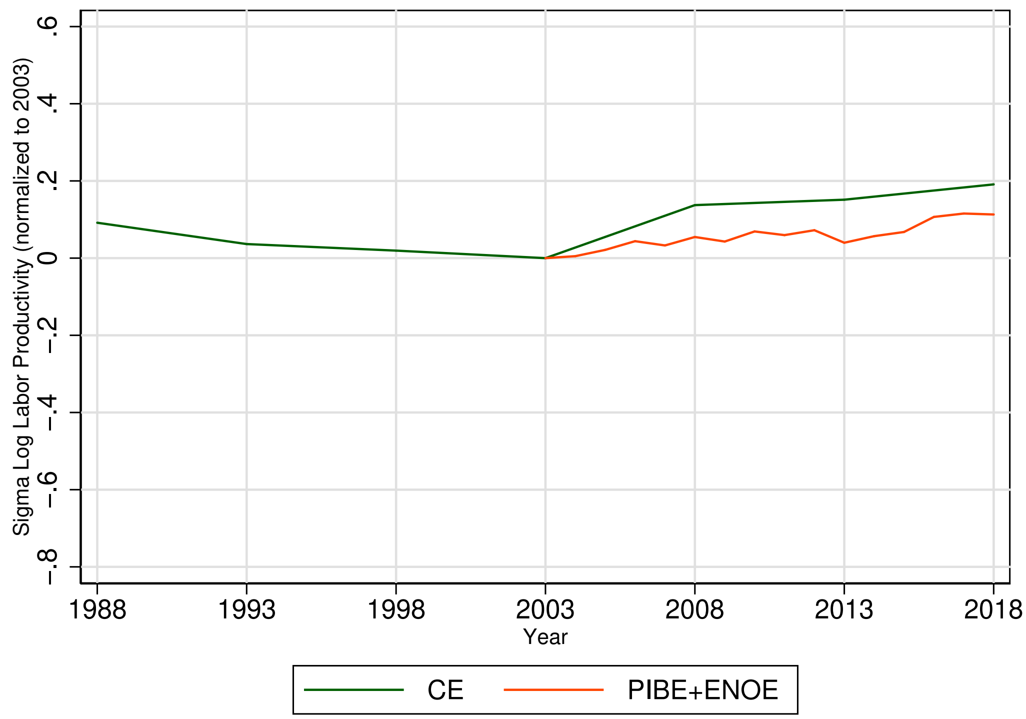
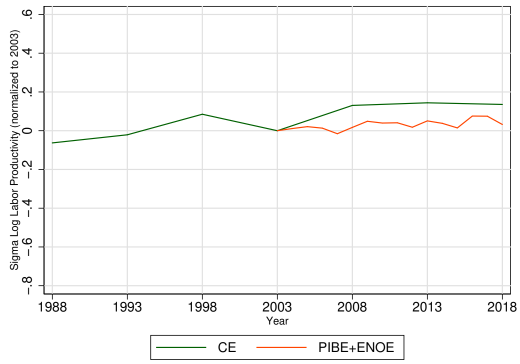


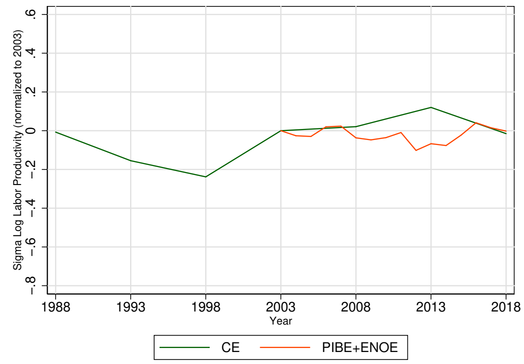
Figure 9: Sigma Manufacturing Log Labor Productivity

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.

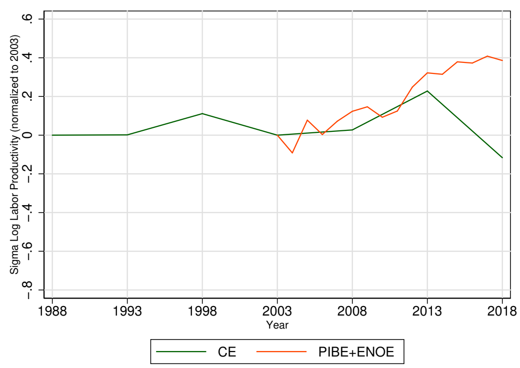
What about sigma-convergence by industry? Figures 10 - 11 show it for each s3-digit subsectors. Despite beta-convergence occur in 5 out of 11 baselines industries for 1988-2018, almost none of them show sigma-convergence for the same period. Only Textile Mills+Textile Product Mills (313-314) displays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



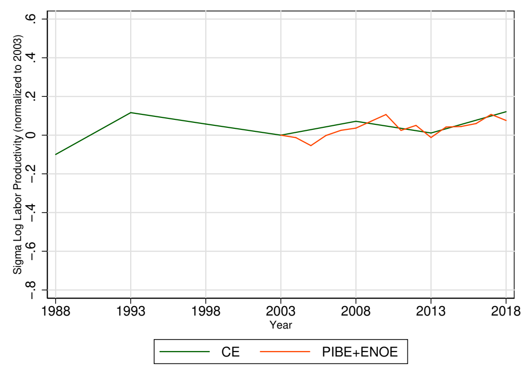
(a) 311: Food Manufacturing



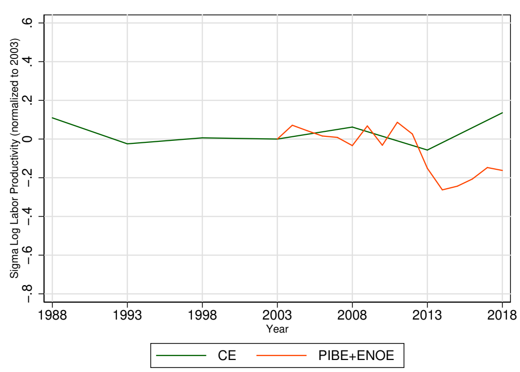
(b) 312: Beverage and Tobacco Product Manufacturing



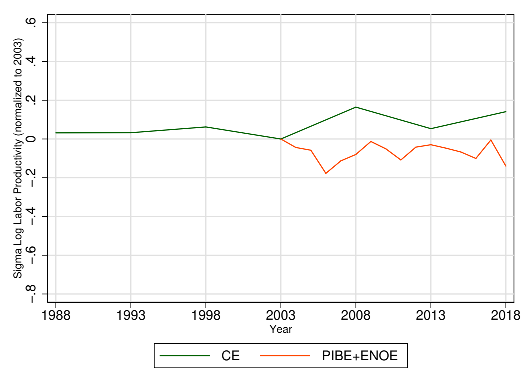
(c) 313-314: Textile Mills; Textile Product Mills



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



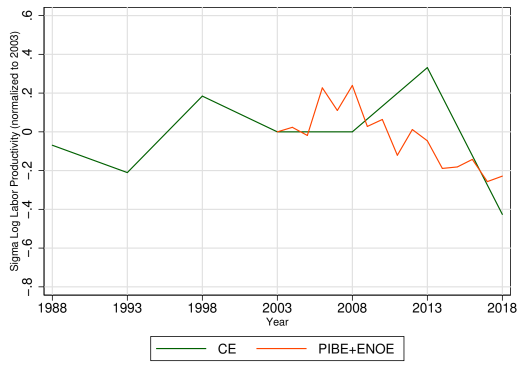
(e) 321: Wood Product Manufacturing



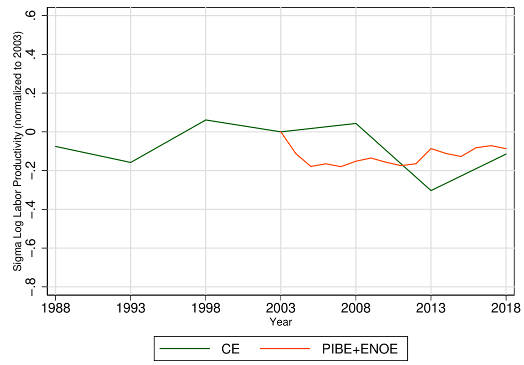
(f) 322-323: Paper Manufacturing; Printing and Related Support Activities

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

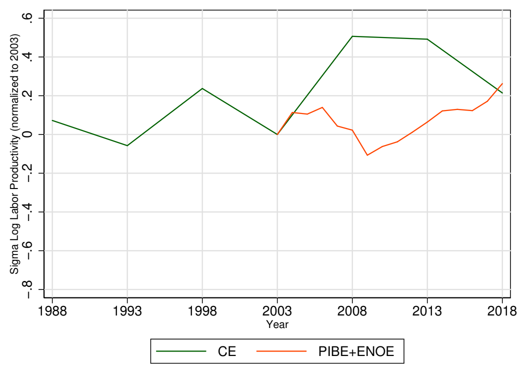
Notes: All series were normalized to their corresponding 2003 value. Data sources: CE; PIBE; ENE-ENOE.



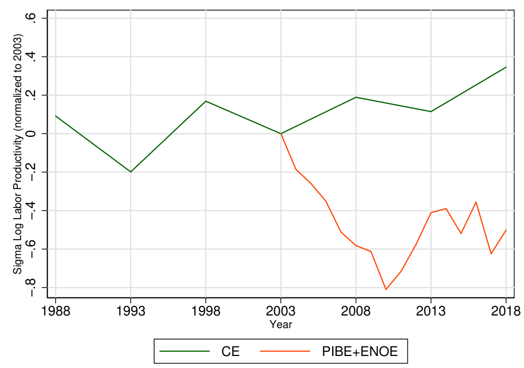
(a) 324-326: Petroleum and Coal Products Manufacturing; Chemical Manufacturing; Plastics and Rubber Products Manufacturing



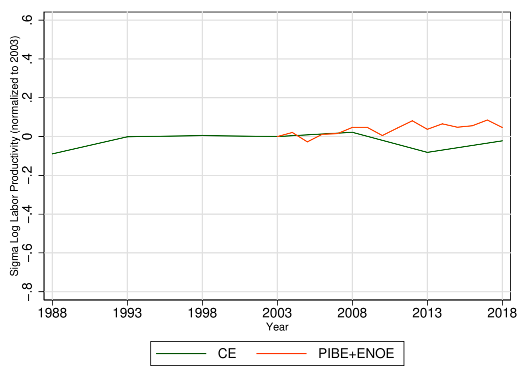
(b) 327: Nonmetallic Mineral Product Manufacturing



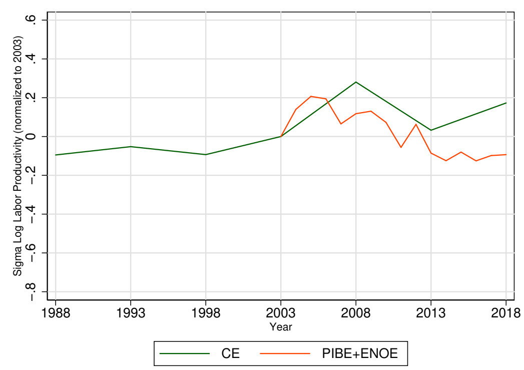
(c) 331-332: Primary Metal Manufacturing; Fabricated Metal Product Manufacturing



(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, it is possible that manufacturing productivity growth in the north has decoupled from the rest of the country, leading to industries in that region to converge at different rates. To test if that was the case, I estimate 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, corresponding to Banxico's regional classification[10]. Table 6 shows the results. For s3-digit industries (columns 5-8), two main observations are obtained. First, from 1988 to 2018, the highest convergence rates were found in the Northern and Central regions, at 2.55% and 2.23% per year, respectively. In contrast, the Central and the Southern regions showed the lowest ones, at 1.5% and 1.25%, respectively. 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. After that period, convergence in each region continued to occur, although at a generally slower pace, particularly in the North-Central and Southern regions.

For the manufacturing sector as a whole (columns 1-4), the highest convergence rate was found in the Central region, at a pace of 2.49% per year, followed by the Northern region, at a rate of 0.78%. The North-Central and Southern regions do not show signs of (statistically significant) convergence. Interestingly, the convergence process in both the Northern and North-Central states seems to have also slowed or stopped at the end of the 1990s. During the same period, there was a process of divergence in the Southern region, with rates of 3.5% and 4.78% per year during 1988-1998 and 1998-2008, respectively, although the latter is not statistically significant. This divergence somehow reversed afterwards.

[10]See for example the Regional Economic Reports. Available in `https://www.banxico.org.mx/publicaciones-y-prensa/reportes-sobre-las-economias-regionales/reportes-economias-regionales.html`.

Table 6: Differences in Convergence across Regions, 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***	-.0281***	-.0397***
XNorth	(.0026)	(.0087)	(.0095)	(.0087)	(.0015)	(.0086)	(.009)	(.0085)
Log initial productivity	-.0135	-.0615**	-.0149	.0373	-.015***	-.0331***	-.013	-.0278***
XCenter-North	(.0168)	(.0297)	(.0155)	(.0357)	(.0026)	(.0085)	(.0077)	(.0089)
Log initial productivity	-.0249***	-.0701***	-.0469**	-.0745**	-.0223***	-.0386***	-.0449***	-.0515***
XCenter	(.0026)	(.0111)	(.0203)	(.0298)	(.0028)	(.0059)	(.0102)	(.0063)
Log initial productivity	.0137	.035*	.0478	-.0261**	-.0125***	-.0505***	-.026	-.044***
XSouth	(.0187)	(.0175)	(.0297)	(.0118)	(.0042)	(.0149)	(.0164)	(.0111)
Observations	32	32	32	32	352	352	351	351
R-squared	.451	.6729	.3339	.3356	.4719	.4142	.2778	.3517
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 manufacture 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 in the aggregate. One possible explanation for the regular convergence in the Central region in all periods may be the reallocation of production from the center to the north, as documented by Hanson (1998). Instead, the Northern region, while showing the highest rates of sub-industry convergence, has a weak rate of convergence in the aggregate. Moreover, the slowing or stopping of the convergence process after 1998, which was previously documented, occurred in all regions except for the Central one. Precisely, in the next section I discuss some of the factors behind this phenomenon in the last decade.

4.2 Some potential determinants of convergence

Since Barro (1991) and Mankiw et al. (1992), a variety of papers in the literature have tried to assess the role of different economic factors on the convergence process. Aside from the fact that the inclusion of some of these 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 in mind these caveats, in this section I try to convey the role of certain economic forces, recently emphasized by several scholars, that could also affect the convergence process. Although their impact on the latter has not been formally studied.

To study how these potential determinants may have affected the convergence process, 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 could be accelerated by it. Instead, if λ is positive, then the considered determinant will slow down, 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	.0125	-.1936	-.2371*	-.0373***	-.1231**	-.0758*
	(.021)	(.1446)	(.1267)	(.0096)	(.048)	(.0444)
Log initial productivityXDeterminant	-.0494	.0184	.0227*	.0118	.0052*	.0027
	(.0372)	(.0146)	(.0128)	(.0165)	(.0026)	(.0024)
Determinant	.5717	-.2191	-.2712*	-.1864	-.0578*	-.0263
	(.4715)	(.1846)	(.1617)	(.1906)	(.0319)	(.0294)
Observations	32	32	32	351	351	350
R-squared	.1085	.1148	.1116	.2672	.2669	.2555
F-statistic			92.4282			606.106
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 of the formal sector. Hence, it could well be the case that once the informal sector is considered, manufacturing convergence may not occur. To have a measure 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. 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 differentially 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.

Overall, the results in Table 7 suggest that informality does not appear to have a significant effect on the convergence process in manufacturing, either at the sub-industry or aggregate level, over the past decade as well. In contrast, the China shock appears to have a negative impact on convergence, as indicated by both OLS and IV estimates. At the aggregate level, the OLS estimates show a negative but statistically insignificant effect, while the IV estimates show a statistically significant effect at the 10%. In that sense, the IV estimates in Column (3) suggest that, without statistical considerations, convergence slows to zero when the China shock exceeds a value of 10.45 (slightly above the median value of 10.21). Figure 12 illustrates the relationship between the China shock and overall convergence in manufacturing. The results suggest that convergence is only statistically significant for relatively low magnitudes of the shock, below 9.8 (percentile 25). It is noteworthy that the China shock has been more concentrated in the northern states of Mexico, as shown in Figure 24 in Appendix D, which may partly explain the results from the previous section. Moreover, these results also suggests that the underperformance of certain key Mexican 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.

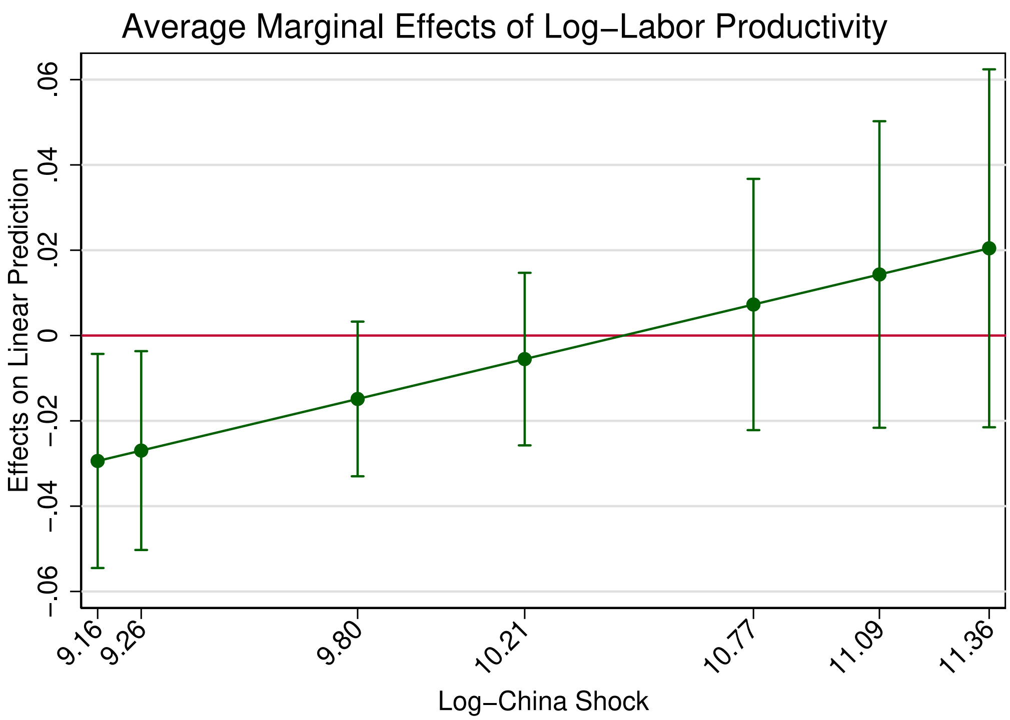


Figure 12: Interaction between convergence and the China shock

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.

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 rate of convergence of 1.18% per year. However, this convergence is not solely characterized by an increase in the labor productivity of followers, 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 also by sigma-convergence. Shift-sharing analysis suggests that the aggregate convergence process stopped then due to the underperformance of several key industries and the failure to reallocate employment towards 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 different 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 manufacture convergence across Mexico differ from the 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, as well as 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 U.S. So, it is likely that manufacture 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 show higher rates of convergence in the aggregate.

Future research may consider the results in this paper as a motivation to further understand why convergence changed in the early 2000s. While this study suggests that the underperformance of critical industries and a lack of reallocation played a major role, it is not clear *why* these trends began during this period. One potential explanation is China's inclusion in the WTO in 2001, which had a negative impact on Mexican labor markets (Chiquiar et al. (2017)). Indeed, I also show that the China shock seems to have had a negative effect on the convergence process in the past decade. Additionally, 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. Lastly, going forward, it is important to expand this class of empirical studies to other countries and regions. The richness of the variety of experiences will surely help us to understand under what conditions and contexts we can expect to observe convergence in manufacturing industries, and how generalizable is the previous cross-country evidence.

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A Data Appendix

Census

As mentioned in the text, I obtained Census data for 1998, 2003, 2008, 2013 and 2018 from INEGI's webpage. In particular, I downloaded the tabulates reported in their Censal Information System (Sistema Automatizado de Información Censal, SAIC). Although all these information use 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 manufacture sector. Hence, I do not homologate the different censal versions as they are all comparable at the level of analysis.

For the case of the 1988 and 1993 censuses, data was digitized from INEGI's physical records[11]. Since this data is reported in CMAP industry codes, I map them into SCIAN 2002 using INEGI's conversion tables[12]. 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.

[11] 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.

[12] 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 states from the ENOE micro-data. Specifically, I consider the pre-codified variable by INEGI that accounts for the informal sector[13].

[13] 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 imports 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[14]. 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 digit 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, Switzerland. For each country, I downloaded separately annual data from 2003 to 2018.

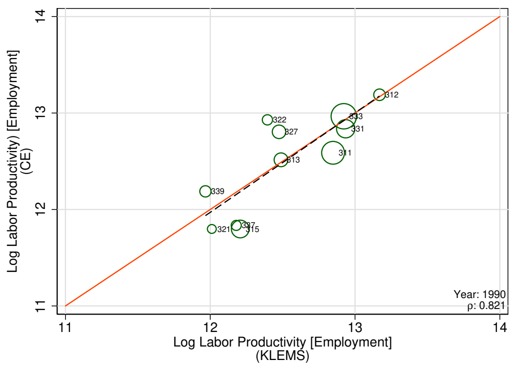
China Shock

To instrument the China shock to the US, I follow Autor et al. (2013) and use imports 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 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 convergence between 2008 and 2018, the shares of employment are built using 2003 data.

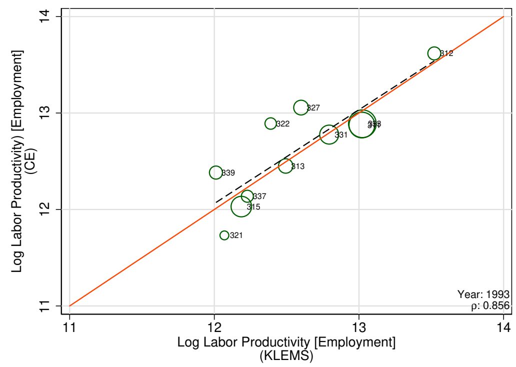
[14]See for example `https://wits.worldbank.org/wits/wits/witshelp/content/data_retrieval/T/Intro/B2.Imports_Exports_and_Mirror.htm`.

B Additional Results

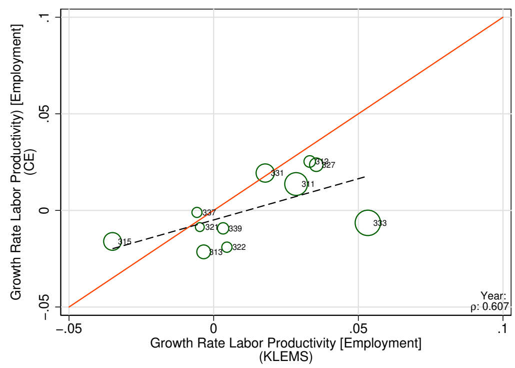
B.1 Validation of Digitized Data



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



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

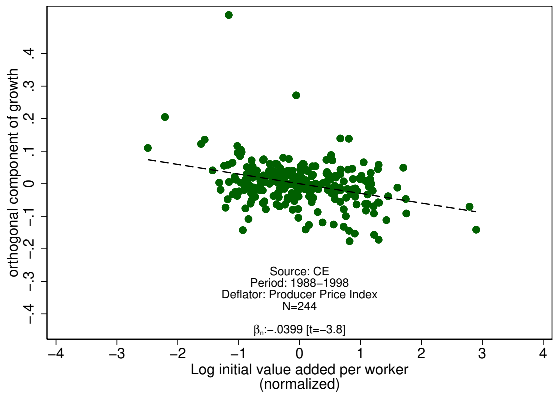


(c) Correlation Growth in Labor Productivity (1988/1990-2018), s3-digit

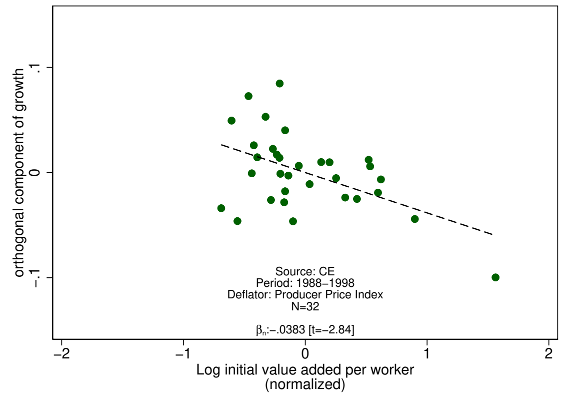
Figure 13: Correlation Growth and Log Labor Productivity across datasets (1988/1990-1993).

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

B.2 Unconditional Convergence (CMAP Nomenclature)



(a) 2-digit Manufacturing Sectors



(b) 1-digit Manufacturing

Figure 14: 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 and coal products, rubber and plastic). t-statistic from clustered standard errors at the state level. Data sources: CE.

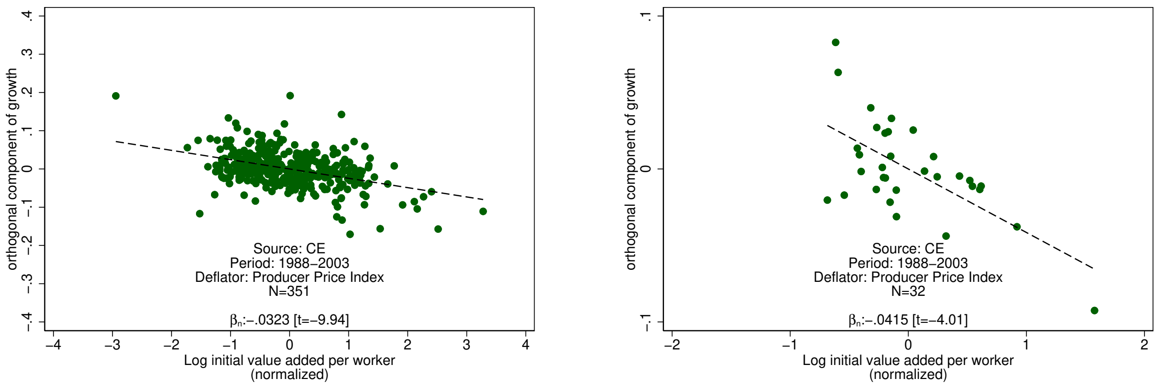
B.3 Correlation between CE and PIBE+ENOE measures

Table 8: Correlation Growth and Levels, across datasets (2008-2018)

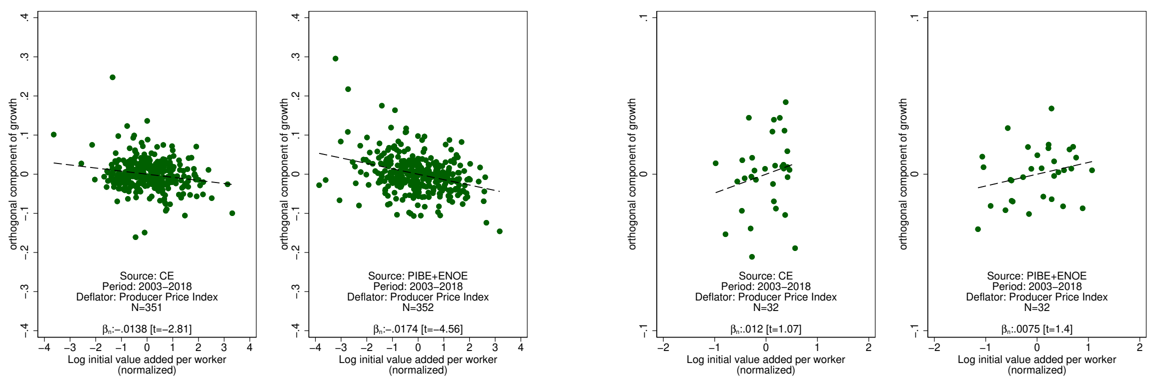
	SCIAN 1-digit			SCIAN s3-digit		
	Value-Added	Employment	Labor Productivity	Value Added	Employment	Labor Productivity
	(1)	(2)	(3)	(4)	(5)	(6)
Levels: 2008	.988	.96	.853	.926	.917	.679
Levels: 2018	.984	.968	.873	.929	.925	.69
Growth: 2008-2018	.65	.685	.354	.308	.383	.067

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

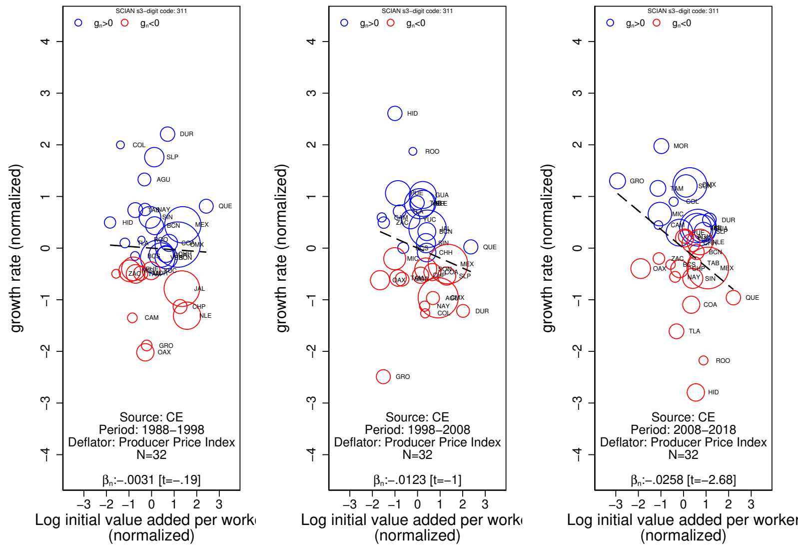


(b) 2003-2018

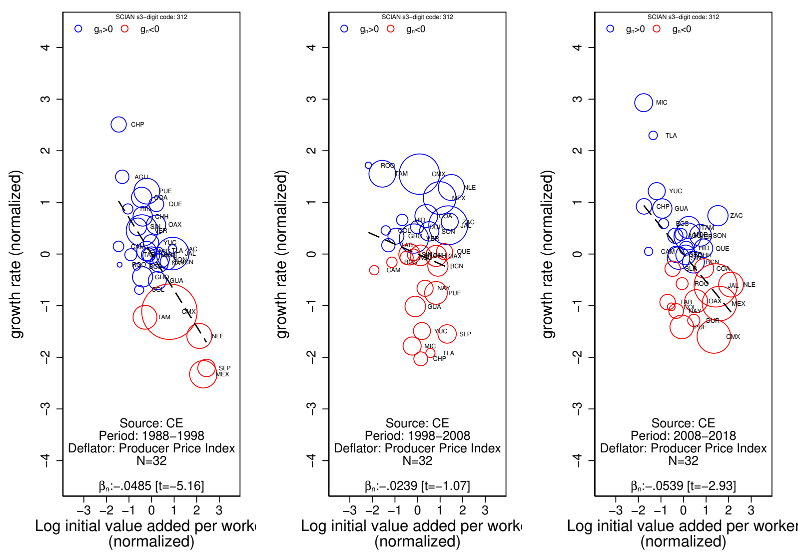
Figure 15: Convergence in Manufacturing Sector (1988-2003), (2003-2018)

Notes: 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: Different Decades



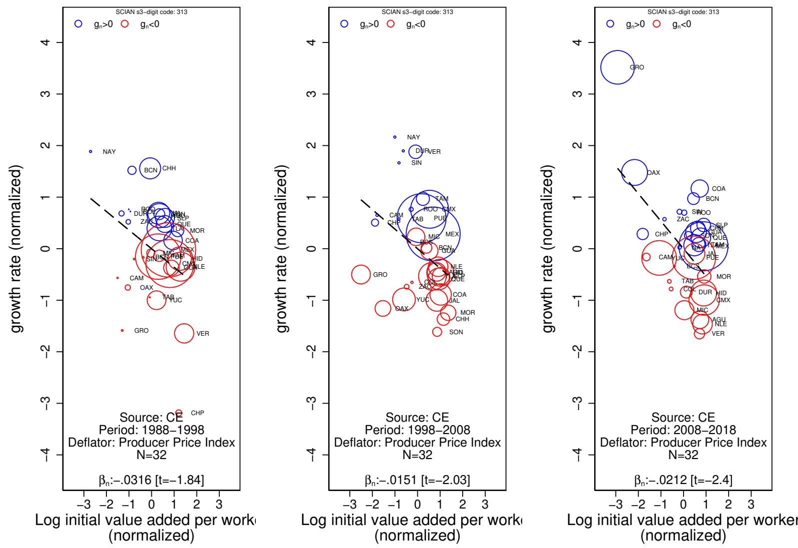
(a) 311: Food Manufacturing



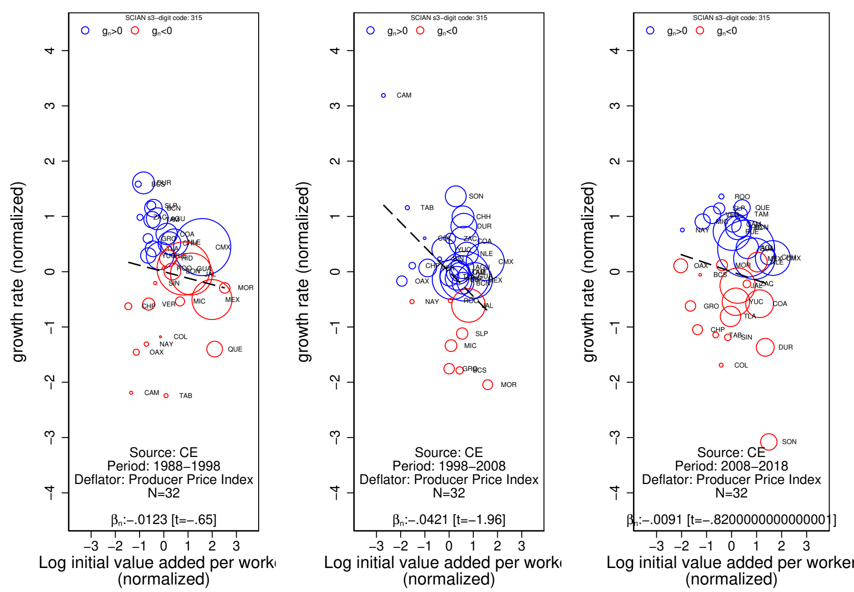
(b) 312: Beverage and Tobacco Product Manufacturing

Figure 16: Convergence by Industry and Decade (I)

Notes: Estimates from $\hat{y_j^i} = -\beta^i \ln y_j + \epsilon_j$, $i \in \{311, 312, \ldots 339\}$ for different periods. 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.



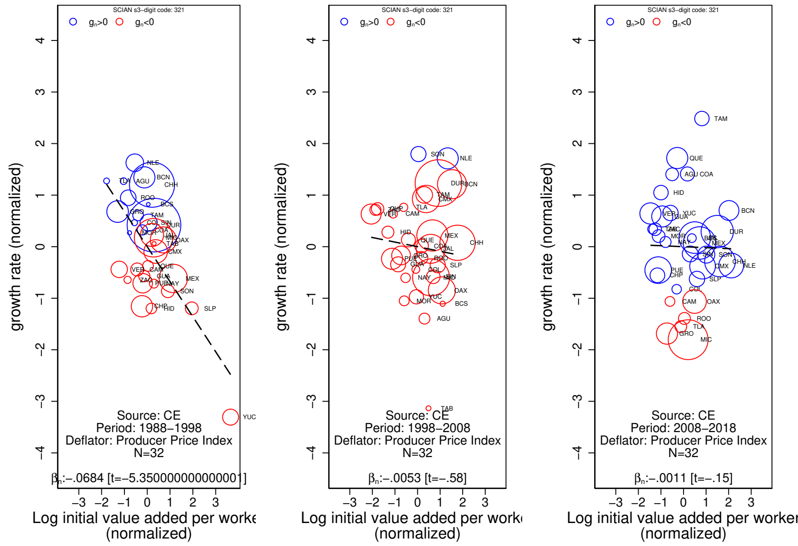
(a) 313-314: Textile Mills; Textile Product Mills



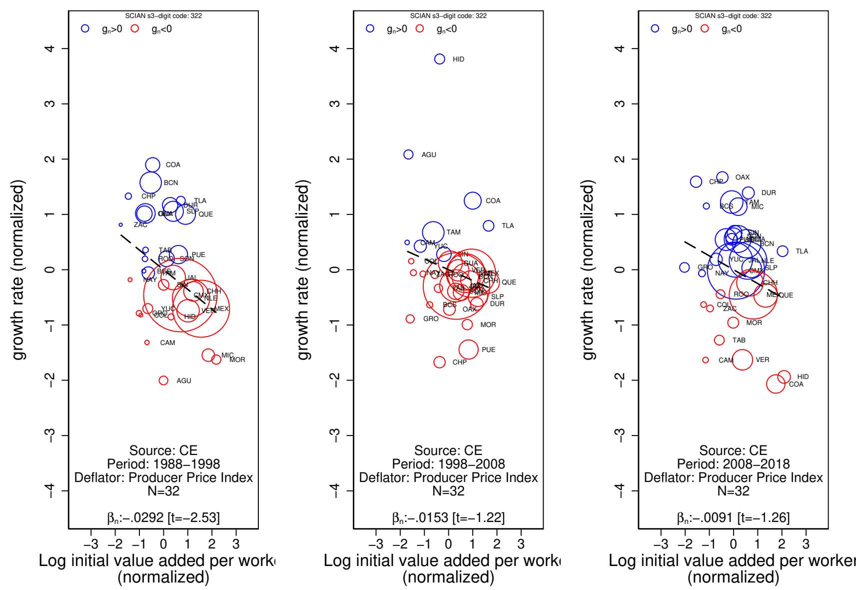
(b) 315-316: Apparel Manufacturing; Leather and Allied Product Manufacturing

Figure 17: Convergence by Industry and Decade (II)

Notes: Estimates from $\hat{y^i_j} = -\beta^i \ln y_j + \epsilon_j, i \in \{311, 312, \dots 339\}$ for different periods. 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.



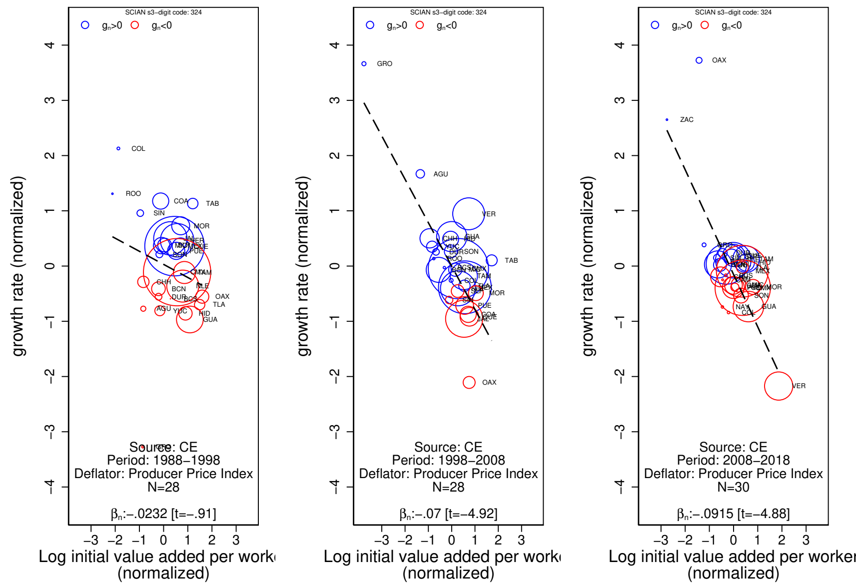
(a) 321: Wood Product Manufacturing



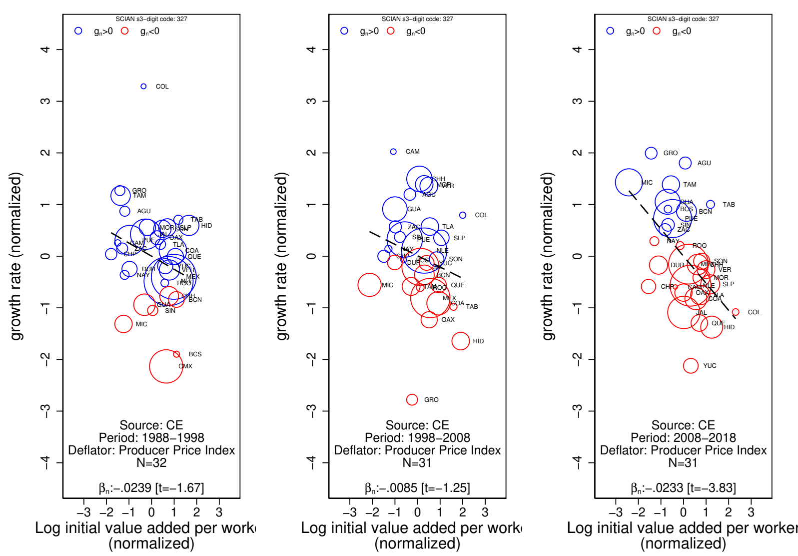
(b) 322-323: Paper Manufacturing; Printing and Related Support Activities

Figure 18: Convergence by Industry and Decade (III)

Notes: Estimates from $\hat{y^i_j} = -\beta^i \ln y_j + \epsilon_j, i \in \{311, 312, \ldots 339\}$ for different periods. 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.



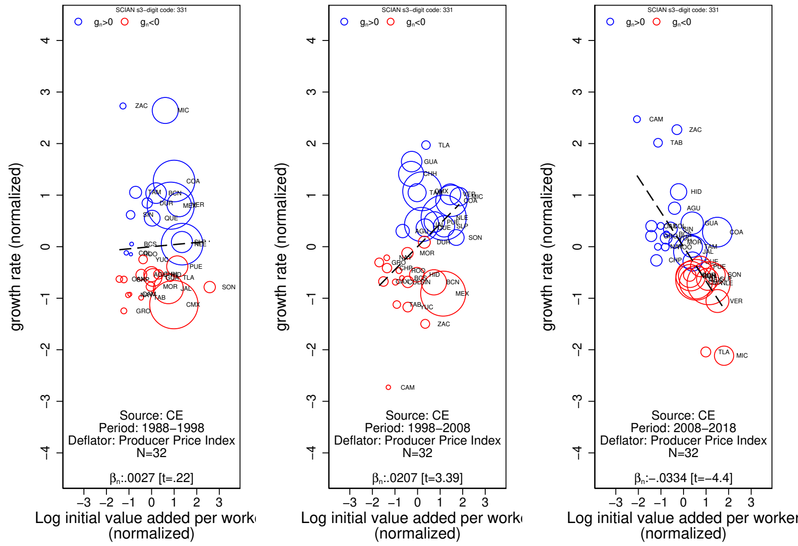
(a) 324-326: Petroleum and Coal Products Manufacturing; Chemical Manufacturing; Plastics and Rubber Products Manufacturing



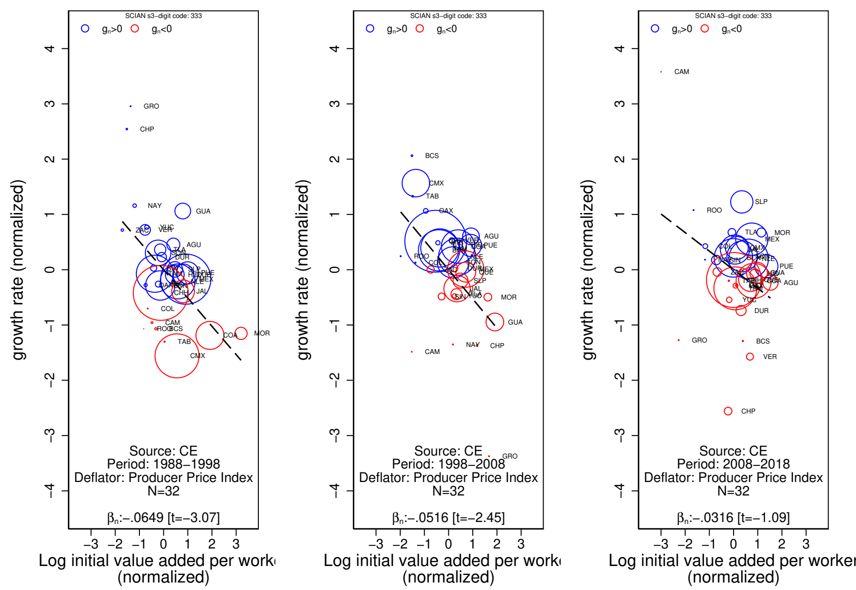
(b) 327: Nonmetallic Mineral Product Manufacturing

Figure 19: Convergence by Industry and Decade (IV)

Notes: Estimates from $\hat{y^i_j} = -\beta^i \ln y_j + \epsilon_j$, $i \in \{311, 312, \ldots 339\}$ for different periods. 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.



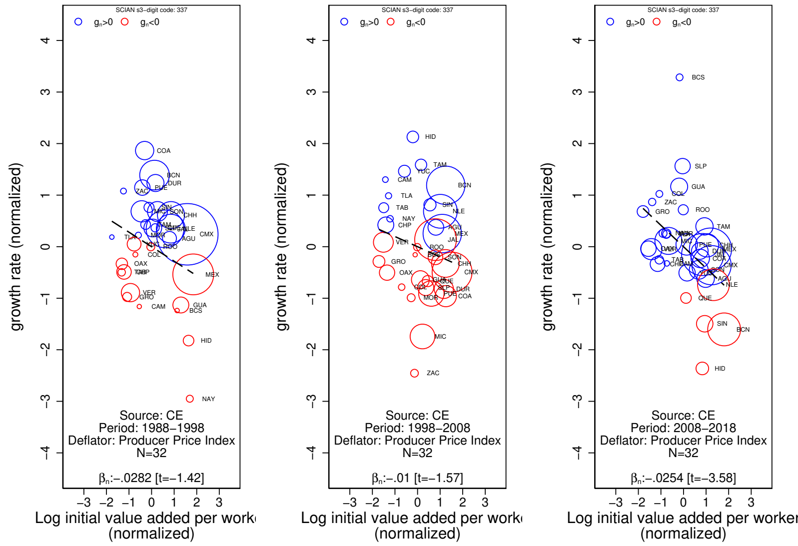
(a) 331-332: Primary Metal Manufacturing; Fabricated Metal Product Manufacturing



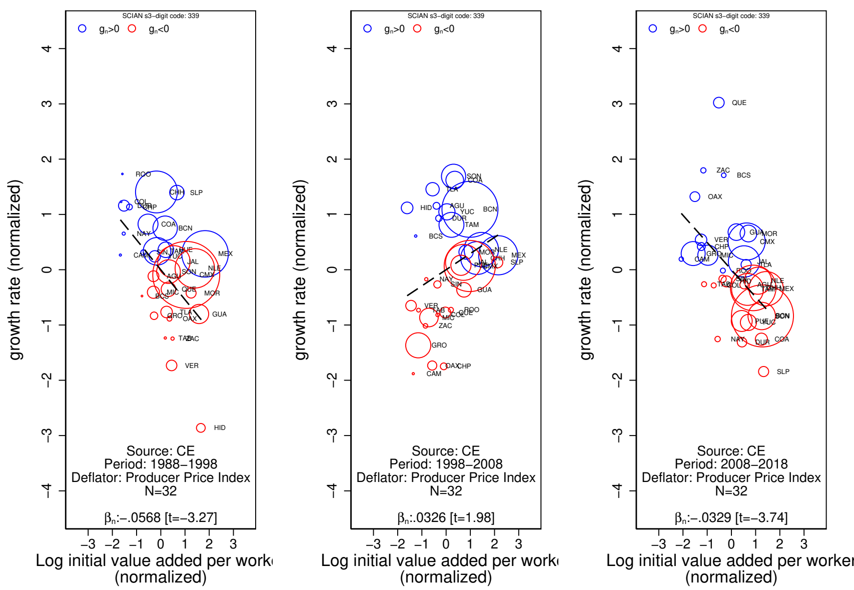
(b) 333-6: Machinery Manufacturing; Computer and Electronic Product Manufacturing; Electrical Equipment, Appliance, and Component Manufacturing; Transportation Equipment Manufacturing

Figure 20: Convergence by Industry and Decade (V)

Notes: Estimates from $\hat{y}^i_j = -\beta^i \ln y_j + \epsilon_j,\ i \in \{311, 312, \ldots 339\}$ for different periods. 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) 337: Furniture and Related Product Manufacturing

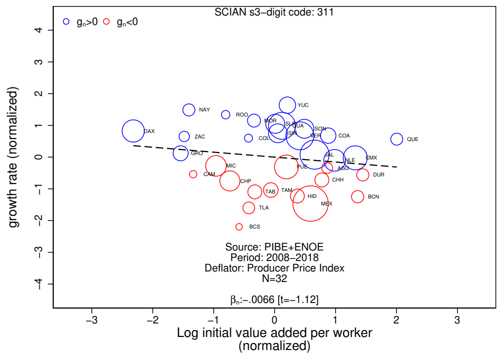


(b) 339: Miscellaneous Manufacturing

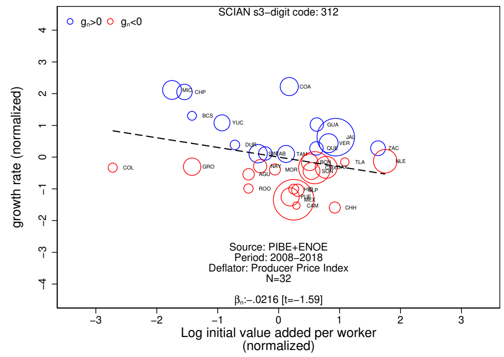
Figure 21: Convergence by Industry and Decade (VI)

Notes: Estimates from $\hat{y_j^i} = -\beta^i \ln y_j + \epsilon_j$, $i \in \{311, 312, \ldots 339\}$ for different periods. 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.

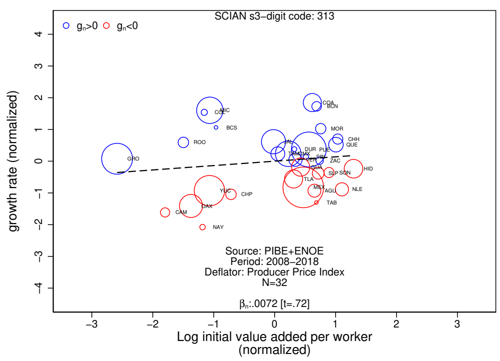
B.6 Convergence by Industry: PIBE+ENOE (2008-2018)



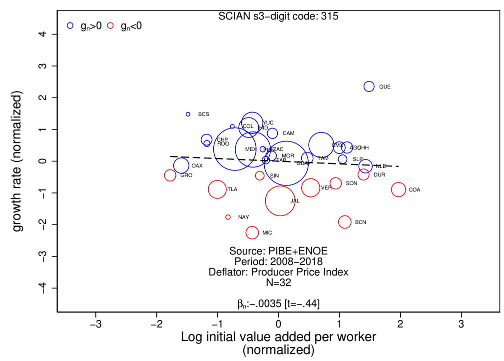
(a) 311: Food Manufacturing



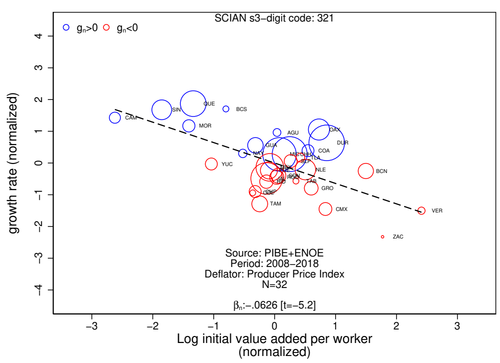
(b) 312: Beverage and Tobacco Product Manufacturing



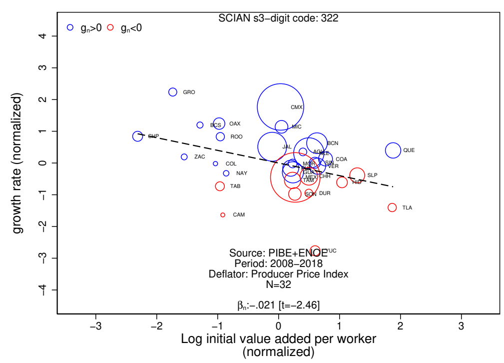
(c) 313-314: Textile Mills; Textile Product Mills



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



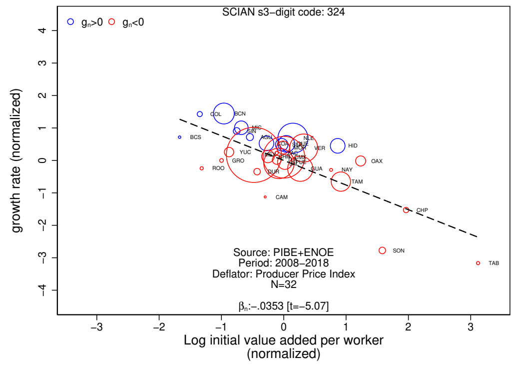
(e) 321: Wood Product Manufacturing



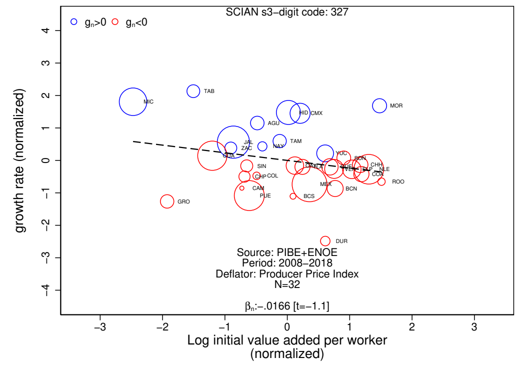
(f) 322-323: Paper Manufacturing; Printing and Related Support Activities

Figure 22: Convergence by Industry (I) 2008-2018

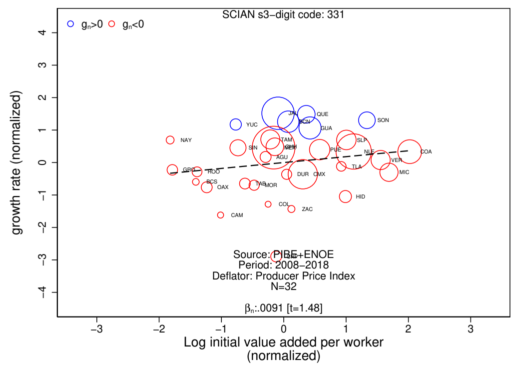
Notes: Estimates from $\hat{y}^i_j = -\beta^i \ln y_j + \epsilon_j$, $i \in \{311, 312, \ldots 339\}$. t-statistic from robust standard errors. The size of markers correspond to the importance of employment at a national level in the initial period. Data sources: PIBE; ENOE.



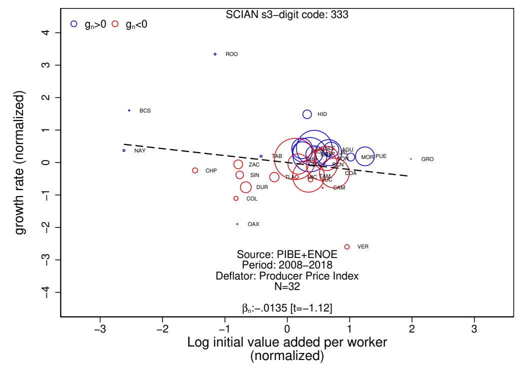
(a) 324-326: Petroleum and Coal Products Manufacturing; Chemical Manufacturing; Plastics and Rubber Products Manufacturing



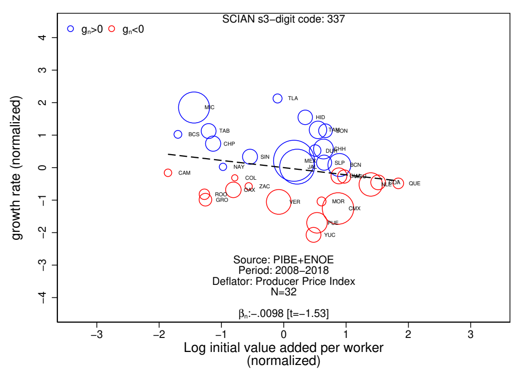
(b) 327: Nonmetallic Mineral Product Manufacturing



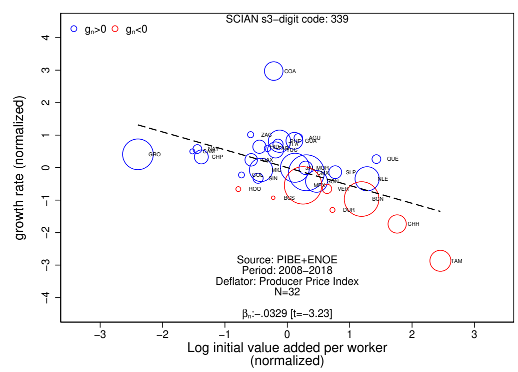
(c) 331-332: Primary Metal Manufacturing; Fabricated Metal Product Manufacturing



(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 23: 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 correspond to the importance of employment at a national level in the initial period. Data sources: PIBE; ENOE.

B.7 Include Petroleum Products Manufacturing (324-326)

Table 9: 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	-.0194*	-.0304*	-.029***	-.0335***	-.0358***	-.0387***
	(.0101)	(.0153)	(.0018)	(.006)	(.0039)	(.0067)
Log initial productivity, 1998		.0349*		.0109		.0041
		(.0177)		(.0092)		(.0103)
Log initial productivity, 2008		.002		.0021		.0041
		(.0212)		(.009)		(.0068)
Observations	95	95	1140	1140	1816	1816
R-squared	.107	.1354	.2189	.2221	.2446	.245
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.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

C Conditional Convergence

Table 10: 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***	-.0433***	-.0516***	-.0554***	-.0568***
	(.0125)	(.0119)	(.0044)	(.0079)	(.0059)	(.009)
Log initial productivity, 1998		.012		.0196***		.0029
		(.0176)		(.0067)		(.0114)
Log initial productivity, 2008		.0175		.0047		.0009
		(.0122)		(.0088)		(.0079)
Observations	96	96	1054	1054	1598	1598
R-squared	.715	.7264	.3155	.3257	.3224	.3226
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: The sample includes all SCIAN s3-digit manufacturing industries, except 324-326. Clustered standard errors at the state level in parenthesis. Data sources: CE.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

D Geographical Distribution of the China shock

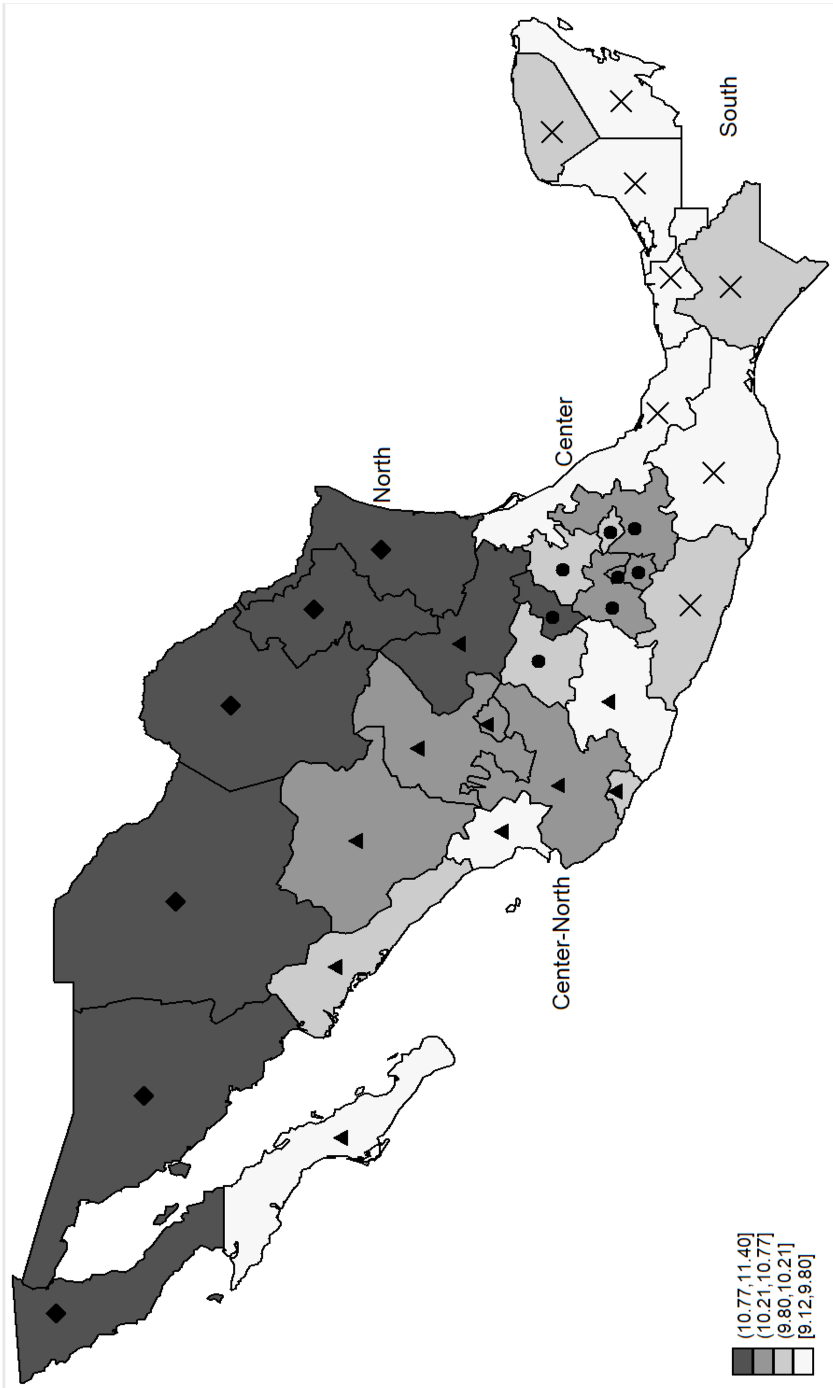


Figure 24: Regional distribution of the China shock

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