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Patterns of Specialization and (Un)conditional Convergence: The Cases of Brazil, China and India

Modèles de spécialisation et convergence économique : les cas du Brésil, de la Chine et de l'Inde

Los patrones de especialización y convergencia económica: los casos de Brasil, China y la India

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Résumé de l'article

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Los patrones de especialización y convergencia económica: los casos de Brasil, China y la India

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RÉSUMÉ

Nous proposons de mesurer la convergence économique pour trois pays émergents : le Brésil, la Chine et l'Inde. Lorsque le niveau de productivité dans une industrie augmente, son taux de croissance diminue montrant une convergence vers la frontière technologique représentée par les États-Unis. Une première contribution est de proposer une nouvelle définition de la convergence, sur la base de la productivité du travail. Une deuxième contribution est que nous utilisons des données au niveau de l'industrie pour mesurer la convergence. Ce faisant, nous cherchons à réduire les biais de l'utilisation de données commerciales recueillies au niveau national.

Mots clés : convergence économique, croissance endogène, Brésil, chine, Inde, productivité du travail

ABSTRACT

We propose to measure economic convergence for three emerging countries: Brazil/China/India. A first result is that the higher the level of productivity in an industry, the lower its growth rate, showing a convergence to the productivity frontier represented by the U.S. A first contribution is to propose a new definition of convergence, based on labor productivity vis-à-vis the technological frontier. A second contribution is that we use industry-level data to measure convergence. In doing so, we aim to reduce the biases of using trade data collected at the national level as in previous models.

Keywords: economic convergence, endogenous growth, Brazil, China, India, labor productivity

RESUMEN

Proponemos medir la convergencia económica para tres mercados emergentes: Brasil, China e India. Cuando el nivel de productividad en una industria aumenta su tasa de crecimiento disminuye, lo que muestra la convergencia de la frontera tecnológica representada por los Estados Unidos. Una primera contribución es proponer una nueva definición de convergencia, sobre la base de la productividad del trabajo. Una segunda contribución es que utilizamos los datos a nivel de la industria para medir la convergencia. De este modo, se busca reducir el sesgo causado porel uso de datos de comercio a nivel nacional.

Palabras claves: convergencia económica, crecimiento endógeno, Brasil, China, India, productividad del trabajo

Introduction

Emerging and developing countries represent roughly half of the world GDP and are the main contributors to the bulk of world growth (Builter and Rahbari 2011). This paper aims at revisiting the models of growth and more specifically the convergence of growth between emerging and developed countries. In the midst of a globalization of the value chains, measuring the world based on data, whose geographical scope is political, does not help capture the new world economic reality. This is why we need to work on the right data to collect as well as use the right methodology to understand these data. The present paper does not pretend to provide all the answers, but our aim is to be part of this conversation.

We will use Brazil, China and India as our illustrations in this paper. But the originality is beyond the empirical analysis. Indeed, when the literature studies international trade, it uses data capturing the flows between countries. It means that the data are constructed with national borders in mind. As a consequence, the literature makes an implicit assumption: it entranches the old theories of Mercantilism or more recent neo-classical trade theories in the analysis.

1. Corresponding author: thierry.warin@hec.ca. We would like to thank CIRANO and the GMT Lab (Polytechnique Montréal) for their support. Our thanks go to the participants of the IAES and IT&FA conferences (Montreal, 2013) and the IFBAE conference (Tours, 2013); the usual caveats apply.

However, the forces of globalization, and in particular the global chain values put in place by multinational entreprises (MNE), make these data aggregated at the national level a little less relevant. We need to correct for intra-industry trade and even further, ideally we would need data at the MNE level to correct for "intra-MNE trade" and thus to really capture the new dynamics of international trade. In short, for a significant data collection, the relevant unit is no longer a country but the MNE level.

From an empirical perspective now, collecting a comprehensive dataset at the MNE level is a huge endeavor. So we need to develop methodologies that will reconcile this theoretical consideration while allowing empiricists to have better proxies of the dynamics of trade. This is precisely what we propose in this paper. Instead of using aggregated data at the country level, we use data at the industry level. We are still looking at industries delimited within the political borders of a country, but by considering the industry level, we also reduce the biases of a too high level of aggregation. For instance, when we want to assess comparative advantages across countries, we propose here to use industry-level data instead of country-level data in order to reduce some of the biases coming from national data.

This new approach is useful for countries to better assess their relative comparative advantages, but it is also useful for MNEs. In the latter case, it is indeed very relevant for an MNE working in a specific industrial sector to be able to identify where in the world companies in similar industrial sectors have lower, similar or higher productivity levels for instance. The reasons are twofold: (1) on the one hand, it allows the company to identify very early on where the new competition is coming from, and (2) on the other hand it allows the company to identify places where it could create a joint-venture, license a product or buy a foreign company. It is not only better to use industry-level datasets for theoretical reasons, but it has also real strategic implications for MNEs to better understand the forces of globalization.

More specifically, the goal of this paper is twofold: (1) based on a large dataset built around industrial sectors in each country (China, India, Brazil, U.S.), we study the notion of convergence based on a pooled approach first, and (2) we study convergence at the industry level. Of course, this work does not intend to be exhaustive, indeed the limitations we have with the data prevent us from being too definitive. Nevertheless, we hope that the approach we design here lays out the path for further interesting research.

This paper is part of the literature on economic growth and most particularly on labor productivity convergence. An important part of the economic growth literature is dedicated to the convergence concept.

Broadly speaking, convergence is defined in two ways: (1) when countries (or regions) converge to a steady state, which is the same for all, (2) but it can also be if countries (or regions) are considered to converge each to their own steady state (Barro and Sala-i-Martin 2004). Generally, convergence is measured through per capita income (GDP per capita) or labor productivity.

More specifically, the convergence literature has started in the 1990s (Barro and Sala-i-Martin 1992; Mankiw, Romer, and Weil 1992). At that time, convergence was defined as a process that leads poor countries to grow faster than rich ones, ending up in theory at the same level of real per capita income. The literature empirically demonstrated that there was a negative partial correlation between the real per capita income growth and the inital level of real per capita income. In other words, the poorer the country, the higher the growth rate, and the richer the country, the lower the growth rate. The value of this partial correlation was captured by a variable called β, leading to the convenient label of β-convergence. The literature has also studied convergence across panel data series (Sala-i-Martin 1996) and made an interesting difference: either β-convergence is absolute (unconditional) or conditional. When all economies converge to the same steady-state, then it is said to be absolute. However, when all economies converge but to different steady-states due for instance to differences in factor endowments, then it is called conditional convergence. Now, we understand that conditional β-convergence means that there will be a difference between countries. The reduction in the dispersion of real per capita income across a group of countries is called σ-convergence. It looks like β-convergence, but the way to measure convergence is different. σ-convergence is often captured by the standard deviation of the coefficient of variation to the mean. In short, β-convergence is a necessary condition for σ-convergence but not a sufficient condition.

So, when we talk about emerging countries, it is clear that these two definitions of convergence matter. In this regard, our contribution is twofold: (1) we use industry-level data instead of data aggreagated at the national level. The definitions of convergence are very useful to characterize which kind of convergence patterns does a country follow. However, considering our criticism of using data aggregated at the national level, we should thus consider these definitions of convergence with industry-level data across countries. (2) And since we are using industry-level data in this study, we can also augment the β-convergence model. Instead of looking at real per capita income growth vis-à-vis the initial level or per capita income, we could look at an efficiency indicator such as labor productivity. Since (1) we do that for each industry and (2) we can compare labor productivity of each sector to the technological frontier (i.e. the highest labor productivity overall for the sector considered), it would be interesting to design a slightly different convergence model. We propose here one out of many options, which we will call δ-convergence to differentiate the model from the original models. This is our second contribution to the literature.

The option we propose is to look at labor productivity growth for each industry in a country and calculate the partial correlation with the distance (hence δ) between labor productivity in this industry vis-à-vis the technological frontier. The hypothesis is that the closer an industry is to the technological frontier, the the closer it is to having converged to a steady-state, hence the lower the labor productivity growth. In this regard, δ-convergence follows the same logic as β-convergence, but is definitely an augmented version. This is the methodology we propose to look at emerging countries.

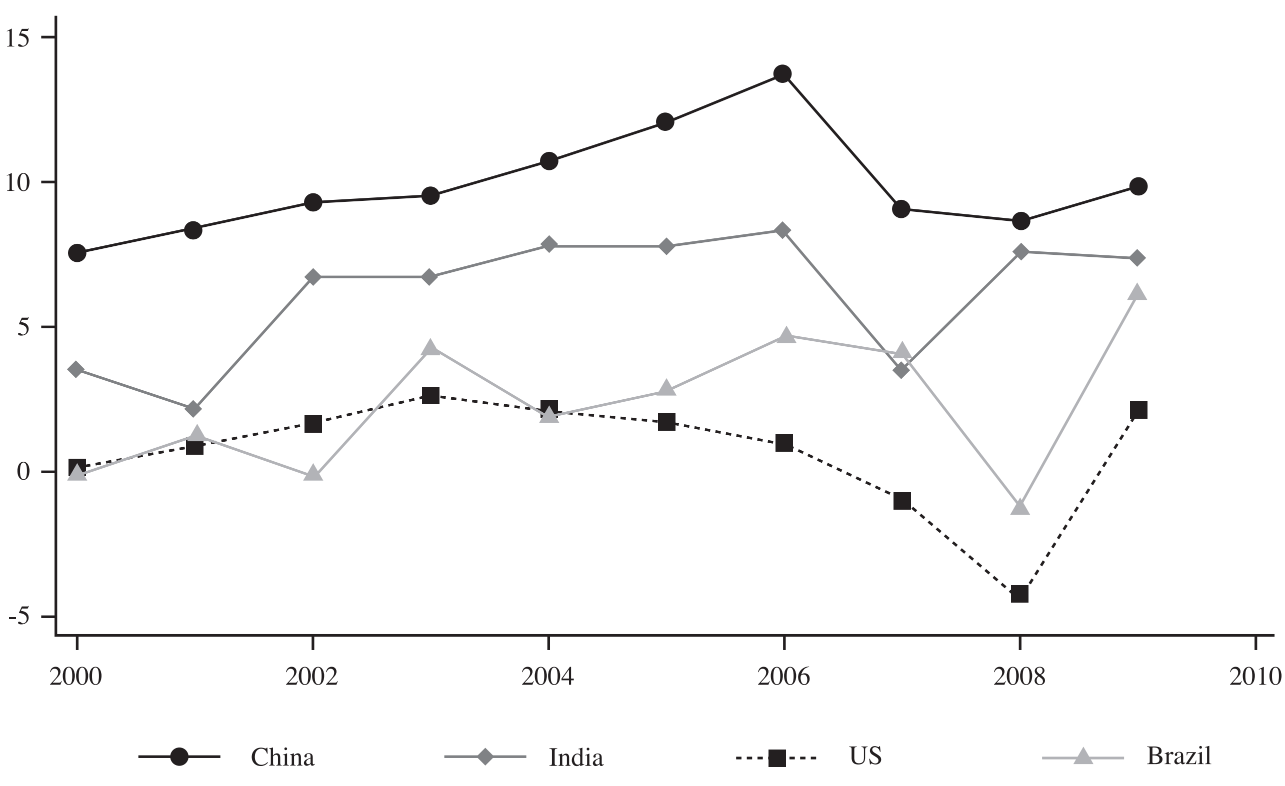
The current study focuses on Brazil, China and India. In 2010, populations of these three countries represented more than 45% of the world population.[1] According to Buiter and Rahbari (2011), China will even become the largest economy in the world by 2030 and will itself be second to India by 2050. The following graph (Figure 1) gives us some interesting information about the economic evolution of Brazil, China and India in the past two decades.

Before the crisis, the high annual growth of Brazil, China and India compared to the United States (which is even negative between 2007 and 2009) is already an indicator of convergence between these emerging economies and the U.S. economy. Brazil, China and India are very interesting case studies in this regard. But instead of looking at this convergence at the aggregate level, our study relies on a more micro-level approach. Indeed, industrial firms play an important role in emergent countries. Exports have drastically increased over the years to levels of 24%, 30% and 25% of the GDP in Brazil, China and India in 2011 (compared, for example, to 12% in the U.S.) (The World Bank 2011). And what is more interesting than overall convergence is to look at which industrial sectors are actually converging.

As the manufacturing sectors account for respectively 60%, 93% and 64% of Brazilian, Chinese and Indian exports in 2010 (The World Bank 2011), we should look more closely at the evolution of these industries. Brazil has experienced an important increase of every industry in general in the manufacturing sector (see Figure 2). As seen on Figure 3, despite a slowdown, the number of manufacturing establishments in China has generally doubled in less than 10 years. India's manufacturing sector has stayed stable or has increased too (see Figure 4). In comparison, we observe that for the U.S., almost every sector has experienced a slowdown (except for beverages, non-metallic mineral products and structure

FIGURE 1

GDP per capita, annual growth in % (constant 2005 international $)

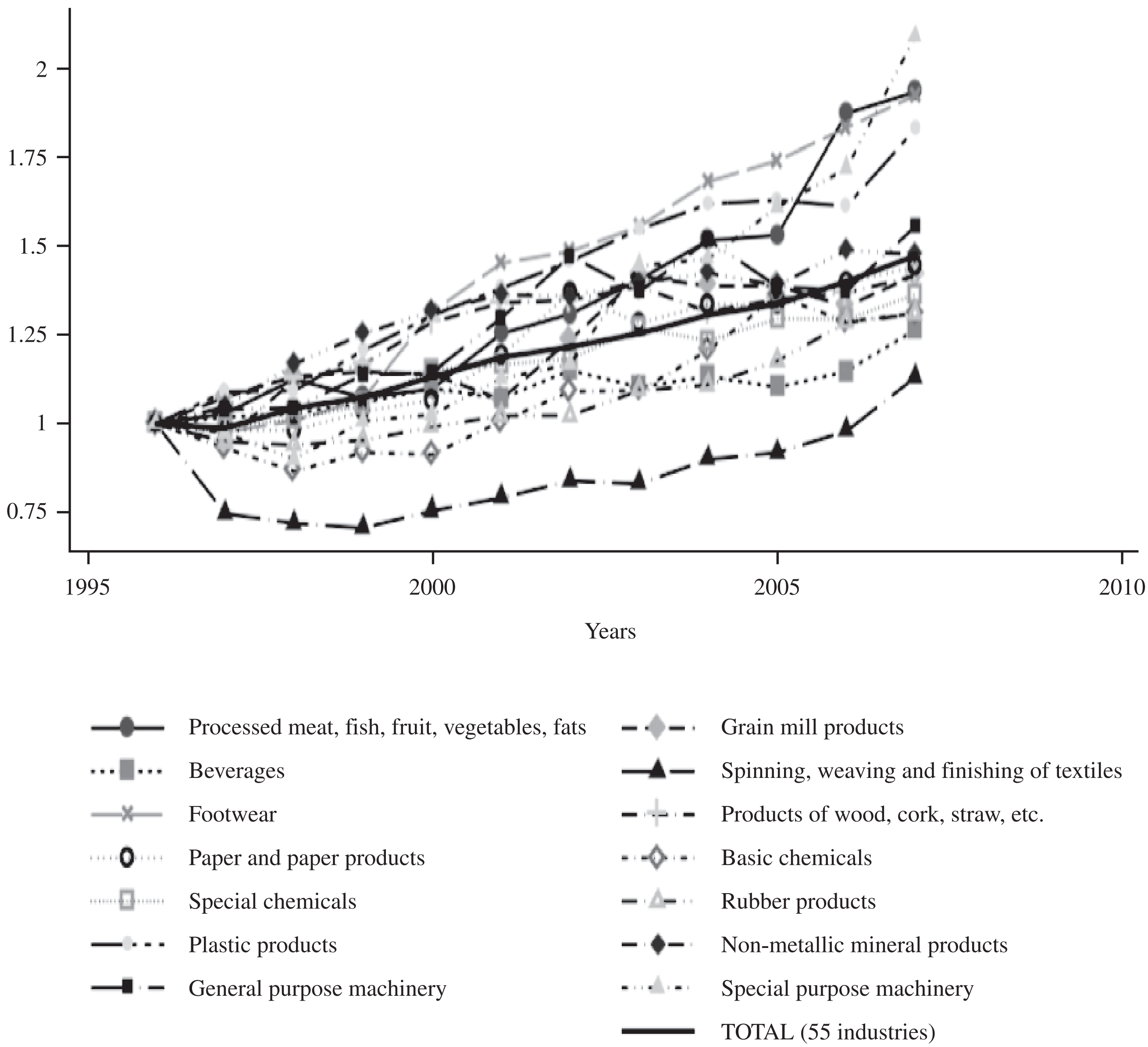


Source: Author's calculations using World Bank 2011 data

1. According to author's calculations from World Bank data

FIGURE 2

Normalized evolution of the number of establishments in the manufacturing sector for major industry types in Brazil



Source: UNIDO database, 2011

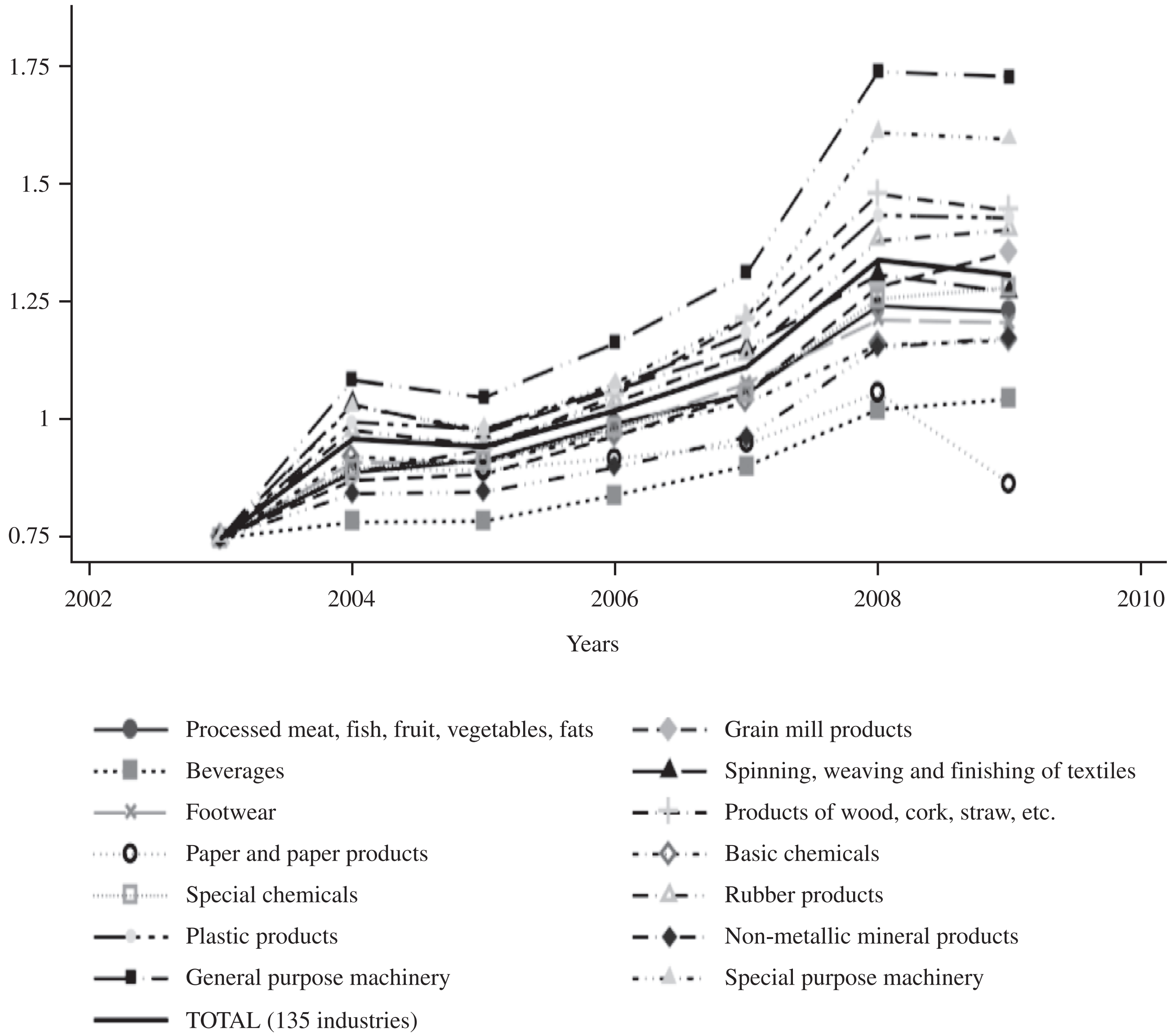
metal products) (see Figure 5). Unfortunately, we do not have the data from 2006 onwards for the U.S. However, we can assume that the economic crisis has not helped and that the number of establishments has continued to fall at least until 2009. This big picture shows that the advantage goes to Brazil, China and India.

In this regard, it might be very interesting to look at the evolution of labor productivity in these countries. Indeed, considering their active population and the recent fast-pace development of the manufacturing sector, we assume that these emerging countries may start having important comparative advantages. Moreover, it is important to emphasize that the size of their own population provides them with a huge domestic market. Independently of any other control variable (political measures, economic measures, etc.), we could eventually find unconditional convergence for these three countries.

It is in this context that this paper tests whether the convergence hypothesis can be validated for these three countries. We will try to identify labor productivity convergence in the

FIGURE 3

Normalized evolution of the number of establishments in the manufacturing sector for major industry types in China



Source: UNIDO database, 2011

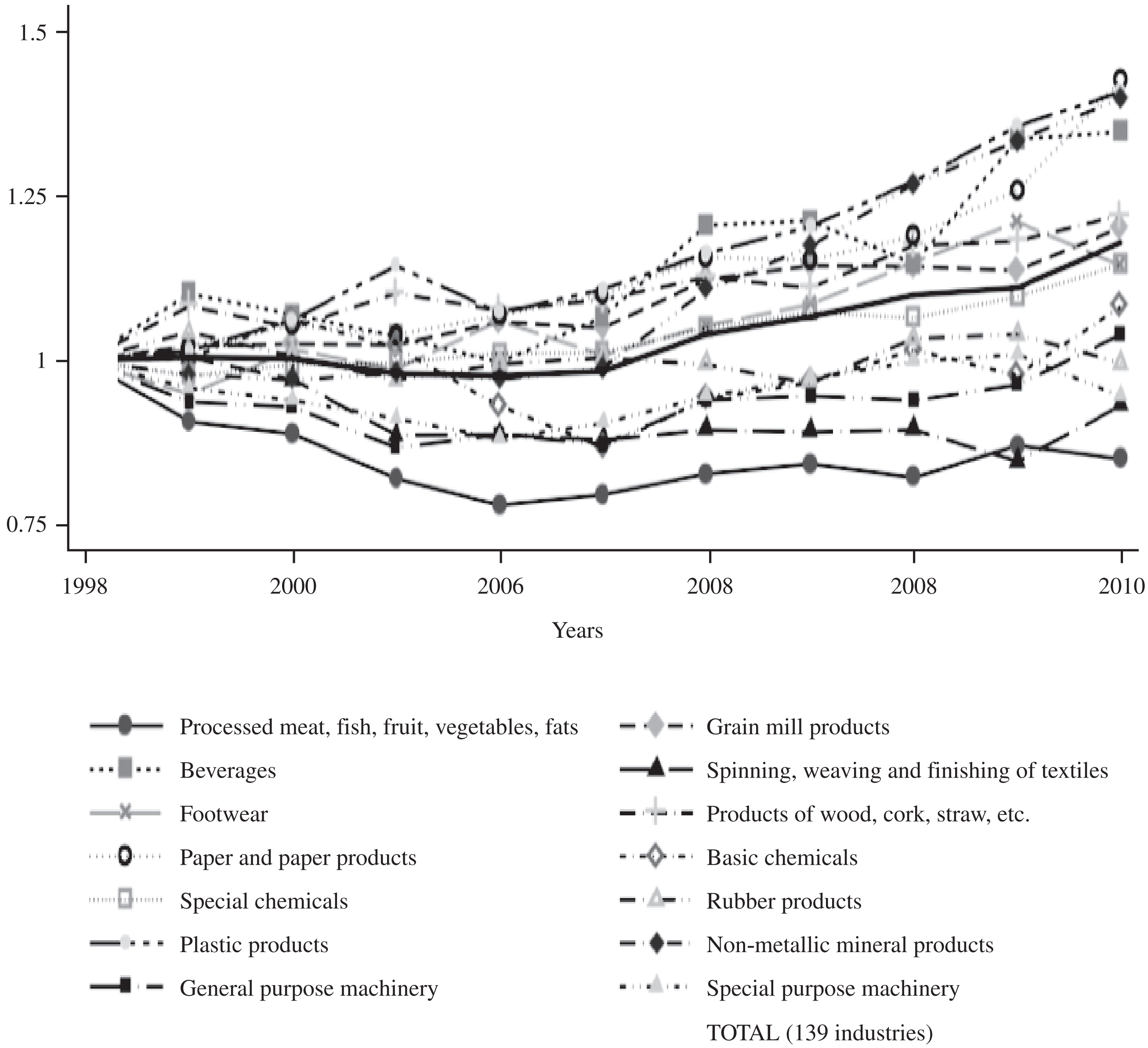
manufacturing sector between each of these countries and the United States. This type of convergence is different from the well-known β-convergence, which checks convergence of an entire sample of countries or regions. It is also different from the **σ-convergence, which is particularly interested in the shape of the variance in** growth rate. The choice of the U.S. as the country of reference is not a coincidence, as it remains up to four times the more productive country at the manufacturing level before Germany or France in the main sectors.[2]

Therefore, in what follows, we present a brief literature review on the types of convergence. Then the research design is described in section 3. In section 4, the models are tested

2. According to author's calculations and using UNIDO data: the productivity is obtained by dividing each sector's added value by the number of employees at the time.

FIGURE 4

Normalized evolution of the number of establishments in the manufacturing sector for major industry types in India



Source: UNIDO database, 2011

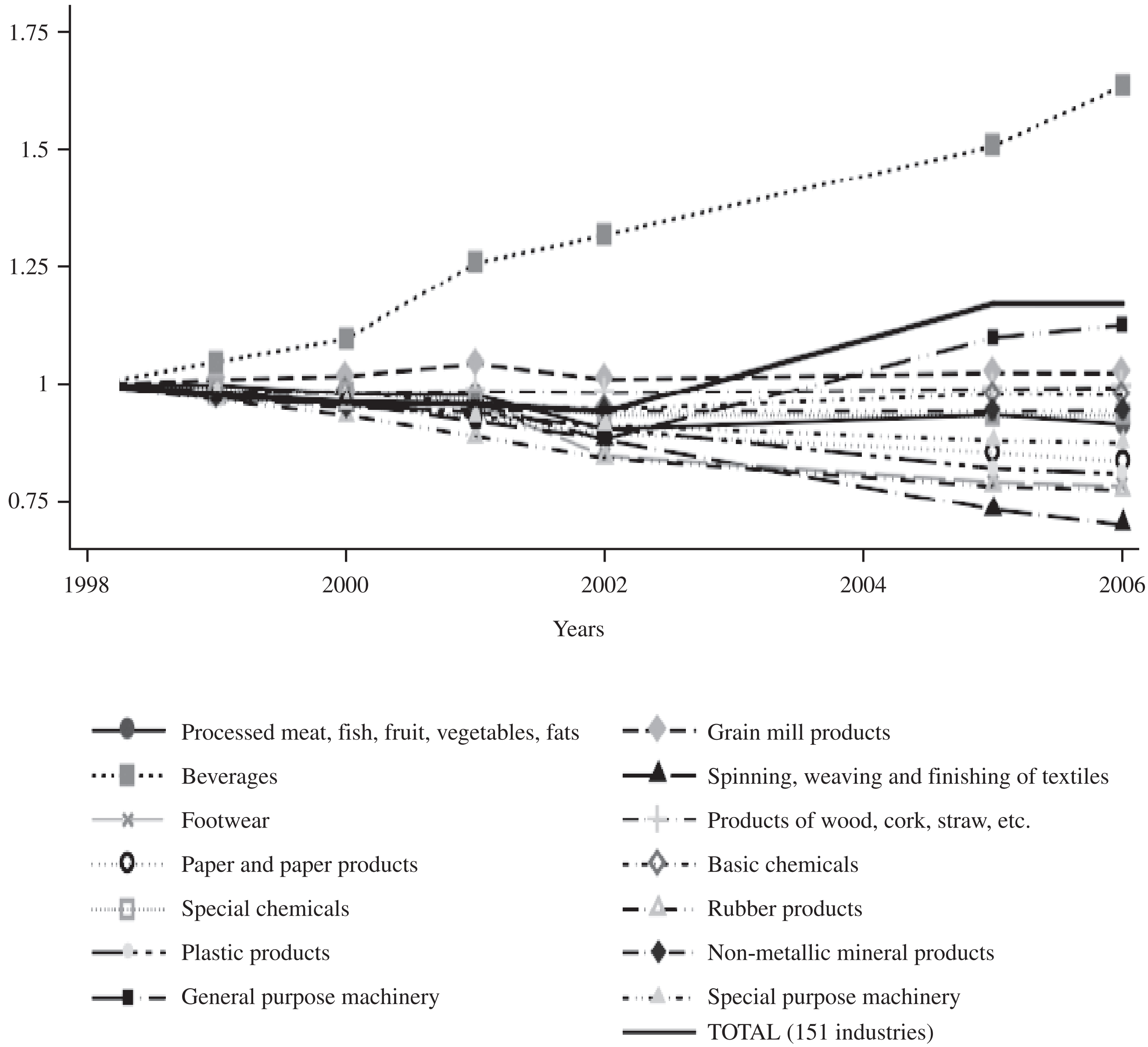
(for all industries and by industry) for each country and the results are presented.

Literature review

This study is inspired by Rodrik (2012) who finds unconditional convergence measured through labor productivity in manufacturing (detailed by type of industry according to the Industrial Statistics Database at the four-digit level) over 10 years for a total of 40 countries. The results are interesting insofar as they oppose the conclusions of recent works on convergence. Indeed, if unconditional convergence was verified for all sectors, then developing countries should have almost caught up with developed countries in terms of labor productivity. Moreover, according to the factor price equalization theorem, ratios of wages over cost of capital in developing countries should evolve towards ratios of wages over

FIGURE 5

Normalized evolution of the number of establishments in the manufacturing sector for major industry types in the U.S.



Source: UNIDO database, 2011

cost of capital in developed countries. If two countries meet the conditions of the H-O model[3] and their inputs do not differ "too much", then the free exchange of goods leads to an equalization of factor prices, even if "there is no mobility of these factors" (Mundell 1957). In other words, since international trade leads to the equalization of ratios of final goods prices between countries, then the factors prices (including wages) should also be adjusted. However, some new theories of international trade came to change the assumptions of the old traditional models. The configuration of international trade, the diffusion of ideas, the elimination of duplication in research were also studied in the literature (Aghion and Howitt 1992; Grossman and Helpman 1990; L. A. Rivera-Batiz and Romer 1991; Segerstrom, Anant, and Dinopoulos

3. For more details on the hypothesis (see Mundell 1957; Ohlin 1933; Rybczynski 1955; Samuelson 1948; Samuelson 1949).

1990). These phenomena have an impact on the production factors. Moreover, the factor price equalization theorem has been questioned in the literature (Leamer and Levinsohn 1994; Repetto and Ventura 1997; Rivera-Batiz and Oliva 2003; Trefler 1995) and unconditional convergence of labor productivity does not automatically imply a convergence of the global economy, which has been widely validated empirically in the literature (Rodrik 2012).

All this literature is, of course, linked to the neoclassical growth model from Solow (1956), which implies that countries with similar production functions at a given time should see their incomes converge to their steady state through time. In short, it is conditional convergence (Mankiw, Phelps, and Romer 1995). The growth rate is regressed on the initial income with other control variables determining the steady state. In the case of σ-convergence, it emerges in response to criticisms (Friedman 1992; Quah 1993) which consider that a negative value of the coefficient is not sufficient to prove convergence and that an assessment of the standard deviation of the distribution of the dependent variable (growth rate of per capita income or productivity) in cross section is required to validate the hypothesis (Islam 2003). Also, according to Islam (2003), the literature about σ-convergence is divided in two branches: (1) one that maintains and tries to explain the relationship between σ and β-convergences and (2) one that emphasizes the limitations of the latter. Indeed, σ-convergence has the advantage of indicating whether the distribution of income across economies is becoming more equitable (Friedman 1992; Quah 1993).

The debate is far from being over and researchers continue to be interested in the β-convergence since it is still a necessary condition, although not sufficient, for σ-convergence (Islam 2003; Andrew Young, Higgins, and Levy 2005).

In 1991, Barro studied the β-convergence of income in 98 countries between 1960 and 1985. He found that the latter is conditional on the initial level of human capital (positive correlation) and government expenditures relative to GDP (negative correlation) (Barro 1991). Mankiw, Romer, and Weil (1992) studied β-convergence in income between 1960 and 1985 on three different samples of countries (those with a developed oil industry, those for whom data were unreliable and, finally, the OECD countries) and found unconditional convergence for the OECD countries and conditional convergence for the two other groups. Barro and Sala-i-Martin (1992) focused on 48 states in the U.S. between 1880 and 1988 and found unconditional β-convergence. More recently, Dawson and Sen (2007) showed an unconditional β-convergence in income for a sample of 29 countries (selected according to availability of data provided by Maddison) between 1900 and 2001. In response to Barro and Sala-i-Martin (1992), Young, Levy, and Higgins (2005) reaffirmed the β-convergence and studied the σ-convergence across U.S. states. They found a significant σ-divergence in most cases. In the same vein, Wang (2004) found a discrepancy in income across Chinese provinces between 1991 and 1999, thus questioning the initial results of Choi and Li (2001) who found a conditional β-convergence between 1978 and 1994. Kaitila, Alho, and Nikula (2007) found unconditional β-convergence of 21 emerging economies of Central Europe and Eastern Europe.

In 2006, Sala-i-Martin published a paper on convergence emphasizing some important problems in the previous convergence studies. He explained the lack of consensus of these works by the use of countries as unit of analysis without taking into account population weights (Sala-i-Martin 2006). Adding this factor, he concluded that incomes of the poors tend to increase (β-convergence) while inequalities seem to decrease (σ-convergence) during the last century.

Very recently, Barro (2012) found conditional convergence of incomes around 2% for a sample of 80 countries (including developed, developing and emerging countries) between 1960 and 2009. He concentrated on the issue of estimation bias by including fixed effects in the regressions. He also confirmed σ-convergence since the late 1970s when China and India were included in the tests (Barro 2012). Finally in 2012, Rodrik used data from the Penn World Tables Data compiled by Maddison and found β-convergence in income for a very large set of countries between 1990 and 2007 periods by regressing 10 years.

Other authors are more focused on the convergence of productivity including labor productivity. Bernard and Jones (1996) examined the unconditional β-convergence based on productivity for 14 OECD countries between 1970 and 1987. Their main result was a lack of convergence in the manufacturing sector as opposed to unconditional convergence in services. Other authors, such as Carree, Klomp, and Thurik (2000) working on 18 OECD countries between 1972 and 1992, found that convergence varies greatly by industry. They explained this phenomenon by the existence of substantial differences in knowledge and capital. However, Landesmann and Stehrer (2000) found an unconditional β-convergence in a sample of 33 countries between 1963 and 1997 for the manufacturing sector. They also showed that it seemed faster for medium and high technologies. Castellacci, Los, and Vries (2010) tried to see whether Bernard's and Jones' 1996 conclusions were valid for a larger set of countries. Their sample included 49 countries between 1970 and 2004 for six major industrial sectors. Overall, they confirmed Bernard's and Jones' results only for a small group of countries. Finally, in a recent study, Rodrik (2012) found an unconditional β-convergence in labor productivity at a highly disaggregated level (more than a hundred manufacturing industry categories) for a set of 72 countries between 1990 and 2007. Hwang (2007) showed that poor countries actually converge towards rich countries unconditionally for all manufactured goods they produce and export. Indeed, Hwang showed that there was a large force of "vertical" convergence: the countries furthest from the technological frontier were those who showed the greatest unconditional economic growth (Hwang 2007). Levchenko and Zhang

(2011) assessed the trend in productivity in 19 manufacturing sectors from 1960 to 2000 and showed that there was some convergence across countries: the areas furthest from the technological frontier were those which saw their productivity grow the fastest (Levchenko and Zhang 2011) studied β-convergence among Chinese provinces based on productivity (of labor, capital and multifactor) at the industry level between 1998 and 2005. They found unconditional convergence. Similarly, Marti, Puertas and Fernandez (2011)both due to how fast it is occurring and also its effect on the world economy as a whole. The size of the economy and the rate at which it is growing has opened up significant internal regional differences that are visible in the trends displayed by industry as the main exponent of this growth. This article analyses regional differences in industrial productivity using a dynamic approach (Malmquist index studied the β and σ-convergences in labor productivity of industrial sectors in the Chinese provinces and found that they were weak. For India, works on convergence were done including the σ and β-convergences of regional growth in agriculture between 1971 and 2007 (Somasekharan, Prasad, and Roy 2011) and the growth of services (services per capita) between 1980 and 2006 (Shingal 2010). The results are respectively a divergence in agriculture and convergence in services. Several econometric issues were also raised in the literature of convergence with a panel-based approach. From a methodological perspective, Islam (2003) concluded that the inclusion of least squares with dummies (LSDV), the minimum distance estimator of Chamberlain (MD) and GMM estimators are among the most reasonable estimators for such models, unless the time frame was not long enough.

Research Design

The research relies on the broad convergence literature and builds on Rodrik (2012)'s reflexions. To our knowledge, there is no work evaluating δ-convergence. Indeed, rather than focusing on the convergence of income or productivity of an entire sample of countries or regions compared to a steady state (shared or not), the δ-convergence analyzes convergence between the level of labor productivity of the manufacturing industries of a country and the productivity frontier of that industry at time *t* in the world.

The data used in this paper are from the United Nations Industrial Development Organization (INDSTAT4 ISIC Rev. 3). For non-OECD members, they were collected from national statistical offices of UNIDO (2012). The database provides the value added (in current U.S. dollars) and the number of employees for 151 manufacturing industries in 127 countries between 1990 and 2008 for the most part. In this paper, we use the data for Brazil, China, India and the United States. The data are available respectively between 1997 and 2007, 2003 and 2007, 1998 and 2007, 1997 and 2007. The data cover respectively 55, 135 and 139 out of the 151 industries for Brazil, China and India. Annual labor productivity is calculated by dividing the value added by the number of employees for each industry and each year. To measure this productivity in real terms, we deflate values by using the consumer price index. Different models are used in the literature to assess the convergence of labor productivity. Some authors regress the growth rate of labor productivity on the initial labor productivity, others regress the growth rate of labor productivity - or the growth rate of the difference in labor productivity between a country and the leading country - on the gap between labor productivity and the leading country's labor productivity.

In our case, data for the labor productivity frontier are the United States'. Indeed, the U.S. remains the most productive in manufacturing according to UNIDO.

Hypothesis. The closer an industry is to the technological frontier, the closer it is to having converged to a steady-state, hence the lower the labor productivity growth.

We will regress the yearly growth rate of labor productivity on the ratio of the distance between the labor productivity of industry *i* at time *t* and the data in the same industry *i* at time *t* in the U.S. The δ-convergence model is specified as follows:

$$\ln(\hat{y}_{it}) = \delta_0 - \delta_1 \cdot \ln\left(RATIO_{it}\right) + \mathcal{E}_{it} \qquad (1)$$

$\ln(\hat{y}_{it})$ represents labor productivity growth between time (*t*) and time $(t-1)$ and $RATIO_{it}$ the distance to the labor productivity frontier for industry *i* at time *t*.

To check the convergence hypothesis, should be significant and negative: the growth rate of labor productivity decreases as the distance to the productivity frontier decreases (and thus increases the variable). In order to stay focused on our hypothesis, we have decided not to add a vector of factors that could capture the absolute or conditional nature of the δ-convergence pattern.

Regarding the estimation techniques, there is a risk that the ordinary least squares (OLS) estimator could not be optimal. Indeed, there may be a positive correlation between and the error term, which includes unobserved variables specific to each industry (*Ci*). These variables might be positively correlated with the regressor, which automatically induces a positive bias on. Since the expected sign of is negative, then the value estimated by OLS will tend to be underestimated, which will translate into an overestimation of convergence. A Hausman test was performed showing that a fixed effect model is superior to a random effect model, which is consistent with the literature (Islam 2003; G. Mankiw, Phelps, and Romer 1995). Therefore, we will regress with industry-related fixed effects.

To further check for robustness, we used three estimations: (1) Beck-Katz, (2) a feasible generalized least squares estimation (FGLS) as in Parks (1967) and Kmenta (1971), (3) a dynamic model with lagged dependent variables with a two-step general methods of moments (GMM) estimators as in Arellano and Bond (1991) or Arellano and Bover (1995).

Our choice of estimation method is not immune to criticisms, such as those found in Beck and Katz (1995). One of the main criticisms of the Kmenta-Parks estimates is the possibility of underestimation of standard errors, consequently resulting in an artificially inflated statistical significance. This is why we decided to use also Beck-Katz and the system-GMM estimators to validate the robustness of our results. Nevertheless, these two estimators should be considered cautiously taking into account the short time frame of the dataset. In our case, there is a possibility that the system-GMM estimates are biased downward. Thus, when reading the results, we should validate that the sytem-GMM estimates lie between the OLS and the OLS with fixed effects results.

As a consequence of our finite sample, we will focus more on the consistency of the statistical significance across the different methods and the sign of the coefficients rather than the size of the coefficients. Our aim here is to provide a preliminary set of guidelines to study convergence with this new database more than providing the exact impact in absolute terms.

The second step in our analysis will be to regress by industry by separating them into 10 groups representing the available data.[4] Thus, we will have used the dataset in two ways and extracted as much information as we could for these three countries. In a couple of years, when the dataset has a longer time frame, the econometric results will be a little more robust.

Results

The results are presented separately for the three countries: Brazil, China and India. These results allow us to determine whether there has been convergence between these countries and the United States during the last decade in terms of labor productivity for the manufacturing sector. Finally, in a second step, we focus at the industry level to analyze the areas of convergence during this period. Several elements can be identified in light of these estimations.

First, with ordinary least squares, the coefficient is significant for the three countries. However, and as predicted, this method of estimation produces positively biased coefficients, which therefore tend to minimize the convergence phenomenon.

These results are actually very interesting as they highlight unconditional convergence of the labor productivity in the manufacturing sector (by OLS) and as this convergence relies on conditions/variables proper to each industry (introduced in the model by the fixed effect dummies). In other words, the difference in the coefficient size implies that even if there is a convergence phenomenon independently of the context, this convergence will be more important considering specific attributes from the different industries.

It proves that convergence is even more important if factors - for example technology transfer through learning-by-doing - are taken into account. Indeed, technology transfer could be easier in certain types of manufacturing industries than in others.

The associated R^2 are not very high (between 0.1 and 0.4). It may be considered as reasonable insofar as the only variable RATIO is not expected to fully explain the variation in growth rate of labor productivity. Standard deviations are reasonable, especially since they are corrected for heteroscedasticity.

Finally, we can see that the convergence phenomenon seems to be faster overall in India and Brazil than in China. Indeed, in absolute value, all the coefficients capturing convergence are greater for India (around 0.4), Brazil (around 0.5) than for China (around 0.1).

Again, the goal of this paper is essentially to lay out a new way of measuring convergence benefitting from the availability of a new database. We can, nevertheless, conclude about convergence of labor productivity between Brazil/China/India and the United States in the manufacturing sector. In other words, the greater the gap between the level of labor productivity between Brazil, China or India and the United States in an industry, the greater the rate of productivity growth in Brazil, China or India. As the distance between the two levels of productivity decreases, the growth rate decreases.

What connection can be made between the convergence of labor productivity and the recent emergence of these countries? As already stated in the introduction, it is important to remember that the manufacturing sector accounts for respectively 60%, 93% and 64% of Brazilian, Chinese and Indian exports in 2010 (World Bank, 2010). These three economies have been largely open to international trade during the last decade, particularly with their entry in the World Trade Organization (1995 for Brazil and India, and 2001 for China). The general intuition, often used in the literature is: the opening of the economy generates higher revenues and faster growth if the sectors stimulated generate technological changes and gains through "learning-by-doing" (Alwyn Young 1991)although bounded in each good, exhibits spillovers across goods, this paper investigates the dynamic effects of international trade. Examining the interaction of an LDC and a DC, the latter distinguished by a higher initial level of knowledge, I find that under free trade the LDC (DC.[5] In the case of Brazil, China and India, the manufacturing sector, which represents the majority of exports, may be considered the most stimulated. Obviously, some further research should assess this point.

4. See groups in appendix.

5. Other elements, such as returns to scale, ideas diffusion, elimination of research duplication or enforcement of creative destruction, have also been reported by literature as vectors of sustainable growth (Aghion and Howitt 1992; Grossman and Helpman 1990; L A. Rivera-Batiz and Romer 1991; Segerstrom, Anant, and Dinopoulos 1990).

TABLE 1

Results for Brazil

Estimation	**OLS**	**Beck & Katz**	**Kmenta-Parks**	**S-GMM**
Dependent variable: ln(yt)	with industry fixed effects			
Independent variables				
l.ln(yt)				0.318*** -0.073
ln(RATIOit)	-0.299*** -0.022	-0.463*** -0.094	-0.590*** -0.025	-0.536*** -0.071
Industry fixed effects:				
I1	-0.011 -0.076	-0.02 -0.039	0.003 -0.111	0.025 -0.148
I2	0.035 -0.076	0.068* -0.038	0.091 -0.107	0.124 -0.119
I3	0.312*** -0.078	0.412*** -0.091	0.475*** -0.117	0.489 -0.308
I4	0.185** -0.086	0.263*** -0.087	0.432*** -0.126	0.264 -0.22
I5	0.203*** -0.074	0.270*** -0.065	0.238** -0.107	0.326** -0.16
I6	0.156* -0.086	0.232*** -0.071	0.295*** -0.115	0.281*** -0.094
I7	0.141* -0.073	0.216*** -0.068	0.293*** -0.107	0.283* -0.144
I8	0.091 -0.087	0.171*** -0.046	0.246** -0.123	0.172 -0.139
I9	0.269*** -0.076	0.396*** -0.084	0.488*** -0.109	0.463*** -0.113
I10				
Constant	-0.667*** -0.077	-0.939*** -0.173	-1.186*** -0.106	-1.027*** -0.159
N	493	493	493	437
Groups	55	55	55	55
R-squared	0.29	0.408		

Standard errors below the coefficients
*** p<0.01, ** p<0.05, * p<0.1

TABLE 2
Results for China

Estimation	OLS	Beck & Katz	Kmenta-Parks	S-GMM
Dependent variable: ln(yt)	with industry fixed effects			
Independent variables				
l.ln(yt)				-0,037 -0,131
ln(RATIOit)	-0.106*** -0,021	-0.101*** -0,019	-0.107*** -0,007	-0,046 -0,092
Industry fixed effects:				
I1	0.127*** -0,048	0.130*** -0,023	0.130*** -0,027	0.078* -0,04
I2	0.115** -0,051	0.114*** -0,01	0.109*** -0,029	0.088** -0,044
I3	0.129** -0,051	0.130*** -0,025	0.114*** -0,031	0.100* -0,056
I4	0,087 -0,053	0.096*** -0,003	0.108*** -0,029	0,037 -0,054
I5	0.210*** -0,047	0.209*** -0,008	0.212*** -0,029	0.178*** -0,05
I6	0.175*** -0,051	0.177*** -0,005	0.172*** -0,029	0.132** -0,054
I7	0,02 -0,055	0,016 -0,037	-0,002 -0,035	-0,013 -0,083
I8	0,089 -0,063	0.092*** -0,032	0.129*** -0,032	0,081 -0,064
I9	0.167*** -0,055	0.170*** -0,014	0.126*** -0,034	0,063 -0,075
I10				
Constant	-0,073 -0,077	-0,061 -0,074	-0.084** -0,036	0,17 -0,295
N	403	403	402	268
Groups	135	135	134	134
R-squared	0,179	0,121		

Standard errors below the coefficients
*** p<0.01, ** p<0.05, * p<0.1

TABLE 3
Results for India

Estimation	OLS	Beck & Katz	Kmenta-Parks	S-GMM
Dependent variable: ln(yt)	with industry fixed effects			
Independent variables				
l.ln(yt)				0.229** -0.112
ln(RATIOit)	-0.183*** -0.018	-0.303*** -0.091	-0.375*** -0.02	-0.915*** -0.141
Industry fixed effects:				
I1	-0.026 -0.055	-0.111 -0.072	-0.185*** -0.053	-0.632** -0.281
I2	0.036 -0.056	0.03 -0.083	-0.022 -0.047	0.005 -0.119
I3	0.09 -0.056	0.072 -0.085	-0.048 -0.048	-0.102 -0.217
I4	0.067 -0.059	0.074 -0.094	-0.037 -0.048	0.178 -0.222
I5	0.141*** -0.051	0.154 -0.099	0.072 -0.044	0.234 -0.157
I6	0.205*** -0.055	0.229** -0.094	0.162*** -0.048	0.328** -0.164
I7	0.190*** -0.06	0.227*** -0.073	0.215*** -0.054	0.471** -0.211
I8	0.172** -0.068	0.204** -0.092	0.158*** -0.052	0.218 -0.181
I9	0.198*** -0.06	0.229*** -0.08	0.178*** -0.052	0.487*** -0.185
I10				
Constant	-0.606*** -0.071	-0.978*** -0.29	-1.135*** -0.073	-2.864*** -0.45
N	1100	1100	1100	960
Groups	139	139	139	139
R-squared	0.1	0.167		

Standard errors below the coefficients
*** p<0.01, ** p<0.05, * p<0.1

Now, for our second step, we could analyze the dataset at the industry level. The following tables (Tables 4, 5 and 6) refer to the regression results for different types of manufacturing industries. Although the small temporal dimension of the data limits the interpretation of these results, it nevertheless provides us with an overview of the levels of convergence of the different industries. It is possible to note that almost all industries seem to converge for Brazil and India, which is consistent with our previous results. It is particularly interesting to see that China is different and convergence will depend on the industry we consider. However, the small sample size could also be the cause of this result.

More specifically, for Brazil, except for wood and paper, all industries seem to converge really fast, with heavy machinery, transport, and textiles in the first places. For China, the areas of medical equipment, wood and paper, and heavy machinery seem to converge faster. In India, we note transport, medical equipment, and textiles.

TABLE 4

Brazil: OLS estimation by industry

Dependent variable: ln(yt)	**Consumables**	**Textiles**	**Wood & Paper**	**Chemicals & Pharmaceuticals**	**Metals and Plastics**	**Heavy Machinery**	**Electrical Machines**	**Medical Equipment**	**Transport industry**	**Others**
ln(RATIOit)	-0.29***	-0.41***	-0.17**	-0.33***	-0.22***	-0.69***	-0.35***	-0.39***	-0.47***	-0.58***
	0,05	0,05	0,06	0,09	0,05	0,08	0,05	0,08	0,06	0,09
Constant	-0.67***	-0.82***	-0.22**	-0.52***	-0.37***	-1.01***	-0.59***	-0.72***	-0.58***	-1.18***
	0,1	0,09	0,09	0,13	0,08	0,1	0,07	0,12	0,08	0,16
N	54	54	54	27	81	27	90	25	63	18
R-squared	0,37	0,49	0,04	0,32	0,17	0,74	0,33	0,53	0,44	0,73

Standard errors below the coefficients
*** p<0.01, ** p<0.05, * p<0.1

TABLE 5

China: OLS estimation by industry

Dependent variable: ln(yt)	**Consumables**	**Textiles**	**Wood & Paper**	**Chemicals & Pharmaceuticals**	**Metals and Plastics**	**Heavy Machinery**	**Electrical Machines**	**Medical Equipment**	**Transport industry**	**Others**
ln(RATIOit)	-0.13*** 0,03	-0.09* 0,05	-0.18** 0,08	-0.18*** 0,06	-0.015 0,04	-0.09 0,07	-0.11 0,11	0.12 0,11	-0.17* 0,1	-0.06 0,08
Constant	-0.01 0,1	0,08 0,13	-0.15 0,21	-0.21 0,21	0.38*** 0,11	0.15 0,18	-0.06 0,28	0.66** 0,33	-0,06 0,26	0,06 0,26
N	63	42	45	33	81	42	30	16	30	21
R-squared	0,27	0,1	0,13	0,21	0	0,14	0,06	0,22	0,08	0,04

Standard errors below the coefficients
*** p<0.01, ** p<0.05, * p<0.1

TABLE 6

India: OLS estimation by industry

Dependent variable: ln(yt)	**Consumables**	**Textiles**	**Wood & Paper**	**Chemicals & Pharmaceuticals**	**Metals and Plastics**	**Heavy Machinery**	**Electrical Machines**	**Medical Equipment**	**Transport industry**	**Others**
ln(RATIOit)	-0.11*** 0,03	-0.31*** 0,07	-0.16*** 0,06	-0.11*** 0,04	-0.07 0,05	-0.29*** 0,06	-0.09 0,07	-0.45*** 0,13	-0.74*** 0,10	-0.65*** 0,08
Constant	-0.35*** 0,12	-0.96*** 0,21	-0.44** 0,20	-0.32*** 0,12	-0.13 0,14	-0.71*** 0,19	-0.17 0,19	-1.21*** 0,39	-2.01*** 0,29	-2.03*** 0,25
N	173	112	120	88	216	130	80	46	79	56
R-squared	0,07	0,17	0,05	0,08	0,01	0,14	0,02	0,19	0,41	0,31

Standard errors below the coefficients
*** p<0.01, ** p<0.05, * p<0.1

Conclusion

At a time when the western world is still struggling with the aftermath of the financial crisis, it is interesting to look at the adjustments operated in the emerging countries. In the past, when the western world would slow down, world demand would cause the emerging countries to slow down as well. It is no longer the case. Demand in the new global players can help sustain their own economy, but moreover, the supply chain is productive enough to keep attracting foreign direct investments. This is probably the time of a paradigm shift.

In this context, the purpose of this paper was to highlight the convergence between Brazil/China/India and the U.S. labor productivity in manufacturing over the past 10 years. We tried to make it original in two ways: (1) The study of convergence was done at the industrial sector level and not at a more aggregated level as previous studies. This allowed us to complement these studies by offering a methodology to design a map of which industrial sectors are catching up with the productivity frontier. (2) We also proposed a new approach to convergence. To the extent that this study is original and differs from the classical studies of convergence, we named it δ-convergence. We tested several different models and estimation methods and found that there was indeed δ-convergence: as the distance between the level of labor productivity in Brazil (or China/India) and the United States decreases, the growth rate of labor productivity within the country, in Brazil, China and India decreases. Also, although we used a different methodology, we showed that there are reasons to be convinced by the unconditional convergence explanation. We recognize that the temporal dimension of our study is its main limitation.

In retrospect, this paper proposed a new methodology to assess economic convergence with two dimensions: (1) the first dimension was to use industry-level data instead of aggregated data and (2) the second dimension was to use a new theoretical approach adjusted to these industry-level data. But this paper has also some interesting applications for MNEs. Indeed, it is very valuable for an MNE to know where in the world companies from the same industry are actually catching-up in terms of productivity. The first benefit is to identify early on where the competition is strengthening, and the second benefit is to be able to map the indsutrial sectors in the world where MNEs should think of mergers, licences or alliances and thus benefit from the rise in local productivity.

While data availability does not allow deeper investigation currently, this work gives a brief overview of what should be further investigated. Indeed, future studies should concentrate at the industry level in order to understand what are the conditions and the mechanisms required to accelerate the convergence phenomenon and, through that, the economic growth. Although study fields of convergence and technology transfer have always been macroeconomic topics, the new globalized world calls for change in our old models and beliefs.

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APPENDIX

Industry groups		
I1= Consumables	151 Processed meat, fish, fruit, vegetables, fats 1511 Processing/preserving of meat 1512 Processing/preserving of fish 1513 Processing/preserving of fruit and vegetables 1514 Vegetable and animal oils and fats 1520 Dairy products 153 Grain mill products; starches; animal feeds 1531 Grain mill products 1532 Starches and starch products 1533 Prepared animal feeds 154 Other food products	1541 Bakery products 1542 Sugar 1543 Cocoa, chocolate and sugar confectionery 1544 Macaroni, noodles and similar products 1549 Other food products n.e.c. 155 Beverages 1551 Distilling, rectifying and blending of spirits 1552 Wines 1553 Malt liquors and malt 1554 Soft drinks; mineral waters 1600 Tobacco products
I2= Textiles	171 Spinning, weaving and finishing of textiles 1711 Textile fibre preparation; textile weaving 1712 Finishing of textiles 172 Other textiles 1721 Made-up textile articles, except apparel 1722 Carpets and rugs 1723 Cordage, rope, twine and netting 1729 Other textiles n.e.c.	1730 Knitted and crocheted fabrics and articles 1810 Wearing apparel, except fur apparel 1820 Dressing and dyeing of fur; processing of fur 191 Tanning, dressing and processing of leather 1911 Tanning and dressing of leather 1912 Luggage, handbags, etc.; saddlery and harness 1920 Footwear
I3=Wood and paper	2010 Sawmilling and planning of wood 202 Products of wood, cork, straw, etc. 2021 Veneer sheets, plywood, particle board, etc. 2022 Builders' carpentry and joinery 2023 Wooden containers 2029 Other wood products; articles of cork/straw 210 Paper and paper products 2101 Pulp, paper and paperboard 2102 Corrugated paper and paperboard 2109 Other articles of paper and paperboard	221 Publishing 2211 Publishing of books and other publications 2212 Publishing of newspapers, journals, etc. 2213 Publishing of recorded media 2219 Other publishing 222 Printing and related service activities 2221 Printing 2222 Service activities related to printing 2230 Reproduction of recorded media
I4: Chemicals and pharmaceuticals	241 Basic chemicals 2411 Basic chemicals, except fertilizers 2412 Fertilizers and nitrogen compounds 2413 Plastics in primary forms; synthetic rubber 242 Other chemicals 2421 Pesticides and other agro-chemical products	2422 Paints, varnishes, printing ink and mastics 2423 Pharmaceuticals, medicinal chemicals, etc. 2424 Soap, cleaning and cosmetic preparations 2429 Other chemical products n.e.c. 2430 Man-made fibres

Industry groups		
I5: Metals and plastics	251 Rubber products 2511 Rubber tires and tubes 2519 Other rubber products 2520 Plastic products 2610 Glass and glass products 269 Non-metallic mineral products n.e.c. 2691 Pottery, china and earthenware 2692 Refractory ceramic products 2693 Structural non-refractory clay; ceramic products 2694 Cement, lime and plaster 2695 Articles of concrete, cement and plaster 2696 Cutting, shaping and finishing of stone 2699 Other non-metallic mineral products n.e.c. 2710 Basic iron and steel	2720 Basic precious and non-ferrous metals 273 Casting of metals 2731 Casting of iron and steel 2732 Casting of non-ferrous metals 281 Structural metal products; tanks; steam generators 2811 Structural metal products 2812 Tanks, reservoirs and containers of metal 2813 Steam generators 289 Other metal products; metal working services 2891 Metal forging/pressing/stamping/ roll-forming 2892 Treatment and coating of metals 2893 Cutlery, hand tools and general hardware 2899 Other fabricated metal products n.e.c.
I6: Heavy machinery	291 General purpose machinery 2911 Engines and turbines (not for transport equipment) 2912 Pumps, compressors, taps and valves 2913 Bearings, gears, gearing and driving elements 2914 Ovens, furnaces and furnace burners 2915 Lifting and handling equipment 2919 Other general purpose machinery 292 Special purpose machinery	2921 Agricultural and forestry machinery 2922 Machine tools 2923 Machinery for metallurgy 2924 Machinery for mining and construction 2925 Food/beverage/tobacco processing machinery 2926 Machinery for textile, apparel and leather 2927 Weapons and ammunition 2929 Other special purpose machinery 2930 Domestic appliances n.e.c.
I7: Electrical machines	3000 Office, accounting and computing machinery 3110 Electric motors, generators and transformers 3120 Electricity distribution and control apparatus 3130 Insulated wire and cable 3140 Accumulators, primary cells and batteries 3150 Lighting equipment and electric lamps	3190 Other electrical equipment n.e.c. 3210 Electronic valves, tubes, etc. 3220 TV/radio transmitters; line communications apparatus 3230 TV and radio receivers and associated goods
I8: Medical Equipment	331 Medical, measuring, testing appliances, etc. 3311 Medical, surgical and orthopaedic equipment 3312 Measuring/testing/navigating appliances, etc. 3313 Industrial process control equipment	3320 Optical instruments and photographic equipment 3330 Watches and clocks
I9: Transports	3410 Motor vehicles 3420 Automobile bodies, trailers and semi-trailers 3430 Parts/accessories for automobiles 351 Building and repairing of ships and boats 3511 Building and repairing of ships 3512 Building/repairing of pleasure/sporting boats 3520 Railway/tramway locomotives and rolling stock	3530 Aircraft and spacecraft 359 Transport equipment n.e.c. 3591 Motorcycles 3592 Bicycles and invalid carriages 3599 Other transport equipment n.e.c.
I10: Others	3610 Furniture 369 Manufacturing n.e.c. 3691 Jewelery and related articles 3692 Musical instruments 3693 Sports goods	3694 Games and toys 3699 Other manufacturing n.e.c. 3710 Recycling of metal waste and scrap 3720 Recycling of non-metal waste and scrap