Report No. 97885-LAC

Understanding Latin America and the Caribbean's Income Gap

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Editors

July 2015

Macroeconomics and Fiscal Policy Management
Latin America and the Caribbean Region

Document of the World Bank

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Acknowledgments

This book was written as part of a World Bank project led by Jorge Thompson Araujo and Ekaterina Vostroknutova, under guidance from John Panzer (Director, GMFDR), Humberto Lopez (Country Director, LCC2C), Rodrigo A. Chaves (Country Director, EACIF), Auguste Tano Kouame (Practice Manager, GMFDR), and Pablo Saavedra (Practice Manager, GMFDR).

Chapter 1 was written by are Jorge Thompson Araujo (LCRVP, World Bank); Ekaterina Vostroknutova (GMFDR, World Bank); Konstantin Wacker (Johannes Gutenberg-Universität Mainz), and Mateo Clavijo (Universitat Pompeu Fabra). Chapter 2 was written by Francesco Caselli (London School of Economics, BREAD, CEP, CEPR, and NBER). Chapter 3 was prepared by Maya Eden (DECMG, World Bank) and Ha Nguyen (DECMG, World Bank). Marc Schiffbauer (DECWD, World Bank), Hania Sahnoun (DECWD, World Bank) and Jorge Thompson Araujo co-authored Chapter 4. Chapter 5 was a result of collaboration by J. David Brown (U.S. Census and IZA); Gustavo A. Crespi (Competitiveness and Innovation, IADB); Leonardo Iacovone (GTCDR, World Bank); and Luca Marcolin (KU Leuven). Chapter 6 was written by Ha Nguyen (DECMG, World Bank) and Patricio A. Jaramillo (DECMG, World Bank). Chapter 6 was authored by Konstantin M. Wacker.

Valuable input and comments were received from Daniel Lederman (Lead Economist, LCRCE), Norman V. Loayza (Lead Economist, DECMG), and Antonio Nucifora (Lead Economist, GMFDR). The peer reviewers were Pedro Cavalcanti Ferreira (Professor, Fundação Getulio Vargas -RJ, Brazil), Zafer Mustafaoglu (Lead Economist and Program Leader, LCC7C), and Margaret McMillan (Professor, Tufts University and IFPRI).

The team are especially grateful to Silvia Gulino (GMFDR), Giselle Velasquez (GMFDR), Patricia Chacon Holt (GMFDR), and Eric Palladini (LCROS) for their administrative and editorial assistance during the preparation of this document.

Executive Summary

Even nearly ten years of solid growth cannot guarantee long-term income convergence. The countries of the Latin America and Caribbean region (LAC), like other emerging economies, have benefited from a decade of remarkable growth and some income per capita convergence towards the United States and other industrialized countries. Yet, despite this recent progress, LAC still faces a significant per capita income gap with the developed world. The studies in this volume contribute to the ongoing debate on the reasons for this persistent income gap and the potential drivers of convergence, and propose some broad avenues for reform.

Differences in total factor productivity (TFP), or efficiency in using the production factors, such as physical and human capital, explain a large part of LAC's persistent income gap. A development accounting exercise conducted for this volume indicates that, if the average LAC country closed its efficiency gap relative to the United States, its income per worker could double from its current level, without any additional accumulation of capital.

To narrow this income gap, it is critical that the region reduces its efficiency gap. To that end, the studies in this volume seek to identify the main candidates to explain the differences in efficiency between LAC and the United States, as well as to look for factors that drive convergence at all levels of the economy. Theory suggests two main channels through which the efficiency gap can be affected: Technology adoption or innovation, on the one hand; and resource allocation, on the other.

Macro-level evidence on the efficiency gap between LAC and the United States suggests that resource misallocation is more important than the speed of technology adoption. At this higher level of aggregation, the analysis in this volume shows that technology adoption explains about one-fifth of the efficiency gap, leaving the rest to be explained by misallocation of resources.

The macro-level diagnostic is broadly confirmed at the sector level. At the sector level, distortions and inefficient allocation of resources also hamper labor productivity growth and convergence. In particular, low services sector productivity has reduced the contribution of the structural change process to growth. In addition, while the manufacturing sector has displayed unconditional convergence at the global level, this effect is subdued in LAC – as manufacturing productivity growth has been slower in the region.

Furthermore, firm-level evidence for Colombia and Mexico also puts the spotlight on resource misallocation. When looking at the drivers of firm-level productivity convergence in these two countries, technology adoption and innovation emerge as the main drivers of productivity convergence in the manufacturing sector. Improvements within the firm, not resource reallocation between firms, are largely behind firms' productivity growth of the last decade. This is in line with the sector-level finding that improvements in resource allocation contributed less than they could have to the growth of firms.

Resource misallocation can also translate into "pockets of inefficiency" associated with relatively high poverty levels and exacerbated by macroeconomic volatility. Confronted with poverty and a dearth of opportunities, poorer workers may not be able to move into high-

productivity sectors. They have no other choice than to perform basic activities, usually in the informal sector, such as working in basic retail trade, becoming street vendors, or working in other informal services. Since these insulated sectors are "pockets of inefficiency," the lack of access to finance and poor entrepreneurship prevent innovation and improved productivity. This phenomenon is magnified by macroeconomic volatility.

At the same time, there is significant room for improvement when it comes to technology adoption and innovation more broadly. In fact, the quality of the available technology in LAC is low, and there is very little innovation. Although firms can use innovation to reach productivity at the global productivity frontier, weak institutions reduce incentives to innovate. Only a few firms catch up to the technological frontier – and even then, convergence seems mostly limited to the *domestic* frontier, not the global one.

Understanding the reasons behind LAC's income gap is a necessary step towards designing appropriate growth strategies – particularly in the context of the current growth slowdown. Drawing on the findings of the studies in this volume, a number of broad policy directions emerge: (i) An increased focus on closing the efficiency gap – beyond mere factor accumulation – is critical to reduce the income gap and improving LAC's convergence prospects; (ii) eliminating distortions that cause misallocation of resources will also improve the incentives to innovate; and (iii) reducing macroeconomic volatility will alleviate the negative impact of the poverty gap on growth.

In practice, some of the key structural and macroeconomic approaches needed to speed up LAC's income convergence can be outlined. On the structural side, the main priorities for improving resource allocation and the incentives to innovate include: (i) enhancing market competition in key network industries (transport, financial, telecommunications, logistics, communication and distribution services); (ii) increasing labor market flexibility (including skill-mismatches and social barriers); (iii) removing informational frictions (including complex tax regimes and credit rationing); (iv) strengthening property rights; and (v) improving the rule of law. From a macroeconomic standpoint, policies aimed at addressing macroeconomic volatility would also have positive longer-run *supply response* effects.

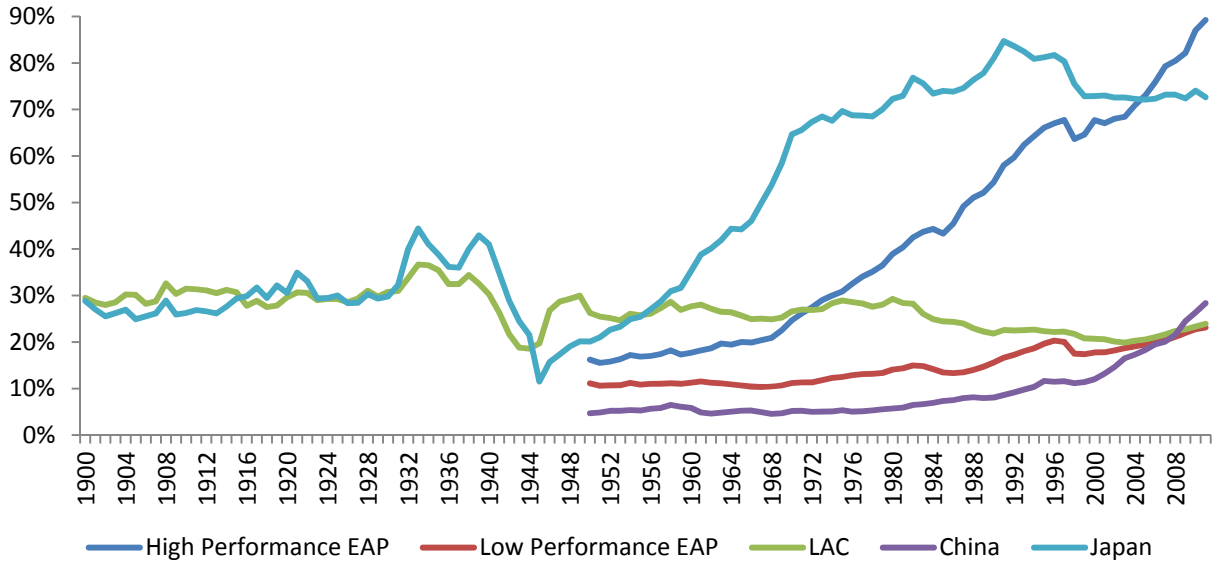
1. Overview

Jorge Thompson Araujo, Ekaterina Vostroknutova, Konstantin M. Wacker, and Mateo Clavijo

1. 1. Introduction

Beginning in the late 1990s, developing economies, including those in the Latin America and Caribbean region (LAC), benefited from remarkable economic growth. The impact of such growth on the welfare of millions of the countries' citizens has been impressive. The accelerated growth of the economies in LAC was underpinned by structural reforms and macroeconomic stabilization, and propelled by a favorable external environment. From the early 2000s, growth rates in LAC, were considerably above those in the earlier decades.[1]

Figure 1.1. LAC has been Overtaken by EAP in Income per capita Convergence[2]
(Average GDP per capita relative to the United States)



Source: World Bank (2011b).[3]

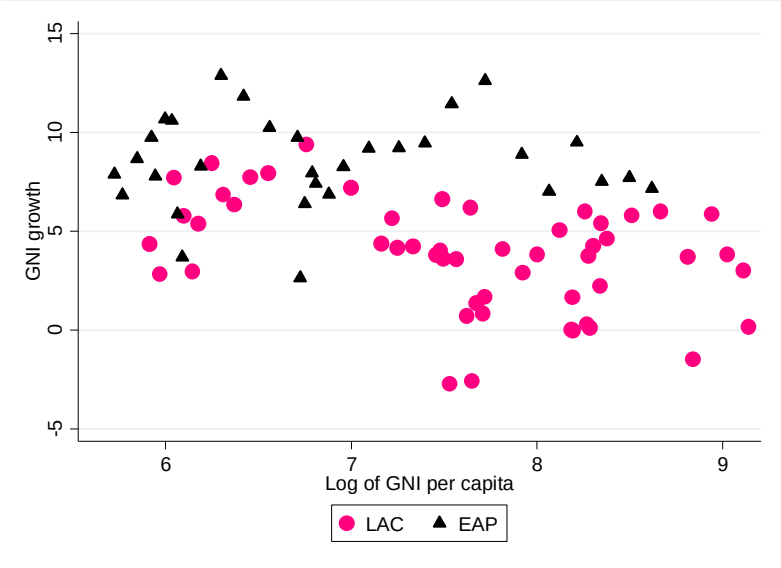
Despite the higher growth rates and improved overall well-being, the LAC region has not been able to close its historical income gap with the United States. In fact, LAC's average per capita GDP has hovered around 30 percent of U.S. per-capita GDP for more than a century.[4] This stands in stark contrast to the performance — during the last century — of Japan, the East Asia and Pacific (EAP) "Tigers," and, more recently, China and EAP's middle-income countries

[1] Araujo *et al*. (2014).
[2] This graph is reproduced from World Bank (2011b). It suggests that LAC has gone through "one hundred years of growth solitude", with the absence of a systematic process of convergence.
[3] The EAP "Tigers" include the island of Taiwan, the Republic of Korea, the SAR Hong Kong, and Singapore. The EAP middle-income countries (EAP MICs) include Indonesia, Malaysia, Philippines, and Thailand. LAC includes Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay, and Venezuela.
[4] World Bank (2011b).

(MICs), all of which went through a process of catching up with the U.S. economy during the second half of the 20th century (Figure 1.1). In addition, income growth in East Asia has been systematically higher than in Latin America and the Caribbean at similar per-capita income levels (Figure 1.2).

Figure 1.2. Income Growth in EAP Countries Has Been Higher than in LAC Countries with Similar per-capita Income Levels

(GNI growth vs. log GNI per capita, countries, 1983 – 2013)



Source: staff calculations based on WDI. GNI is measured using the Atlas method (in current US$)
Regional averages including developing countries only (following WDI classification).

This volume looks into the reasons for LAC's failure to consistently reduce its income gap with the United States (and the developed world more generally). The starting point for the analysis is a development accounting exercise,[5] in which the income gap is decomposed into an *efficiency gap* (differences in the efficiency of use of inputs) and a *capital gap* (differences in physical and human capital).[6] Recognizing the macroeconomic data's varied quality and limited ability to shed light on micro-foundations of convergence in per-capita incomes, we include other levels of analysis. However, working at the macro, sectoral, and micro levels requires the use of different, but complementary, empirical strategies.

The papers in the volume provide a multi-dimensional view of the possible causes of slow productivity growth and convergence speed in the region. They focus on how efficiency, including technology adoption, innovation, and allocation of production factors between firms and sectors can influence productivity. Based on the questions asked and the availability of the data, each paper adopts a different empirical approach, sample size, time horizon, and comparator countries or regions. The first paper, by Francesco Caselli, explains differences in income using a

[5] See Caselli (2008): "Level accounting (more recently known as development accounting) consists of a set of calculations whose purpose is to find the relative contributions of differences in inputs and differences in efficiency with which inputs are used to cross-country differences in GDP. It is therefore the cross-country analogue of growth accounting." (p. 1, online version).
[6] See Caselli, in this volume.

development accounting framework to measure the relative importance of gaps in terms of efficiency, or total factor productivity (TFP), and the accumulation of quantity and quality of the basic factors used to produce goods and services. The second paper, by Maya Eden and Ha Nguyen, analyzes the relationship between the timing of technological innovations in the United States and the timing of these innovations in LAC. The authors use aggregate and sector-level time series data to identify the significance of these lags in technology adoption. The third paper, by Marc Schiffbauer, Hania Sahnoun and Jorge T. Araujo, looks into structural change issues and considers whether resources were increasingly allocated towards sectors, products, and technologies with lower productivity, and how this could explain the region's slow productivity growth. The fourth paper, by J. David Brown, Gustavo Crespi, Leonardo Iacovone and Luca Marcolin, focuses on Colombia and Mexico and analyzes the process and drivers of firm-level convergence towards the domestic and global productivity frontiers.[7] The fifth paper, by Ha Nguyen and Patricio Jaramillo, measures returns to innovation among Latin American firms and compares the returns of LAC countries, to those in the Europe and Central Asia region (ECA). Finally, the paper by Konstantin Wacker examines the implications of poverty gaps (and their interaction with macroeconomic volatility) for income convergence.

1. 2. Closing the Efficiency Gap Is Fundamental for Income Convergence

Differences in efficiency or accumulation of physical and human capital explain the gap in income per worker between LAC and the United States. Output per worker can be thought of as a product of human capital per worker, physical capital per worker (quality-adjusted labor), and a term called total factor productivity (TFP) or "efficiency" (see Box 1.1). Growth in output per worker can therefore be attributed to the changes in accumulation of factors of production or to changes in efficiency.

Differences in efficiency—or total factor productivity (TFP)—explain a large part of the income gap and variation across countries. Previous work, often relying on growth accounting, had already stressed the role of TFP to explain a large part of growth variation across countries, as well as the differences in the speed of convergence. Based on the aggregate production function, low efficiency means low income per capita. But low efficiency also reduces incentives to invest in equipment, infrastructure, and schooling. It reduces the potential returns on these investments and, as a result, prevents faster capital accumulation and perpetuates existing income gaps. By contrast, higher efficiency can reduce the income gap by improving returns on existing investments and motivating increased investments in factors of production.[8]

[7] The domestic productivity frontier is defined as the average productivity of the top decile of firms, in terms of sales per worker, in an economy or sector. The same indicator for the United States is the proxy for the international frontier.

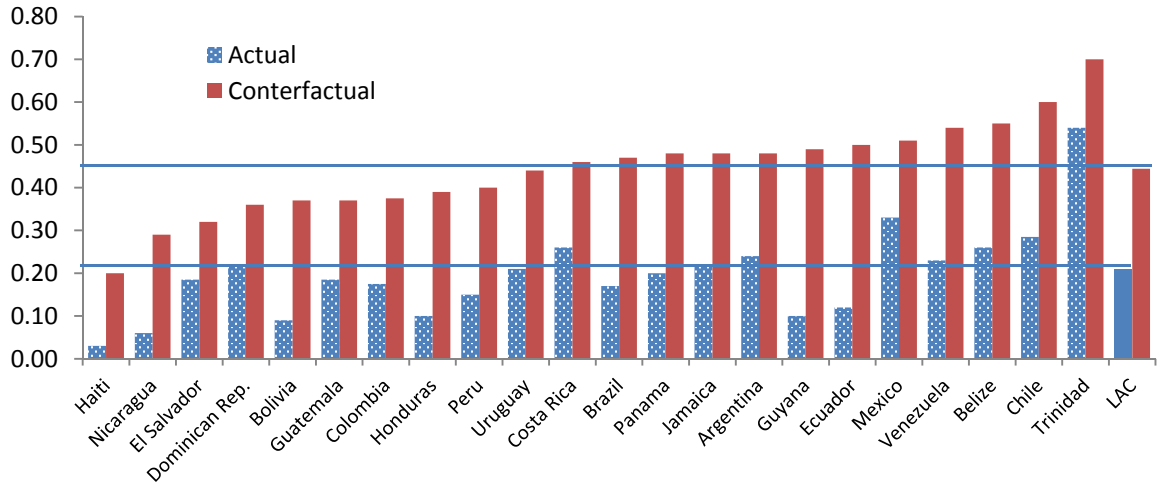
[8] See a review of the literature in Annex 2. See also Loayza, N., P. Fajnzylber, and C. Calderon (2004); Cole, H.L., L.E. Ohanian, A. Riascos, and J.A. Schmitz Jr. (2005); Daude, C. and E. Fernandez-Arias (2010); and Ferreira, P.C., S.A. Pessoa, and F. Veloso (2012).

Box 1.1. Total Factor Productivity (TFP) or "Efficiency"

The analytical tool at the core of development accounting is the aggregate production function which maps the amount of physical and human capital (the aggregate input quantities) to the amount produced (the output quantities). Assuming that increasing the amount of inputs leads to an equivalent increase in outputs (constant returns to scale), the aggregate production function can be written in per- worker terms. Thus, using the augmented Cobb-Douglas aggregate production function, output per worker is a product of human capital per worker (adjusted for quality), physical capital per worker, and a term called total factor productivity (TFP) or "efficiency."
However, the TFP is subject to much controversy. Practitioners refer to it as technology, a "measure of our ignorance", or the "Solow residual". In this volume, we refer to it as "efficiency." See Annex 2 for a literature review.

Source: Caselli, in this volume.

Figure 1.3. Capital and Efficiency Gaps are Large and Heterogeneous
(Income per worker in LAC countries relative to the US,
with their current efficiency (Actual) and U.S. efficiency (Counterfactual))



Source: Caselli, in this volume.
Note: Actual: relative actual income per worker. Counterfactual: relative capital per worker, or relative counterfactual income per worker with the same TFP as the US. The baseline calibration for broad sample is used. Horizontal lines show sample means.

If the average LAC country closed its *efficiency* gap relative to the United States, its income per worker could double from its current level, without any additional accumulation of capital. The LAC region generally suffers from an efficiency gap and a capital gap, although there is considerable heterogeneity within the region. Average factor accumulation per worker in LAC is about 40 percent of that in the United States.[9] LAC workers produce on average about one-fifth

[9] Caselli, in this volume, considers several calibrations to arrive to the estimates of relative capital and relative efficiency for LAC countries. The capital and efficiency gaps vary depending on the sample (defined by data availability) and whether or not quality of human capital measures are taken into account. Relative efficiency estimates for LAC vary between 0.44 (broad sample, baseline calibration) to 0.6 (narrow sample, aggressive calibration). Broad sample estimates are used throughout the overview.

of the output of U.S. workers (Figure 1.3).[10] Their efficiency is about half of U.S. workers. In addition, the stocks of physical and human capital in LAC are far lower than in the United States. But part of this capital gap itself is likely to be explained by the efficiency gap and diminished incentives to invest.

Slow technology adoption and misallocation of resources are the main candidates to explain the efficiency gap between LAC and the United States. Annex 2 summarizes the empirical literature on the determinants of TFP, or economy-wide efficiency. Based on this review, the reasons for the efficiency gap include: (i) delayed adoption and diffusion of technology and lack of innovation; (ii) poor allocation of resources between firms or sectors; and (iii) organizational inefficiency (within firms).

The remainder of this chapter looks at technology adoption and allocation of resources in LAC countries at the economy-wide (macro), sectoral, and firm levels. We review the lag in technology adoption at the macro- and micro-levels between LAC and the United States and the role it plays in income convergence.[11] We also consider structural changes operating through the technology and resources allocation channels that contribute to low efficiency.[12] We consider firm-level productivity and factor allocation between firms and sectors as drivers of the overall economy-wide productivity.[13] Because we find that innovation is the main driver of firm-level productivity convergence, we look at factors outside the firm—such as institutions—that affect incentives to innovate.[14] Finally, this chapter looks at other factors—such initial poverty rates—that can have an impact on convergence.[15]

1.2.1. The quality of technological make-up is low, and there is very little innovation

LAC's relative technological backwardness is reflected in lower overall productivity, idiosyncratic production structures in manufacturing, and lower innovation effort. The 40 percent efficiency gap in itself is a manifestation of LAC's technological backwardness. This means that the technologies used in LAC are less productive and obsolete compared to those in the United States. Other factors—such as efficient allocation of resources—are also at play, suggesting that the technologies used in LAC are less productive compared to those in the United States. The level and quality of frontier or adaptation-based innovation are also good indicators of the ability of an economy to invent or absorb technology.

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[10] For each country, this exercise calculates the actual income per worker (based on actual factor accumulation and efficiency) relative to the United States and the counterfactual income per worker (based on actual factor accumulation) relative to the United States for the year 2005. The counterfactual income level is a hypothetical income level for LAC economies, assuming that they used their physical and human capital as efficiently as the United States. The actual income per worker in LAC amounts on average to one fifth of the U.S. level; the difference with the counterfactual income level can be used to determine the size of the efficiency gap.

[11] See Comin and Hobijn (2010) and Akcigit, Alp, Eden, and Nguyen (2014).

[12] See McMillan and Rodrik (2011) and Rodrik (2013a).

[13] See Hsieh and Klenow (2009), Iacovone and Crespi (2010) and IADB (2010).

[14] The innovation-related hypotheses come from a large literature on returns to innovation, including, more recently, Elmslie and Tebaldi (2014).

[15] The hypothesis that poverty is an impediment to convergence builds on the findings of Ravallion (2014) and Crespo-Cuaresma, Klasen, and Wacker (2013) and the literature on poverty traps.

LAC firms do very little innovation, compared to other regions. The level and quality of innovation are good indicators of the ability to invent or absorb technology. Defining innovation as the introduction of new or improved products, only 22 percent of LAC firms innovate, compared to 62 percent of firms in ECA. LAC firms have also not kept pace with industries in the EAP region and other middle income economies.[16] This means that less than a fifth of firms in LAC have introduced a new or significantly improved product onto the market in the last three years (see Figure 1.4).

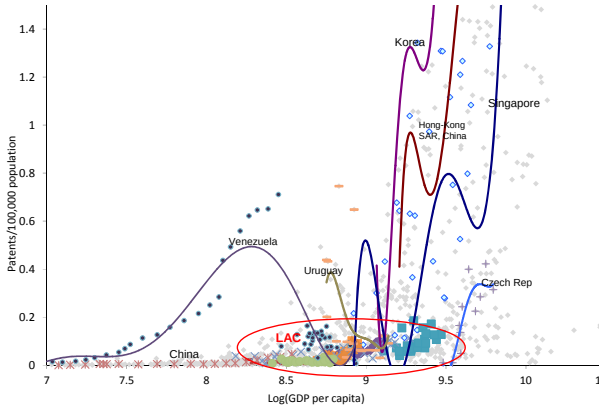
Moreover, the quality of innovation and technological make-up in LAC tends to be low.[17] In addition, the ability of LAC firms to produce complex goods or perform "tasks" needed for production is lower than in similar countries in East Asia. The difference is in terms of "knowledge applicability." Some knowledge (such as technology or processes) can be more readily adapted to make new products in other sectors while other knowledge is limited in its scope of application. Compared to EAP, LAC's history of developing such abilities has been relatively erratic and inconsistent (Figure 1.5).

Despite substantial progress achieved over the last 30 years, LAC countries have tended towards lower export diversification than their peers in EAP. Overall, Latin America succeeded in developing a relatively diversified manufacturing base over the last 30 years. The region's prospects for further diversification into new and potentially higher technology products are higher than in the Middle East and North Africa (MENA) or Sub-Saharan Africa. However, LAC countries have lagged consistently behind EAP countries with similar levels of income in terms of diversification and formation of clusters.[18]

The prevalence of "idiosyncratic" production structures limits the capacity of LAC firms to absorb or imitate more productive foreign technologies. Economies that initially specialize in exporting goods that embody broadly applicable knowledge subsequently grow faster. However, the LAC region appears to have specialized in technologies that are "idiosyncratic," or not well-connected. An idiosyncratic export means that there are fewer capabilities to create products from other product groups. Consequently, most countries in LAC have low and slow growing knowledge applicability, except for Chile.

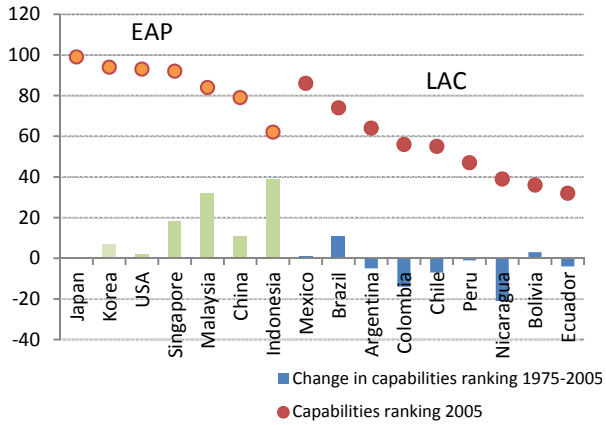
[16] See Nguyen and Jaramillo, in this volume. Based on a sample of 1,229 firms in LAC and 2,526 firms in ECA, from the WB Enterprise Survey.
[17] By technological make-up, we mean the level of the available technology and the ability to use it effectively. We also mean whether the technology is up to date.
[18] See Schiffbauer *et al*., in this volume, for detailed evidence for this and the following paragraphs.

Figure 1.4. LAC Economies have Stagnated or Regressed on Frontier Innovation Outcomes
(patents per 100,000 of population)



Source: Staff calculations based on Brahmbhatt and Hu (2010). Note: Only a fragment of the distribution is shown.

Figure 1.5. Capability to Produce Complex Products is Low and Slow Moving in LAC
(index)



Source: Staff calculations based on Hidalgo (2011). Note: Capabilities refer to the level of sophistication of companies in a country to perform more tasks so as to produce a greater variety of products. Original indicator is normalized so that higher number reflects more capabilities.

As a result, manufacturing in LAC is less productive than the worldwide average. The average growth of manufacturing labor productivity (net of year-industry specific effects) has only been 1.2 percent, compared to 4.2 percent across all 104 countries with available data. There are also substantial growth differences across the region. This calls for a more detailed analysis of manufacturing productivity developments on a micro level, which we discuss throughout this volume.

1.2.2. Innovation drives firm-level productivity catch-up

Aggregate productivity growth depends on productivity growth of individual firms and allocation of factors between them.[19] A country's productivity rises because the firms' productivity has risen ("within firm" aspect). However, it could also be that the more productive firms within the country acquire more production factors and thus expand their production while less productive firms decline in importance or went out of business ("between firms" aspect). This section looks at what drives manufacturing firms' convergence to the productivity frontier by comparing manufacturing firm-level data for Mexico, Colombia and the United States.[20] In these countries, after 2000, the main driver of manufacturing productivity was productivity growth *within* firms and not reallocation of factors or resources *between* firms.[21]

[19] Following Hsieh and Klenow (2009).
[20] The productivity frontier is defined as the mean of the top quartile of the firm-level distribution of value added per employee. The U.S. frontier is taken as a proxy for the international productivity frontier.
[21] See Brown et al., in this volume. We chose Mexico and Colombia because the appropriate data were available at the time of the study.

In Mexico and Colombia, only a small number of firms are productive at the global level.[22] Figure 1.6 shows the number and percent of Mexican firms that have achieved the global productivity frontier. Figure 1.7 compares the within-firm productivity of the two countries and the domestic frontier. It appears that the domestic productivity frontiers of Mexico and Colombia are not converging towards the international productivity frontier because the manufacturing productivity frontier in the United States is growing much faster than that of its neighbors.

Figure 1.6. A Fraction of Mexican Firms Have Caught up with the Global Productivity Frontier

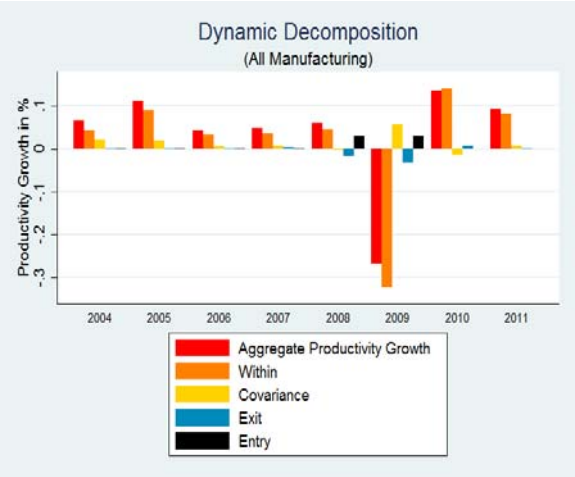
Source: Brown et al. (2014), in this volume.

In these economies, innovation is the most important determinant of firm-level productivity growth – with little contribution from the resource reallocation channel.[23] This is true even among more capital intensive firms, which seem to enjoy higher productivity growth. The degree of engagement in international trade does not seem to influence productivity growth positively, except in the case of the United States. On average, the "within" firm productivity growth (that is driven by technological adoption or innovation) accounts for more than two thirds of overall productivity growth in the manufacturing sector. In Mexico, on average, changes in allocation of factors between firms accounted for 22 percent of overall productivity growth and for 8 percent in the United States. Reallocation made almost no contribution to productivity growth in Colombia. This also means that Mexico and Colombia during the 2000s have done relatively better on technology adoption than on reducing resource misallocation.

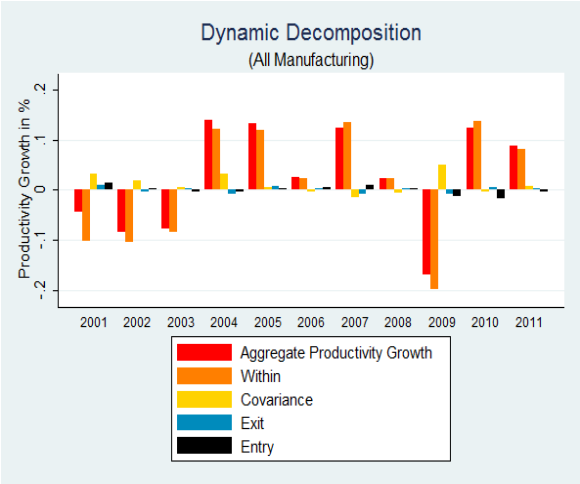
[22] Although their share is quite different across industries.
[23] Innovation was defined as firm-level expenditure shares in innovation and investments in capital equipment.

Figure 1.7. Within-firm Productivity Drives Convergence to the Domestic Frontier

Mexico



Colombia



Source: Brown et al., in this volume.

Note: The covariance component describes the joint distribution of firms' productivity and market share. The extent of resource misallocation can be inferred by the covariance term, with a larger positive value indicating that more productive firms use higher industry inputs shares. Increases in the covariance term would therefore imply improvements in the allocation of productive inputs (i.e. workers) across firms (within the industry).

1.2.3. Incentives to innovate are inhibited by weak institutions

In Brazil, Ecuador, Guatemala, Honduras, and Nicaragua returns to innovation are low, creating little incentive for firms to innovate.[24] Overall, it is found that, after a firm innovates, its sales per worker increase by 18 percent.[25] In contrast, in the Latin American countries for which this analysis was conducted – namely, Brazil, Ecuador, Guatemala, Honduras, and Nicaragua – the difference in sales and sales per worker between firms that do and do not innovate is not statistically different from zero.[26] This indicates that returns to innovation in Latin America are very small.

Institutional factors such as weak property rights protection and the rule of law explain such low returns. Returns to innovation increase in LAC—disproportionately more than in ECA—with better property rights protection (7.4 percent vs. 0.8 percent) and better institutions (12.6 percent vs. 1.9 percent). Regulations and other institutional arrangements can prevent firms from absorbing existing technologies or from innovating, even after correcting for the economic structure and level of development. These weak institutions constrain technology adoption and reduce firm-level incentives to innovate. This "innovation shortfall" due to these distortions seems particularly

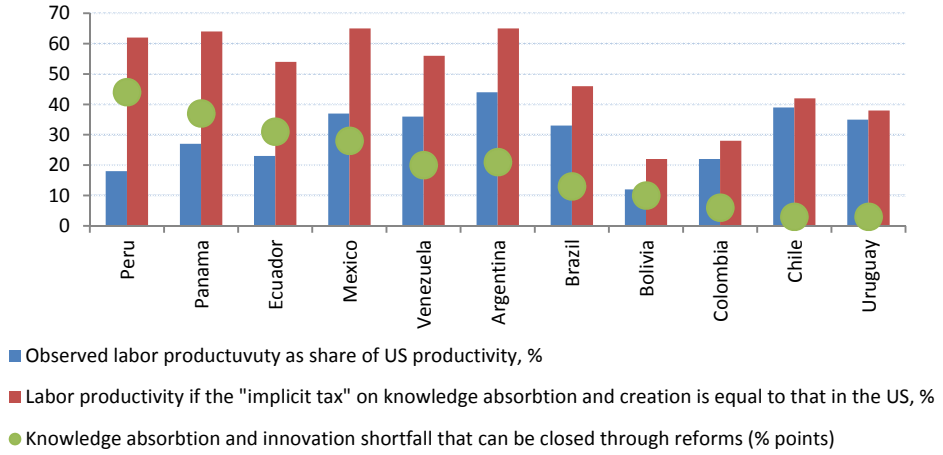
[24] Innovation is an introduction of a line or a product that are new to a firm, but do not necessarily represent innovation at the technological frontier.

[25] This result is for a pulled sample of Eastern Europe and Central Asia (ECA) and LAC (including only Brazil, Ecuador, Guatemala, Honduras, and Nicaragua) regions. See Nguyen and Jaramillo, in this volume.

[26] In a spin-off of the model in Akcigit et al. (2014) and Eden and Nguyen, in this volume. Akcigit et al. (2014) show that technology adoption incentives decrease with the level of distortions in economy, which they call "static wedges" and proxy by misallocation and competitiveness. They also show that the distance to the world knowledge frontier is positively affected by "static wedges."

pronounced in Argentina, Ecuador, Panama, Peru, Mexico, and Venezuela (Figure 1.8). This is one example of the distortions that inhibit productivity growth, discussed in the following sections.

Figure 1.8. Barriers to Knowledge Absorption Reduce Productivity in LAC
(percent)

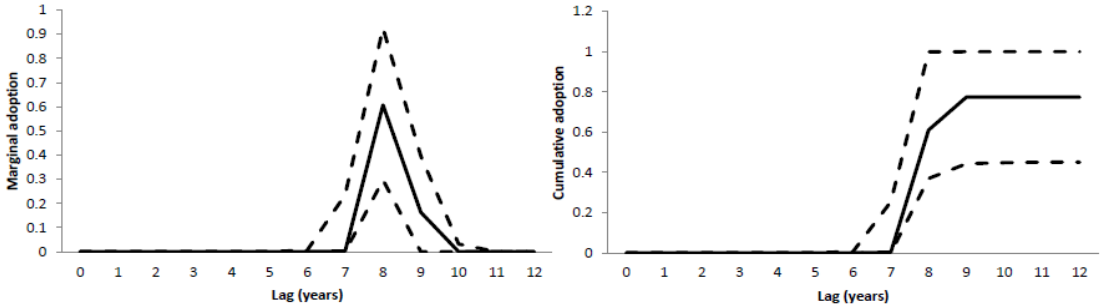


Source: World Bank staff calculations based on Maloney and Rodriguez-Clare (2007).

1.2.4. Distortions leading to misallocation of factors explain most of the efficiency gap

Technology adoption explains about one-fifth of the efficiency gap between countries, leaving the rest to be explained by misallocation of factors. The role of technology in the region's efficiency gap with the United States is a function of the speed of technology adoption. An adoption lag of technology is the length of time between the invention of the technology and its eventual adoption. Estimated at the macro level, the rate at which an economy adopts new technology indicates the degree to which technology improves efficiency. Slow adoption indicates that technology backwardness is indeed a major problem. Fast adoption means that other factors, such as institutions and misallocation of resources, are more important. Any shock to TFP growth in the United States that affects the adopting countries with a lag is a technology shock. Based on the TFP time series data, we find that, on average, technologies in the United States are fully or nearly-fully adopted by LAC firms after eight to 10 years (Figure 1.9). Assuming that the technology frontier in the United States grows about 1 percent a year, an eight-year lag translates into an 8 percentage-point widening of the productivity gap. This leaves 80 percent of the efficiency gap to be explained by distortions leading to misallocation of factors of production.

Figure 1.9. Adoption of Frontier Technology in LAC Takes Around Eight Years
(marginal and cumulative adoption rates)



(a) Marginal adoption rates (b) Cumulative adoption

Source: Eden and Nguyen (2014). Note: The figure depicts the marginal rate and cumulative adoption of frontier technology in LAC, based on a baseline estimation from Akcigit et al. (2014). Measured TFP growth is constructed as the growth of a Solow residual, at an annual frequency. The United States is the frontier country and the adopting country is a GDP-weighted average of LAC countries. Dotted line represents 90 percent confidence intervals.

This result is consistent with the fact that technology adoption and innovation drove convergence to domestic productivity frontiers in Mexico and Colombia. It is important to distinguish between what explains the efficiency gap between countries and the drivers of the observed convergence to domestic productivity frontiers. While technology adoption only explains 20 percent of the existing efficiency gap, based on macro-level evidence of shocks to TFP, this does not mean that *changes* in the speed of technology adoption, or in conditions that determine this speed—such as incentive structure for innovation, institutions, etc.—account for the same share in the observed firm-level productivity increases. Indeed, we find that innovation has been driving firm-level productivity, which in turn drove productivity convergence to the *domestic* frontier in Mexico and Colombia; while the lack of improvements in between-firms factor allocations prevented them from converging to the global productivity frontier. There has therefore been very little reallocation of factors towards more productive firms: factors that experience little change also contribute little to the dynamics of convergence.

There is some heterogeneity in the speed of technology adoption among LAC countries, sectors of the economies, and specific technologies. Studies using data on specific technologies, have estimated longer lags (about 20 years), potentially explaining about half of the efficiency gap. We find, however, that the various results can be reconciled, taking into account the differences between macro and micro-data estimations (see Box 1.2).

Box 1.2. Reconciling the Different Technology Adoption Lags at Macro and Micro Levels

Comin and Hobijn (2010) using microeconomic evidence on specific technologies find the technology adoption gap to be around 20 years on average. This, at least on the surface, is inconsistent with the result found in this volume and in Akcigit et al. (2014), which shows an eight-year lag for LAC. Eden and Nguyen, in this volume, discuss this result in detail and show that due to different definitions of technology adoption lag measured at macro and micro levels, these results are broadly in line. They reconcile the two findings with two insights. First, technologies tend to be adopted first in more productive firms. Because the first adopting firms tend to be more productive, the productivity gains from the first technology adopters are relatively larger than the productivity gains from later adopters. The macro-level adoption lag accounts for this, by weighting technology adoptions by their respective productivity gains. The micro-level adoption lag, in contrast, assigns equal weights to all adopters; thus, it is likely to be relatively longer than the macro-level lag. Second, more effective technologies are likely to be adopted faster. Technologies that improve productivity are more likely to be adopted faster, as the return to adoption is higher. This implies shorter lags associated with technologies that are more productivity enhancing. The macro-level adoption lag focuses on aggregate productivity gains from technology adoption, which is likely driven disproportionately by more productive technologies. In contrast, the micro-level adoption lag weighs technologies equally, and is thus likely to be longer. Since the relative importance of adopting firms and of productivity improvements matters for aggregate productivity, the macro-approach is more important to explain the latter.

Source: authors.

Misallocation can affect efficiency directly, and through the optimal technology adoption decisions by firms. Weak institutions can reduce firm-level incentives to innovate, and thus become a binding constraint to innovation and technology adoption. Moreover, these weak institutions can result in misallocation of factors and can affect efficiency through the optimal technology adoption decision of agents.[27]

1.2.5. Distortions and factors outside the firm hamper productivity growth in manufacturing

LAC's efficiency gap is not all about sectoral resource allocation, but also about inefficient resource use *within* key sectors. Structural change has contributed less to growth in the region not only due to the movement of labor from manufacturing to lower-productivity activities, but also due to slower manufacturing productivity growth. Unconditional convergence in manufacturing labor productivity across countries has emerged as an empirically robust stylized fact.[28] That is, manufacturing labor productivity in poorer countries is catching up (on average) with manufacturing labor productivity in high income countries unconditional on developing countries' policies, qualities of institutions, education, or other growth determinants. In one interpretation, this phenomenon can be attributed to the tradable nature of manufacturing as well as to its cross-border technological transferability.[29]

[27] In a spin-off of the model in Akcigit et al. (2014) and Eden and Nguyen, in this volume, it is shown that technology adoption incentives decrease with the level of distortions in economy, which they call "static wedges" and proxy by misallocation and competitiveness. They also show that the distance to the world knowledge frontier is positively affected by "static wedges."
[28] See Rodrik (2013a).
[29] See Rodrik (2013b).

Firm-level productivity is also affected by factors and distortions outside of the firm, including through spillover effects. One example, considered above, is the reduction in returns to innovation caused by weak institutions. For example, when an industry improves overall productivity, the firms in the same sector of the same country also improve their productivity. However, the variation in productivity among firms within an industry can also hinder an individual firm's ability to catch up. That is, the spillover effect of improved productivity dissipates with the distance from the frontier. The farther away a firm is from the productivity frontier, the less it benefits from the improvements. Similarly, there was no evidence of spillovers from the global frontier (which is generally more distant).

High labor costs and wage inequality also hinder convergence. In Mexico and Colombia, high wages reduce the catch-up speed towards the domestic frontier. In Colombia, the wage differential between skilled and unskilled workers also negatively affected productivity convergence. In contrast, the opposite was true for the U.S. firms. This reflects the fact that convergence is more difficult in an environment where high skills are scarce and costs of labor mobility are high,[30] as in Colombia, and where skilled workers thus earn a considerable wage premium.

1.2.6. Low labor productivity in "insulated" sectors reduces overall value added per worker

The movement of labor to the sectors with lower value-added per worker is correlated with the overall slow growth in value added in LAC. When workers move to sectors with lower value-added per worker, the growth in overall value-added is found to be lower.[31] This aspect of structural transformation appears to have been the pattern across the region in recent decades. In seven out of a sample of nine LAC countries between 1990 and 2005, structural change was associated with lower value-added per worker.[32] The cases of Argentina and Costa Rica illustrate the issue of labor productivity. In Argentina, a number of large services sectors with experienced the highest increases in employment. While these "insulated" economic activities provide a large number of jobs, they also tend to generate lower value added per worker. The result was an overall decline in value added per worker in the entire economy. By contrast, in Costa Rica, while structural change also shifted labor to services, the workers' productivity was higher, thus resulting in an overall increase in value added per worker in the economy. Figure 1.10 illustrates the cases of Argentina and Costa Rica.

The role of the services sector in explaining the contribution of structural change to average value-added per worker varies across the region. In cases where the tertiary sector remains relatively less productive than the manufacturing sector, which seems the more common pattern in the region, employment re-allocation from the latter to the former would reduce economy-wide growth in value-added per worker in LAC. In contrast, higher services sector productivity helps explain why countries such as Mexico and Costa Rica have seen structural change contributing to aggregate productivity growth.

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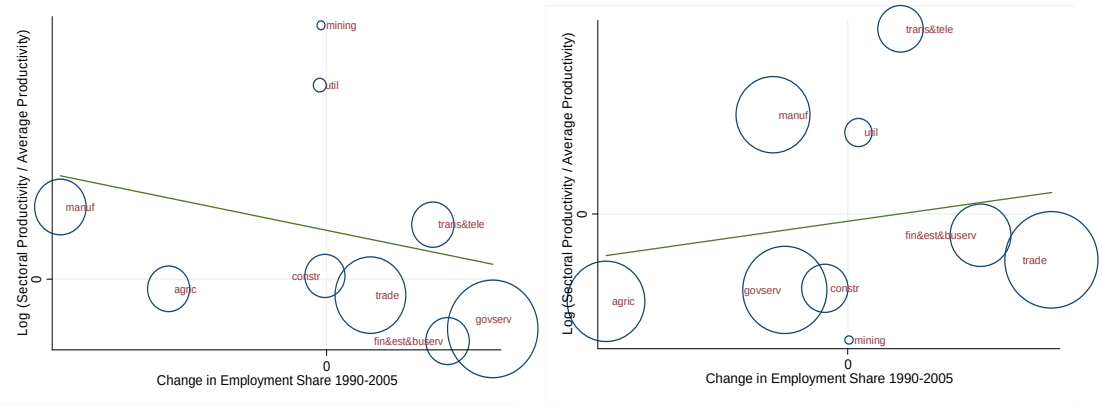
[30] See Artuç, Lederman, and Porto (2013).
[31] See MacMillan and Rodrik (2011).
[32] The exceptions were Mexico and Costa Rica. High productivity in the services sectors explain why structural change contributed to aggregate productivity growth in these economies.

Figure 1.10. Structural Change and Value-Added Per Worker: Two Contrasting Cases

Argentina **Costa Rica**



Source: Schiffbauer, Sahnoun and Araujo, in this volume.
Note: Figures plot logarithm of sectoral value added per worker (relative to the average across all sectors) and the change in the employment share for 9 sectors of an economy between 1990 and 2005. The size of the circle reflects the employment share in 2005. On the vertical axis, sectors above zero are relatively more productive compared to an average sector in an economy. On the x-axis, sectors to the right from zero have had increases in their employment shares.

1.2.7. High poverty rates weaken income convergence through sectoral misallocation

Countries with deep initial poverty converge more slowly in income per capita. Although there are additional forces influencing poverty and convergence, the initial poverty and associated lack of opportunity *do* play a role in income convergence. Figure 1.11 shows how the convergence speed of income per capita depends on the initial poverty level. Lower poverty gaps (on the left) are associated with faster convergence speed while convergence speed slows down as poverty rises (moving towards the right on the horizontal axis). Interestingly, controlling for poverty is sufficient to observe convergence in a sample of 102 developing countries that do not converge unconditionally.

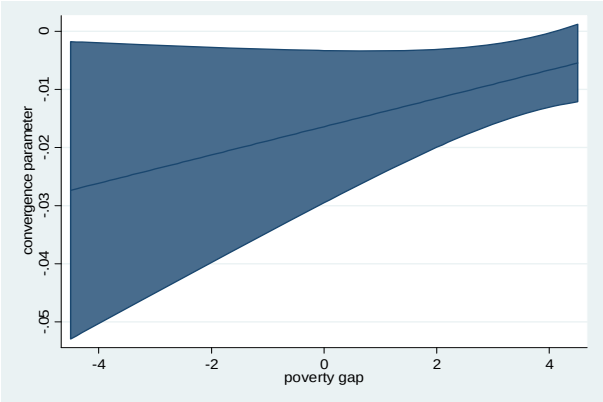
Poverty and slow convergence reduce opportunities for low-skill workers and favor the development of inefficient insulated sectors. Workers, facing poverty and lacking opportunity, may not be able to move into high-productivity sectors, for any number of reasons.[33] They have no other choice than to perform basic activities, usually in the informal sector, such as basic retail trade, becoming street vendors, or performing other informal services. Many of these services are essentially non-tradable and do not operate in a competitive environment. In addition, because these insulated sectors are "pockets of inefficiency," the lack of access to finance and poor entrepreneurship prevent innovation and improved productivity.

The LAC region's relatively high poverty rates, given the levels of income, have hindered convergence. LAC countries stand out for their higher than expected poverty gaps, given their income levels. In addition, the region's history of informality, limited access to finance, and skill-mismatches have counteracted the "advantages of backwardness" that should otherwise have helped these countries to converge towards higher income levels.

[33] For example, workers may not have the necessary education or skills, or they may not be able to move to another part of the country, or they may not be aware of opportunities.

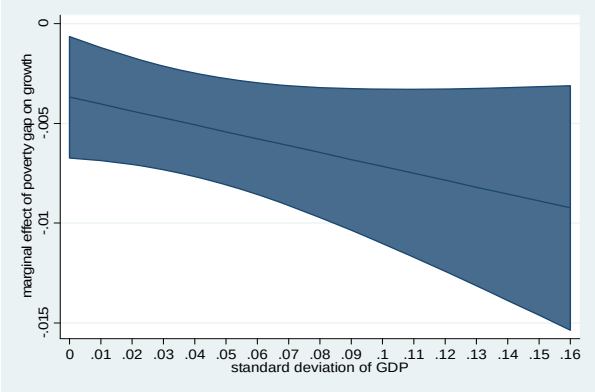
This effect is magnified by macroeconomic volatility, potentially creating a vicious cycle. The negative effect of poverty on growth further increases with macroeconomic volatility and uncertainty because the poor will refrain from investing.[34] This would prevent poorer workers from moving to sectors that are more profitable and productive. This "missing reallocation" will thus give rise to an *ex post* allocation inefficiency, that could adversely impact growth and poverty reduction further.[35] Figure 1.12 shows the impact of poverty on growth at different levels of volatility (measured by the standard deviation of GDP). The adverse effect of poverty on growth becomes more pronounced as GDP volatility increases.

Figure 1.11. Convergence Speed Depends on the Initial Poverty Level



Source: WBG staff calculations based on WDI data.

Figure 1.12. The Impact of Poverty on Growth Increases with Volatility



Source: WBG staff calculations based on WDI data.

1. 3. What These Findings Mean for Growth Policies

Understanding the reasons behind LAC's income gap is a necessary step towards designing appropriate growth strategies. To inform the ongoing debate on growth strategies for Latin America and the Caribbean, the findings of the papers in this volume point to a number of broad policy directions:

- Prioritizing policies to reduce the efficiency gap is an effective way to address the income gap.
- Policies aimed at reducing distortions and misallocation of factors can improve both efficiency and the speed of technology adoption.
- Reducing macroeconomic volatility will improve income convergence by alleviating the negative impact of the poverty gap on growth.[36]

[34] Wacker, in this volume, and Crespo-Cuaresma et al. (2013).

[35] Dixit and Rob (1994). Most countries in the region had relatively liberalized capital accounts – which gave rise to boom and bust cycles (aside from Dutch-disease type effects on economic structure) – while being less open to trade in goods and services which could help mitigate the adverse effect of volatility on growth (see Kose *et al*., 2006). Notably, the situation in East Asia was quite the reverse.

[36] These results complement in a number of ways, the findings and conclusions of the 2010 IDB flagship *The Age of Productivity*. While the present volume finds that addressing resource allocation issues would play a significant role in addressing the efficiency gap, in line with the IDB flagship, it also shows the criticality (and the costs) of innovation

1.3.1. To reduce the income gap, close the efficiency gap

Closing the efficiency gap will lead to significant growth and welfare gains. If LAC had closed its efficiency gap relative to the United States, the region's income per worker would have been twice as high as its current level. This result would not have required a massive savings or investment effort to close the capital gap. In addition, efficiency improvements would themselves have provided the incentive for investments, thereby reducing the capital gap.[37]

However, the supply-side angle—the determinant of TFP—is critical if LAC is to achieve higher and sustained rates of non-inflationary growth. Since many of the economies in LAC are already operating close to their full capacity, it is not enough to seek alternative (domestic) sources of demand. The region's economies also need to remove or relieve constraints to productivity growth. Otherwise, policies that focus exclusively on stimulating aggregate demand run the risk of further straining countries' productive capacity and leading to inflationary pressures.

1.3.2. To increase productivity, reduce distortions that lead to resource misallocation and weak incentives to innovate

Building more efficient economic institutions will improve the allocation of factors. Misallocation plays a major role in explaining the LAC region's overall efficiency gap.[38] Barriers for the flow of labor and capital to the most productive entities reduce aggregate productivity. Where there is a great variety of efficiency levels within an industry, convergence is slow and the benefits of knowledge spillovers are reduced. In addition, firms that are farther away from the frontier find innovation efforts too costly and ineffective and cannot benefit from advances in technology. Therefore, improving the allocation of resources towards more productive firms will boost aggregate productivity and expand production further.

Identifying and addressing country-specific distortions that prevent resources from moving to the most productive activities (sector or firm level). In a well-functioning policy and market environment, capital and labor should move from firms and sectors with low productivity to firms with high (marginal) productivity and allow the latter to grow and the former to shrink (or exit the market). However, myriad policy and market failures can affect the efficient allocation of capital and labor across firms. This reduces productivity because it gives an inordinate market share to less productive firms, while restricting growth of the more productive ones. Some of the policy inadequacies that discourage the ability of productive firms to survive and grow, and the closure of unproductive ones include: (i) limited market competition in key network industries (transport,

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for firm-level convergence as well as the importance of reducing macroeconomic volatility for the simultaneous pursuit of growth and equity.

[37] Furthermore, as shown by other research, TFP can be interpreted as a measure of aggregate welfare and, TFP comparisons across countries and time would proxy for welfare comparisons along the same dimensions. See Basu et al. (2012).

[38] As noted by Jones (2015): "Development accounting tells us that poor countries have low levels of inputs, but they are also remarkably inefficient in how they use those inputs. Misallocation provides the theoretical connection between the myriad of distortions in poor economies and the TFP differences that we observe in development accounting." (p. 55).

financial, telecommunications, logistics, communication and distribution services); (ii) limited labor market flexibility (including skill-mismatches and social barriers); and (iii) informational frictions (including complex tax regimes and credit rationing).

Therefore, the goal should be to lift productivity levels in lagging sectors that are receiving labor and upgrade human capital across the board – so that newly-unemployed workers can find jobs in more productive sectors that could potentially absorb labor.[39] At the sector level, a number of considerations follow from the analysis in this volume:

- Natural resource wealth, if appropriately managed, can generate economy-wide benefits. Although Chile's economy is missing an industrialized manufacturing core, its economic performance has been impressive.
- High productivity services are not unlike manufacturing in some respects and could also potentially display unconditional convergence.[40] Given the relatively low levels of service exports in LAC, a key policy goal for the region would be to make the services sector more productive and tradable.[41]
- "Insulated" economic activities—particularly in the tertiary sector—are less productive, but provide a large number of jobs. Enhancing product and labor market competition can remove the implicit protection that such insulated sectors receive and thus reduce resource misallocation.[42]

Innovation effort is the main driver of firm-level convergence, but certain factors prevent firms from absorbing the technology that is readily available. Both the firm-level study of convergence to the domestic frontier (innovation largely contributes to observed productivity convergence), and the discussion on the "technology space" (the importance of knowledge applicability as a growth engine) highlight the importance of innovation in the convergence process. It takes about eight years for frontier technologies to have an impact on efficiency in LAC. Moreover, macro-level factors, such as institutional quality and slow technology absorption, reduce firms' incentives to innovate and have a disproportionately larger negative effect in LAC than elsewhere.

Removing distortions will also speed up technology adoption. Similar distortions adversely affect *both* resource allocation and incentives to innovate, suggesting that certain "horizontal" policies can operate through both resource allocation and technology adoption. To increase their capabilities to innovate or absorb new technology, LAC countries need to invest more in human

[39] For a similar approach applied to the case of Brazil, see World Bank (2014a).
[40] Rodrik (2013, p. 53): "(…) some service industries may be acquiring manufacturing-like properties (…) If such service activities are also subject to absolute productivity convergence, as seems plausible, they could act as the escalator industries of the future." See also Ghani and O'Connell (2014).
[41] See World Bank (2013): "At any rate, rather than completely discarding it as an undesired Dutch Disease by-product, proactive development policies should embrace sophisticated services as crucial to the Latin American path to sustainable development." (p. 45).
[42] Silva and Ferreira (2013) argue that low growth in the tertiary sector explains much of the divergence between LAC and the United States after 1980.

capital and work towards removing distortions.[43] Furthermore, a weak or adverse institutional environment discourages firms from investing in new products. These distortions also affect the ability of resources to move towards their most productive use, thereby contributing to resource misallocation. Therefore, certain "horizontal" policies—focused on institutional strengthening, human capital accumulation and infrastructure upgrading—can help raise efficiency through both channels examined in this volume.[44]

1.3.3. Reduce macroeconomic volatility to alleviate the negative impact of the poverty gap on growth

Containing macroeconomic volatility helps reduce the negative impact of the poverty gap on growth. Policies that reduce macroeconomic volatility will also weaken the negative link between "initial" poverty and income convergence. As a result, the potential vicious cycle between relatively high poverty and aggregate growth can be addressed. This conclusion also supports the notion that growth strategies need to take into account both equity and volatility. As a corollary, policies aimed at addressing macroeconomic volatility would also have positive longer-run *supply response* effects. [45]

1.3.4. Issues for future research

As this volume narrows the search for the determinants of LAC's income gap, it also raises new issues for future research. The volume emphasizes the relevance of closing the efficiency gap and the fact that technology adoption only plays a limited role in this process. Issues of structural change, innovation, and equity deserve more attention. Despite these insights, this volume is only one contribution in an ongoing debate, with the need to focus on more detail on certain aspects. For example, why do we see domestic convergence for firms' productivity despite the fact that the more productive firms are adopting new technologies faster than the less productive firms? Is this because of the low importance of technology adoption for productivity or because domestic convergence is a phenomenon of just the last decade (or of only Colombia and Mexico)? Does LAC's progress in terms of equity during the last decade contribute to this pattern and what is the causal relationship between poverty, volatility, and convergence more generally? Under which conditions does productivity-increasing structural change (between and within sectors) occur? We hope that this volume provides a basis upon which these and other research questions can be addressed.

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[43] Examples of distortions include credit market failures that prevent firms from investing in "lumpy" and risky innovations and labor market rigidities that act as barriers to new technology adoption. See Maloney and Rodriguez-Clare (2007).

[44] This does not mean that "vertical" policies cannot be effective in some contexts. However, the appropriateness of vertical approaches was not addressed in this volume.

[45]Therefore, by incorporating equity and volatility concerns, development policy design needs to go beyond the "incomplete agenda" of Washington Consensus for growth in LAC. See Birdsall *et al* (2010).

1. 4. Annexes

1. 4. 1. Annex 1. Understanding LAC's Income Gap: A Summary

Motivation: Despite a decade of convergence, LAC still faces a significant per capita income gap vis-à-vis the US.			
Working Hypotheses	**Level of Analysis**	**Key Findings**	**Policy Implications**
• Low Total Factor Productivity (TFP) may be the main explanation for LAC's long-term performance in terms of income convergence.	Macro	The region suffers from an *efficiency gap* as much as it suffers from a *capital gap*. However, much of the capital gap itself is likely due to diminished incentives to invest in equipment, structure and schooling caused by the efficiency gap. (Caselli)	If LAC closed its efficiency gap relative to the United States, its income per worker would have been twice as high as its current level – without requiring a massive savings/investment effort to close the capital gap, which would probably be inconsistent with the "social compact" observed across the region and the maintenance of the recent gains made in terms of inequality reduction.
• The efficiency gap between LAC and the United States could be driven by slow technology adoption or resource misallocation.	Macro/sectoral	Macro-based evidence indicates that the technology adoption lag between the U.S. and LAC (8 years) is shorter than the current micro-based evidence suggests and explains only little of the observed productivity gap. (Eden and Nguyen)	Given the relatively limited contribution of adoption lags to the income gap, attention should also be paid to policies aimed at improving domestic institutions and correcting misallocation of resources.
• Structural change – operating both through the technology and resource allocation channels – may have contributed	Sectoral	(i) Structural change has been resulted in decreased economy-wide value-added per worker in most LAC countries in the sample; (ii) LAC's manufacturing productivity growth has been below the	Searching for an "optimal economic structure" is futile. The conditions under which *any* sector would contribute to productivity growth are more important than the sectoral composition of output per se. "Insulated" economic activities – particularly in the

negatively to productivity growth in LAC.		world average; (iii) there is a prevalence of idiosyncratic production structures, which hurt technology adoption prospects. (Schiffbauer, Sahnoun and Araujo)	tertiary sector – display lower productivity and have become a recipient of labor in many LAC countries. Enhancing product and labor market competition can remove the implicit protection that such insulated sectors receive and thus lead to more productive resource allocation.
• Both firm-level growth ("within" component) and market reallocation ("between" component) may be important in explaining productivity growth and convergence at the firm level.	Micro (Colombia and Mexico)	(i) On average the "within" component (firm-level growth) accounts for more than two thirds of overall productivity growth in the manufacturing sector. (ii) convergence towards the global frontier is much weaker than convergence to the domestic one; (iii) firms' innovation effort is the most important determinant of firm-level productivity growth, and therefore of convergence to the domestic productivity frontier. (Brown, Crespi, Iacovone and Marcolin)	Since the contribution of the "between" component (market reallocation) is weak, there is a degree of misallocation that has not been addressed. At the same time, *when it occurs*, innovation effort – operating through the "within" component – is a key driver of convergence, at least to the domestic frontier.
• Even though innovation effort is key for firm-level growth, incentives to innovate might be inadequate in LAC.	Micro (Brazil, Guatemala, Honduras, Ecuador, and Nicaragua)	Looking at both ECA and LAC, after a firm innovates, its sales per worker increase by 18 percent. When only looking at firms in LAC, the difference in sales and sales per worker between firms that do and do not	Weak institutions reduce firm-level incentives to innovate, and thus become a constraint to innovation and technology adoption.

		innovate is not statistically different from zero. Returns to innovation are influenced by institutional factors, such as property rights protection and the rule of law. Existing regulations and institutional arrangements can prevent firms from absorbing existing technologies or from innovating. (Nguyen and Jaramillo)	
• Convergence may be slowed down even further by high initial poverty.	Macro/micro	The negative impact of the poverty gap on growth is exacerbated by macroeconomic volatility. (Wacker)	Equity and volatility need to be taken into account in the formulation of growth strategies – providing an empirical basis for the Birdsall *et al* (2010) notion of an "incomplete agenda" for growth in LAC in the past and suggesting that shared prosperity is also supportive to income convergence.

1. 4. 2. Annex 2. A Survey of the Literature on the Determinants of Total Factor Productivity[46]

Recent advances in development accounting confirm that the large income differences across countries cannot be explained by differences in the accumulation of physical or human capital. Instead, variations in total factor productivity (TFP) have been found to account for at least 50 percent of cross-country income differences directly (among others, Caselli, 2005; Caselli and Coleman, 2006; Caselli and Feyrer, 2007). What is more, variations in TFP also indirectly affect income differences through their impact on physical and human capital accumulation (Hsieh and Klenow, 2010). It follows that a successful theory of economic growth and convergence needs to explain why some countries experience high TFP growth while others lag behind. The subsequent literature explaining TFP differences can be broadly classified into three different approaches.

[46] Prepared by Marc Schiffbauer.

I. Technology Diffusion and Adoption

A first strand of the literature extends endogenous growth theories to show differences in international technology diffusion and adoption rates across countries (e.g., Barro and Sala-i-Martin, 1997; Howitt, 2000). Among others, Keller (2004) summarizes the empirical evidence on international technology diffusion documenting also the importance of geographic, economic, or cultural distances between countries. He also measures that 90 percent of technology diffusion occurs through indirect technology spillovers rather than through the acquisition of technology licenses. Comin and Hobjin (2010) use data on the diffusion of 15 technologies in 166 countries over the last two centuries and reveal significant lags in adoption (on average, countries have adopted technologies 45 years after their invention). But why are firms in some countries more successful or eager to adopt new technologies than firms in other countries?

Differences in the speed of diffusion have been associated with several economic factors influencing the incentives of firms in developing countries to adopt new (foreign) technologies. It should be noted that most of these contributions are based on theoretical models, in some cases paired with some suggestive cross country or case study evidence. Several studies highlight the role of cross-country differences in (the quality of) human capital (Benhabib and Spiegel, 1994, 2005; Hanushek and Kimko, 2000; Hanushek and Woessmann, 2012). However, while all of these studies imply higher social relative to private returns from schooling, a number of studies reject different returns empirically (e.g., Krueger and Lindahl, 2001), suggesting that there might be a non-trivial mapping from (quality) measures of schooling to the quality of the labor-force. Other explanations focus on transmission channels for the diffusion of technologies that differ across countries, such as trade (Grossman and Helpman, 1995; Keller, 2002; Eaton and Kortum, 2002; Caselli and Wilson, 2004) and foreign direct investment (Rodriguez-Clare, 1996; Larrain et al., 2000; Xu, 2000; Javorcik, 2004; Antras and Helpman, 2004; Keller and Yeaple, 2009). Other factors, that have been shown to affect (distort) the incentives of firms to adopt superior foreign technologies include macroeconomic volatility (Acemoglu and Zilibotti, 1997; Aghion et al., 2010); financial development (Benhabid and Spiegel, 2000; Levine et al., 2000), product market competition (Aghion et al., 2001; Aghion et al., 2005; Aghion et al., 2009); industrial or innovation policy (Grossman and Helpman, 1995; Hausman and Rodrik, 2003); or institutional barriers to technology adoption (Parente and Prescott, 1999; Fisman, 2001; Acemoglu et al. 2002, 2005; Faccio, 2005; Bloom et al., 2012).

II. Efficiency in Resource Allocation

A parallel strand in the literature focusses on cross-country differences in resource allocation within or across industries to explain differences in TFP. These contributions document that resources in developing countries are over-proportionally allocated towards sectors with lower productivity. McMillan and Rodrik (2011) and Rodrik (2013a) show that such misallocations of labor across sectors, in particular a decline in the manufacturing sector, lead to productivity differences across countries. Similarly, Arnold et al. (2012) reveal strategic linkages between sub-sectors in the economy that matter for firm productivity growth. Restuccia and Rogerson (2008), Hsieh and Klenow (2012) and Bartelsman et al. (2013) show the extent to which the allocation of resources across heterogeneous firms induce aggregate cross-country TFP differences. Hsieh and

Klenow (2012) reveal substantial differences in productivity growth over the life cycle of firms in the U.S., Mexico, and India.

While the empirical significance and theoretical underpinnings of cross country differences in resource allocation are by now well established, most approaches fall short in mapping these distortions to specific policies. The fundamental question arises if policy distortions leading to resource misallocation across firms are any different from policies affecting firms' incentives to adopt new technologies?

III. Managerial Quality

Finally, other approaches argue that differences in the organizational efficiency of firms across countries lead to cross-country TFP differences (Prescott, 2008). In particular, Bloom and Van Reenen (2007) and Bloom et al. (2013) attempt to measure cross-country differences in managerial efficiency based on surveys of management practices and find that managerial efficiency varies significantly across firms in different countries.

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2. The Latin American Efficiency Gap

Francesco Caselli[47]

2. 1. Introduction

The average Latin American country produces about 1 fifth of the output per worker of the US. What are the sources of these enormous *income gaps*? This paper reports development-accounting results for Latin America. Development accounting compares differences in income per worker between developing and developed countries to counter-factual differences attributable to observable components of physical and human capital. Such calculations can serve a useful preliminary diagnostic role before engaging in deeper and more detailed explorations of the fundamental determinants of differences in income per worker. If differences in physical and human capital – or *capital gaps* – are sufficient to explain most of the difference in incomes, then researchers and policy makers need to focus on factors holding back investment (in machines and in humans). Instead, if differences in capital are insufficient to account for most of the variation in income, one must conclude that developing countries are also hampered by relatively low efficiency at using their inputs - *efficiency gaps*. The research and policy agenda would then have to focus on technology, allocative efficiency, competition, and other determinants of the efficient use of capital.[48]

I present development-accounting results for 2005 for three samples of Latin American countries: a " broad" sample of 22 countries, a " narrow" sample of 9, and an " intermediate" sample of 15.

The three samples differ in the data available to measure human capital. In the broad sample human capital is measured in the context of a " Mincerian" framework, where the key inputs are schooling (years of education) and health (as proxied by the adult survival rate). In the narrow and intermediate samples I augment the Mincerian framework with measures of cognitive skills, to account for additional factors such as schooling quality, parental inputs, and other influences on human capital not captured by years of schooling and health. The measures of cognitive skills are based on tests administered to school-age children. In the narrow sample, the test is a science test whose results are directly comparable between Latin America and the benchmark developed country. In the intermediate sample the tests were only administered in Latin America and can be compared to the benchmark country only on the basis of a number of ad hoc assumptions.

In all three samples I measure physical capital as an aggregate of reproducible and " natural" capital. Reproducible capital includes equipment and structures, while natural capital primarily includes subsoil resources, arable land, and timber.

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[48] For a detailed exposition of development accounting see, among others, Caselli (2005). For previous applications with a focus on Latin America see Cole, Ohanian, Riascos, and Schmitz (2005) and Hanusheck and Woessman (2012a). Cole et al. in particular stress the importance of TFP gaps, consistent with my findings.

Given measures of physical capital gaps, as well gaps in the components of human capital, development-accounting uses a calibration to map these gaps into counter-factual income gaps, or the income gaps that would be observed based on differences in human and capital endowments only. Because these counterfactual incomes are bundles of physical and human capital, I refer to the ratio of Latin American counterfactual incomes to the US counterfactual income as *relative capital*.

For each of the three samples I present results from two alternative calibrations, a " baseline" calibration and an " aggressive" calibration. The baseline calibration makes use of the existing body of microeconomic estimates of the Mincerian framework in the way that most closely fits the theoretical framework of development accounting. As it turns out, this leads to coefficients for the components of human capital that are substantially lower than in much existing work in development accounting - leading to relatively smaller estimated capital gaps and, correspondingly, larger efficiency gaps. The aggressive calibration thus uses more conventional figures as a robustness check.

When I use my benchmark calibration, irrespective of sample/cognitive skill correction, I find that relative capital and relative efficiencies are almost identical. For example in the broad sample average relative capital and average relative efficiency are both 44 percent - or roughly double actual average relative incomes. Hence, both capital gaps and efficiency gaps are very large: the average Latin American country has less than half the capital (human and physical) per worker of the US, and uses it less than half as efficiently.

Using the aggressive calibration, capital gaps are naturally larger, and efficiency gaps correspondingly smaller. Nevertheless, even under this " best-case scenario" for the view that capital gaps are the key source of income gaps, average Latin American efficiency is at most 60 percent of the US level, still implying a vast efficiency gap.

In assessing this evidence, it is essential to bear in mind that efficiency gaps contribute to income disparity both directly – as they mean that Latin America gets less out of its capital – and indirectly – since much of the capital gap itself is likely due to diminished incentives to invest in equipment, structure, schooling, and health caused by low efficiency. The consequences of closing the efficiency gap would correspondingly be far reaching.

Explaining the Latin American efficiency gap is therefore a high priority both for scholars and for policy makers. It is likely that this task will require firm-level evidence. Firm level evidence would also be invaluable in checking the robustness of the development-accounting results, which are subject to severe data-quality limitations.

2. 2. Conceptual Framework

The analytical tool at the core of development accounting is the aggregate production function. The aggregate production function maps aggregate input quantities into output. The main inputs considered are physical capital and human capital. The empirical literature so far has failed to uncover compelling evidence that aggregate input quantities deliver large external economies, so

it is usually deemed safe to assume constant returns to scale.[49] Given this assumption, one can express the production function in intensive form, i.e. by specifying all input and output quantities in per worker terms. In order to construct counterfactual incomes a functional form is needed. Existing evidence suggests that the share of capital in income does not vary systematically with the level of development, or with factor endowments [Gollin (2002)]. Hence, most practitioners of development accounting opt for a Cobb-Douglas specification. In sum, the production function for country i is

$$y_i = A_i k_i^{\alpha} h_i^{1-\alpha}, \qquad (1)$$

where y is output per worker, k is physical capital per worker, h is human capital per worker (quality-adjusted labor), and A captures unmeasured/unobservable factors that contribute to differences in output per worker.

The term A is subject to much speculation and controversy. Practitioners refer to it as total factor productivity, technology, a measure of our ignorance, etc. Here I will refer to it as " efficiency" . Countries with a larger A are countries that, for whatever reasons, are more efficient users of their physical and human capital.

The goal of development accounting is to assess the relative importance of efficiency differences and physical and human capital differences in producing the differences in income per worker we observe in the data. To this end, one constructs counterfactual incomes, or capital bundles,

$$\tilde{y}_i = k_i^{\alpha} h_i^{1-\alpha}, \qquad (2)$$

which are based exclusively on the observable inputs. Differences in these capital bundles are then compared to income differences. If counter-factual and actual income differences are similar, then observable factors are able to account for the bulk of the variation in income. If they are quite different, then differences in efficiency are important. Establishing how significant efficiency differences are has important repercussions both for research and for policy.

In order to construct the counterfactual $\tilde{y}$ s we need to construct measures of k_i and h_i, as well as to calibrate the capital-share parameter α. Standard practice sets the latter to 0.33, and we stick to this practice throughout. In the appendix I present robustness checks using a larger capital share, i.e. 0.40. This higher share implies somewhat larger capital gaps and somewhat smaller efficiency gaps, though the main message of the paper is unchanged.[50]

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[49] See, e.g. Iranzo and Peri (2009) for a recent review and some new evidence on the quantitative significance of schooling externalities.

[50] There may well be significant heterogeneity among Latin American countries, and, more importantly, between Latin America and the benchmark rich country, in the value of α. However, it is not known how to perform development-accounting with country-specific capital shares. This is because measures of the capital stock are indices, so that a requirement for the exercise to make sense is that the results should be invariants to the units in which k is measured. Now $\left(k_i/k_j\right)^{\alpha}$ is unit-invariant, but $\left(k_i^{\alpha_i}/k_j^{\alpha_j}\right)$ is not.

The rest of this section focuses on the measurement of physical and human capital.

Existing development-accounting calculations measure k exclusively on the basis of *reproducible* capital (equipment and structures). But in most developing countries, where agricultural and mining activities still represent large shares of GDP, natural capital (land, timber, ores, etc.) is also very important. Caselli and Feyrer (2007) show that omitting natural capital can lead to very significant understatements of total capital in developing countries relative to developed ones. Hence, this study will measure k as the sum of the value of all reproducible and natural capital.

Human capital per worker can vary across countries as a result of differences in knowledge, skills, health, etc. The literature has identified three variables that vary across countries which may capture significant differences in these dimensions: years of schooling [e.g., Klenow and Rodriguez-Clare (1997), Hall and Jones (1999)], health [Weil (2007)], and cognitive skills [e.g. Hanushek and Woessmann (2012a)]. In order to bring these together, we postulate the following model for human capital:

$$h_i = \exp(\beta_s s_i + \beta_r r_i + \beta_t t_i). \qquad (3)$$

In this equation, s_i measures average years of schooling in the working-age population, r_i is a measure of health in the population, and t_i is a measure of cognitive skills. The coefficients β_s, β_r, and β_t map differences in the corresponding variables into differences in human capital.[51]

The model in (3) is attractive because it offers a strategy for calibration of the parameters β_s, β_r, and β_t. In particular, combining (1), (3), and an assumption that wages are proportional to the marginal productivity of labor, we obtain the " Mincerian" formulation

$$\log(w_{ij}) = \alpha_i + \beta_s s_{ij} + \beta_r r_{ij} + \beta_t t_{ij}, \qquad (4)$$

where w_{ij} (s_{ij}, etc.) is the wage (years of schooling, etc.) of worker j in country i, and α_i is a country-specific term[52]. This suggests that using within-country variation in wages, schooling, health, and cognitive skills one might in principle identify the coefficients β. In practice, there are severe limitations in following this strategy, that we discuss after introducing the data.

[51] Some caveats as to the validity of the functional form assumption in (3) are in order. There is considerable micro and macro evidence against the assumption that workers with different years of schooling are perfect substitutes [e.g. Caselli and Coleman (2006)]. In this paper I abstract from the issue of imperfect substitutability. Caselli and Ciccone (2013) argue that consideration of imperfect substitution is unlikely to reduce the estimated importance of efficiency gaps.

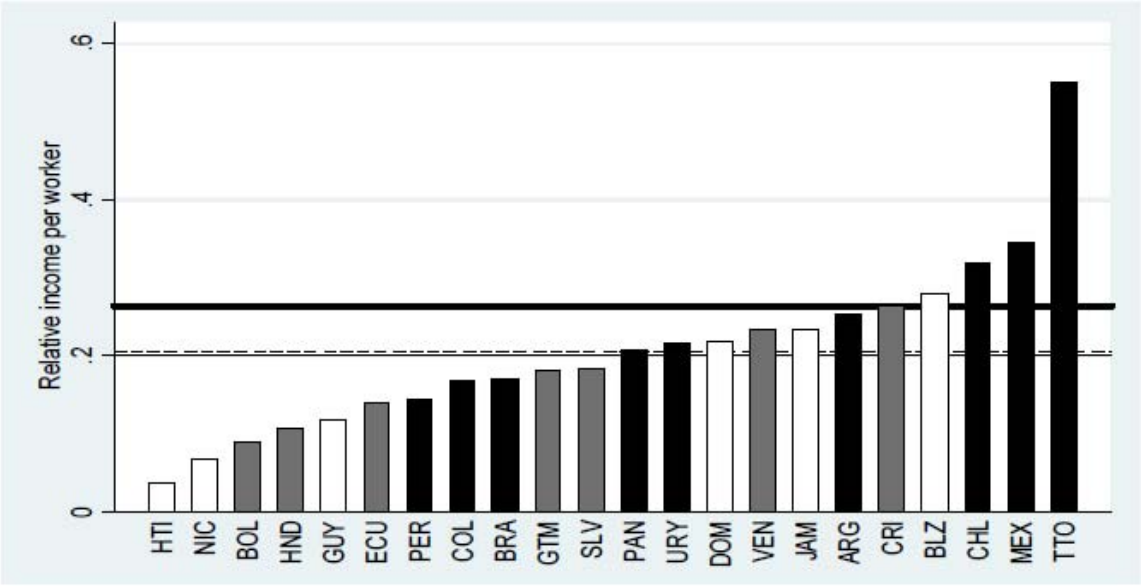
[52] Note that this approach to the measurement of human capital is robust to a broad range of deviations from perfect competition. In particular, the wage does not need to equal the marginal productivity of labour, but just be proportional to it. Many models of monopsony in labor markets and monopolistic competition have this property

2. 3. Data

We work with three samples, broad, narrow, and intermediate. The broad data set contains all Latin American countries for which we have data for y, k, s, and r, all observed in 2005. There are 22 such countries (excluded are Barbados, Cuba, and Paraguay, for which we have no capital data). The other two samples add alternative measures of t. The trade-off is that one measure offers a more credible comparison with the benchmark high-income country, but is only available for 9 Latin-American economies. The more dubious but more plentiful measure is available for 15 countries. All but one of the countries in the narrow sample are also in the intermediate sample (Trinidad and Tobago is the exception). The dataset also includes data from the USA, which we use as the benchmark rich country.

Per-worker income y_i is variable *rgdpwok* from version 7.1 of the Penn World Tables (PWT71). Figure 2.1 shows per-worker income in each country in the broad sample relative to the USA, or y_i/y_{US}. Countries that are also included in the narrow sample are in black, and countries that are in the intermediate but not the narrow sample are in grey. With the exception of Trinidad and Tobago, all Latin America countries have per-worker incomes well below 40 percent of the US level, sometimes much below. The horizontal lines show the three (unweighted) sample averages, indicating that the average country is only one fifth as productive as the USA.[53]

Figure 2.1. Income per worker relative to the US



Source: PWT71.
Notes: White bars; only broad sample. Grey bars: only broad and intermediate samples. Black bars: all samples (except TTO not in intermediate). Dashed line: broad sample mean. Light solid line: intermediate sample mean. Heavy solid line: narrow sample mean.

[53] In the narrow sample the average is higher due to the disproportionate weight of Trinidad and Tobago. Labor-force weighted averages are reported in Table 7.1.

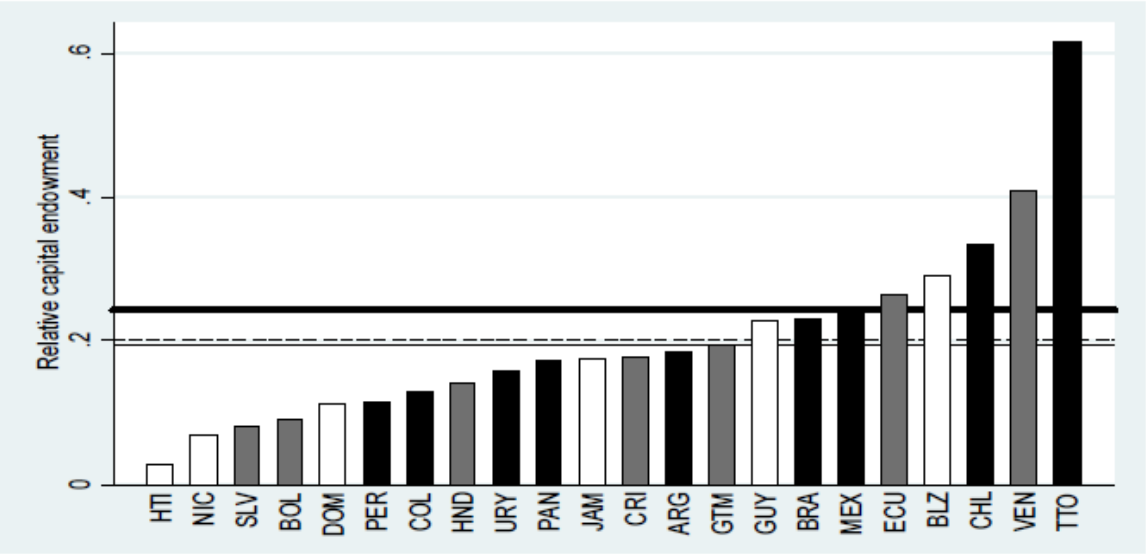
World Bank (2012) presents cross-sectional estimates of the *total* capital stock, k , as well as its components, for various years. The total capital stock includes reproducible capital, but also land, timber, mineral deposits, and other items that are not included in standard national-account-based data sets. The basic strategy of the World Bank team that constructed these data begins with estimates of the rental flows accruing from different types of natural capital, which are then capitalized using fixed discount rates. I construct the total capital measure by adding the variables *producedplusurban* and *natcap*.

Measuring the total capital stock as the sum of natural and reproducible capital amounts to an assumption of perfect substitutability between the two capital types. To evaluate this assumption, it is useful to conceive of GDP as the sum of the added values of the primary sector (essentially agriculture and mining), where natural capital is heavily used, and of the secondary and tertiary sectors (essentially manufacturing and services), where natural capital plays virtually no role. Then, perfect susbstitutability is most defensible if the primary sector uses little or no reproducible capital, or if the primary sector is a relatively small share of the economy. Admittedly, the former assumption is not particularly credible, while the latter clearly does not apply to the typical Latin American country. Intuitively, though, this should result in an overestimate of the capital gap, and consequently an underestimate of the efficiency gap. If the primary sector is large, and reproducible capital plays a significant role in the primary sector, reproducible capital and natural capital should boost each other's productivity, resulting in a larger capital bundle than in the case they are perfect substitutes. In other words, by assuming perfect substitutability we are underestimating the total contribution of capital more in poorer, Latin American, countries than in the richer, benchmark country.

Figure 2.2 shows total (reproducible plus natural) capital per worker estimates for Latin American countries relative to the US, k_i/k_{US}. The average Latin American worker is endowed with approximately one fifth of the physical capital of the average US worker.

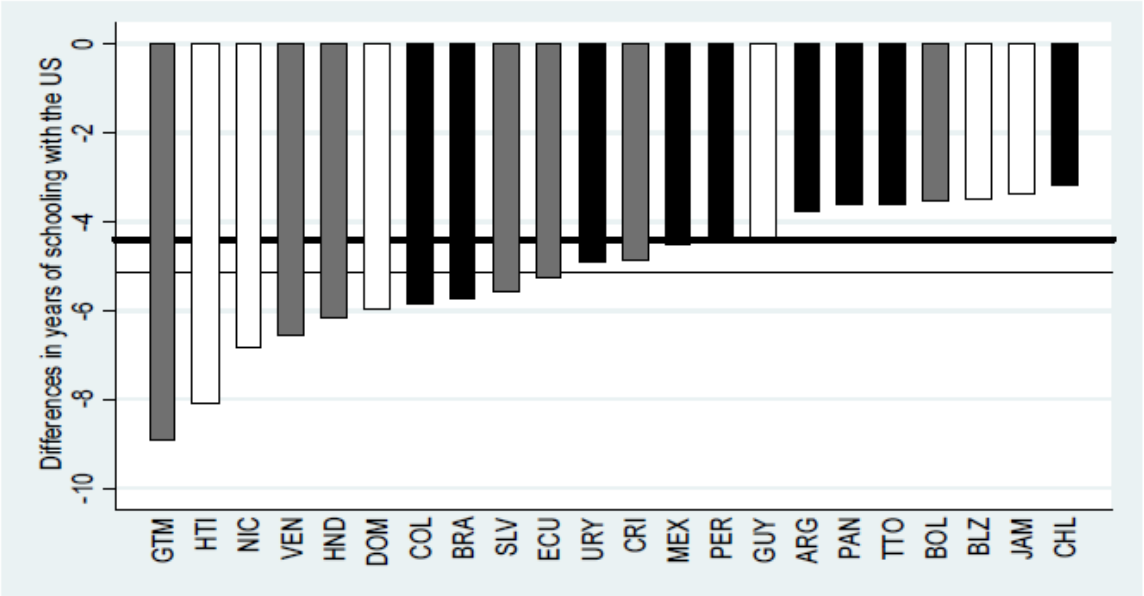
For average years of schooling in the working-age population (which is defined as between 15 and 99 years of age) I rely on Barro and Lee (2013). Note from equation (3) that for the purposes of constructing *relative* human capital h_i/h_{US} what is relevant is the *difference* in years of schooling $s_i - s_{US}$. The same will be true for r and t. Accordingly, in Figure 2.3. I plot schooling-year differences with the USA in 2005. Latin American workers have always at least three year less schooling than American ones, and five on average.

Figure 2.2. Physical capital per worker relative to the US



Source: World Bank (2012).
White bars; only broad sample. Grey bars: only broad and intermediate samples. Black bars: all samples (except TTO not in intermediate). Dashed line: broad sample mean. Light solid line: intermediate sample mean. Heavy solid line: narrow sample mean.

Figure 2.3. Differences in years of schooling with the US

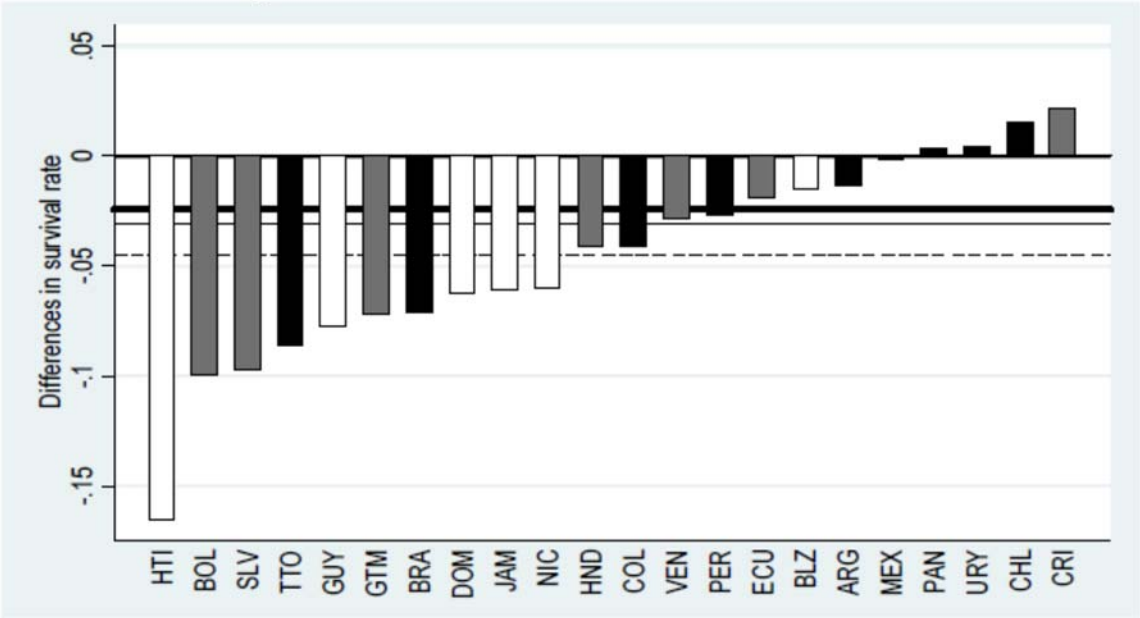


Source: Barro and Lee (2013).
White bars; only broad sample. Grey bars: only broad and intermediate samples. Black bars: all samples (except TTO not in intermediate). Dashed line: broad sample mean. Light solid line: intermediate sample mean. Heavy solid line: narrow sample mean.

As a proxy for the health status of the population, r , Weil (2007) proposes using the *adult survival rate*. The adult survival rate is a statistic computed from age-specific mortality rates at a point in time. It can be interpreted as the probability of reaching the age of 60, conditional on having reached the age of 15, *at current rates of age-specific mortality*. Since most mortality before age

60 is due to illness, the adult survival rate is a reasonably good proxy for the overall health status of the population at a given point in time. Relative to more direct measures of health, the advantage of the adult survival rate is that it is available for a large cross-section of countries. I construct the adult survival rate from the World Bank's World Development Indicators. Specifically, this is the weighted average of male and female survival rates, weighted by the male and female share in the population.

Figure 2.4. Differences in survival rate with the US



Source: WDI.
White bars; only broad sample. Grey bars: only broad and intermediate samples. Black bars: all samples (except TTO not in intermediate). Dashed line: broad sample mean. Light solid line: intermediate sample mean. Heavy solid line: narrow sample mean.

In Figure 2.4., I plot adult survival rate differences with the USA. Survival rate probabilities are lower in Latin America than in the US, but perhaps not vastly so. On average, Latin American 15-year olds are only 4 percentage points less likely to reach the age of 60 than US 15-year olds.[54]

Following work by Gundlach, Rudman, and Woessman (2002), Woessman (2003), Jones and Schneider (2010) and Hanushek and Woessmann (particularly 2012a), we also wish to account for differences in cognitive skills not already accounted for by years of schooling and health. The ideal measure would be a test of average cognitive ability in the working population. Hanushek and Zhang (2009) report estimates of one such test for a dozen countries, the International Adult Literacy Survey (IALS), but only one of these is in Latin America (Chile).

As a fallback, I rely on internationally comparable test scores taken by school-age children. In the narrow sample, I will use scores from a science test administered in 2009 to 15 year olds by PISA (Program for International Student Assessment). There are in principle several other internationally-comparable tests (by subject matter, year of testing, and organization testing) that

[54] The population-weighted mean survival rate in the broad sample is 0.85.

could be used in alternative to or in combination with the 2009 PISA science test. However there would be virtually no gain in country coverage by using or combining with other years (the PISA tests of 2009 are the ones with the greatest participation, and virtually no Latin American country participated in other worldwide tests and not in the 2009 PISA tests).[55] Focusing only on one test bypasses potentially thorny issues of aggregation across years, subjects, and methods of administration. Cross-country correlations in test results are very high anyway, and very stable over time.[56] Data on PISA test score results are from the World Bank's Education Statistics.

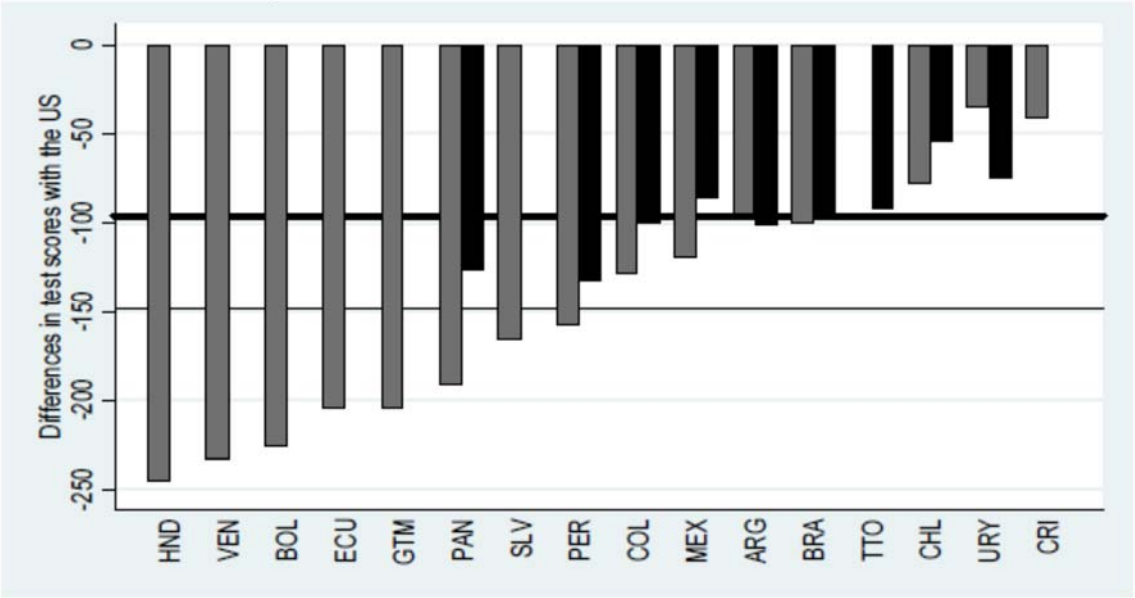
Aside from the world-wide tests of cognitive skills used in the narrow sample, there are also two " regional" tests of cognitive skills that have been administered to a group of Latin American countries: the first in 1997 by the *Laboratorio Latinoamericano de Evaluación de la Calidad de la Educación* (LLECE), covering reading and math in the third and fourth grade; the second in 2006 by the Latin American bureau of the UNESCO, covering the same subjects in third and sixth grade. These tests are described in greater detail in, e.g., Hanushek and Woessman (2012a), who also argue that these tests may better reflect *within Latin-American* differences in cognitive skills.

From the perspective of this study, the main attraction of these alternative measures of cognitive skills is that they cover a significantly larger sample. The biggest problem, of course, is that they exclude the United States (or any high-income country) and so, on the face of it, they are unusable for constructing counterfactual relative incomes. However, Hanushek and Woessman (2012a) propose a methodology to "splice" the regional scores into their worldwide sample. While this splicing involves a large number of assumptions that are difficult to evaluate, it is worthwhile to assess the robustness of my results to these data.[57]

Needless to say measuring t by the above-described test scores is clearly very unsatisfactory, as in most cases the tests reflect the cognitive skills of individuals who have not joined the labor force as of 2005, much less those of the average worker. The average Latin American worker in 2005 was 36 years old, so to capture their cognitive skills we would need test scores from 1984.[58] Implicitly, then, we are interpreting test-score gaps in current children as proxies for test scores gaps in current workers. If Latin America and the US have experienced different trends in cognitive skills of children since 1984 this assumption is problematic.

[55] The only exception is Belize, which participated in some of the reading tests administered by PIRLS (Progress in International Reading Literacy Study).
[56] Repeating all my calculations using the PISA math scores yielded results that were virtually indistinguishable from those using the science test.
[57] Hanushek and Woessman (2012a) splice the regional scores into world-wide scores that are themselves aggregates of multiple waves and multiple subject areas - obtained with a methodology described in Hanushek and Woessman (2012b).
[58] The method for estimating the average age of workers is described in footnote 25 of Caselli (2005).

Figure 2.5. Differences in test scores with the US



Source: World Bank's Education Statistics and Hanushek and Woessman (2012a, 2012b).
Grey bars: regional test/intermediate sample. Black bars: PISA test/narrow sample. Light solid line: regional-test mean. Heavy solid line: PISA-test mean.

The 2009 PISA science tests are reported on a scale from 0 to 1000, and they are normalized so that the average score *among OECD countries* (i.e. among all pupils taking the test in this set of countries) is (approximately) 500 and the standard deviation is (approximately) 100.[59] The regional scores are put on the PISA scale by Hanushek and Woessman's splicing, so they can be directly compared. Figure 2.5 shows test score differences $t_i - t_{US}$ for the narrow and intermediate samples. Differences in PISA scores are very significant: the average Latin American student in 2009 shows cognitive skills that are below those of his US counterpart by about one standard deviation of the OECD distribution of cognitive skills. Only Chile is a partial stand-out, with a cognitive gap closer to one half of one standard deviation. Differences in Hanushek and Woessman's spliced regional tests are even more significant, with the average gap exceeding 1.5 standard deviations. Recall that the PISA scores are directly comparable between Latin American and USA, while the spliced regional tests – while arguably giving a more accurate sense of within Latin America differences – are less suitable for poor country-rich country comparisons. Hence, the discrepancy in cognitive-skill gaps between the PISA and the regional scores implies that the latter should be treated with caution.

[59] I say approximately in parenthesis because the normalization was applied to the 2006 wave of the test. The 2009 test was graded to be comparable to the 2006 one. Hence, it is likely that the 2009 mean (standard deviation) will have drifted somewhat away from 500 (100) - though probably not by much. The PISA math and reading tests were normalized in 2000 and 2003, respectively, so their mean and standard deviation are more likely to have drifted away from the initial benchmark. This is one reason why I use the science test for my baseline calculations.

2. 4. Calibration

The last, and most difficult, step in producing counter-factual income gaps between US and Latin America is to calibrate the coefficients β_s, β_r, and β_t. As discussed, equation (4) indicates that, using *within country* data on w, s, r, and t, one could in principle identify these coefficients by running an extended Mincerian regression for log-wages. In implementing this plan, we are confronted with (at least) two important problems.

The first problem is that one of the explanatory variables, the adult survival rate r, by definition does not vary within countries. Estimating β_r directly is therefore a logical impossibility. To solve this problem Weil (2007) notices that, in the time series (for a sample of ten countries for which the necessary data is available), there is a fairly tight relationship between the adult survival rate and average height. In other words, he postulates $c_i = \alpha_c + \gamma_c r_i$, where c_i is average height and the coefficient γ_c is estimated from the above-mentioned time series relation (he obtains a coefficient of 19.2 in his preferred specification). Since height does vary within countries as well as between countries, this opens the way to identifying β_r by means of the Mincerian regression

$$\log(w_{ij}) = \alpha_i + \beta_s s_{ij} + \beta_c c_{ij} + \beta_t t_{ij},$$

where $\beta_r = \beta_c \gamma_c$.[60]

The second problem is that measures of t are not consistent at the macro and at the micro level. In particular, while we do have micro data sets reporting both results from tests of cognitive skills and wages, the test in question is simply *a different test* from the tests we have available at the level of the cross-section of countries. Call the alternative test available at the micro level d. Once again the solution is to *assume* a linear relationship $d_i = \gamma_d t_i$. The difference with the case of height-survival rate is that, as far as I know, there is no way to check the empirical plausibility of this assumption. Given the assumed linear relationship, one can back out γ_d as the ratio of the *within country* standard deviation of d_{ij} and t_{ij}. With γ_d at hand, one can back out β_t from the modified Mincerian regression

$$\log(w_{ij}) = \alpha_i + \beta_s s_{ij} + \beta_c c_{ij} + \beta_d d_{ij}, \qquad (5)$$

using $\beta_t = \beta_d \gamma_d$.

In choosing values for β_s, β_c, and β_d from the literature it is highly desirable to focus on microeconomic estimates of equation (5) that include all three right-hand variables. This is because s, c, and d are well-known to be highly positively correlated.[61] Hence, any OLS estimate of

[60] Needless to say if we had cross-country data on average height there would be no need to use the survival rate at all.
[61] See, e.g., the literature review in Vogl (2014).

one of the coefficients from a regression that omits one or two of the other two variables will be biased upward.[62]

A search of the literature yielded one and only one study reporting all three coefficients from equation (5). Vogl (2014) uses the two waves (2002 and 2005) of the nationally-representative Mexican Family Life Survey to estimate (5) on a subsample of men aged 25-65. In his study, w is measured as hourly earnings, s as years of schooling, c is in centimeters, and d is the respondent's score on a cognitive-skill test administered at the time of the survey.[63] The cognitive skill measure is scaled so its standard deviation in the Mexican population is 1.[64]

The coefficients reported by Vogl are as follows (see his Table 4, column 7). The return to schooling β_s is 0.072, which can be plugged directly in equation (3). The "return to height" β_c is 0.013. Hence, the coefficient associated with the adult survival rate in (3) is 0.013 x 19.2 = 0.25, where I have used Weil's mapping between height and the adult survival rate. Finally, the reported return to cognitive skills β_d is 0.011. Since the standard deviation of d is one by construction, and the standard deviation of the 2009 Science PISA test in Mexico is 77, the implied coefficient on the PISA test for the purposes of constructing h is 0.011/77=0.00014.[65]

The coefficients in my baseline calibration are considerably lower than those used in other development-accounting exercises. For schooling, applications usually gravitate towards the "modal" Mincerian coefficient of 0.10. For the adult survival rate, Weil (2007) uses 0.65, on the basis of considerably higher estimates of the returns to height than those reported by Vogl. For the return to cognitive skills, Hanushek and Woessmann (2012a) advocate 0.002, which is more than one order of magnitude larger than the value I derive from the Vogl's estimates.[66]

The fact that the parameters calibrated on Vogl's estimates are smaller than those commonly used is consistent with the discussion above. In particular, the alternative estimates are often based on regressions that omit one or two of the variables in (5), and are therefore upward biased. Another

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[62] An alternative would be to use IV estimates of the βs, but instruments for the variables on the right hand side of equation 5 are often somewhat controversial - especially for height and cognitive skills.

[63] The test is the short-form Raven's Progressive Matrices Test.

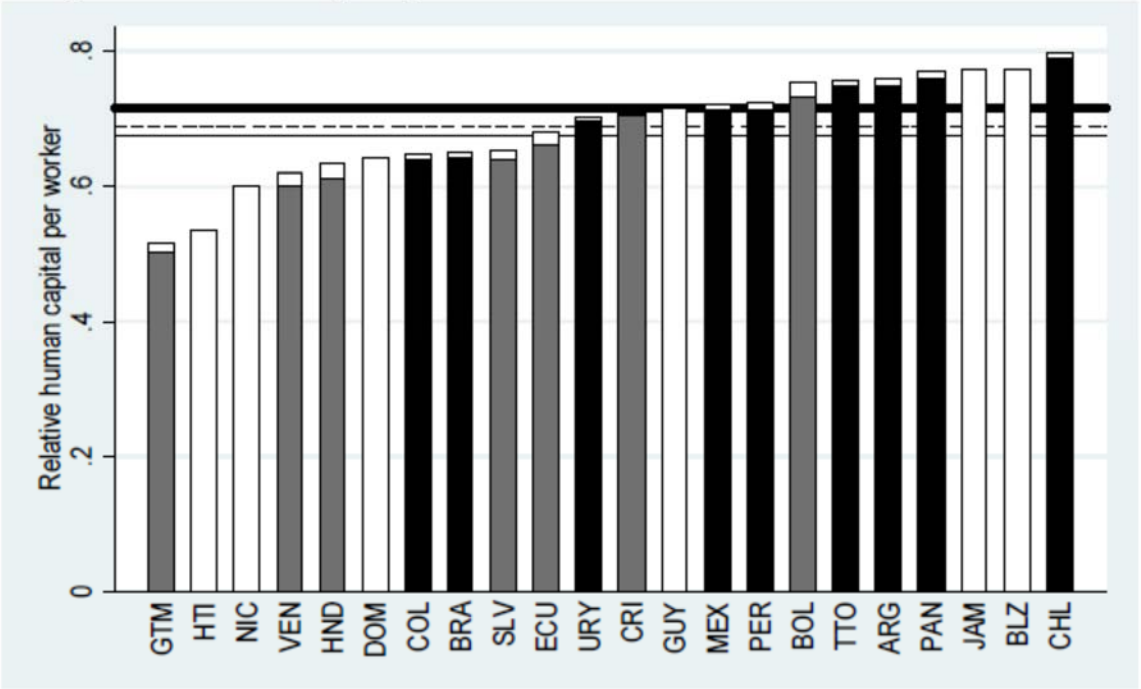
[64] Needless to say there are aspects of Vogl's treatment that imply the regressions he runs are not a perfect fit for the conceptual framework of the paper. It may have been preferable for our purposes to include both men and women. He also controls for ethnicity, age, and age squared, which do not feature in my framework. Finally, he notes that the Raven's core is a coarse measure of cognitive skills, giving raise to concerns with attenuation bias (more on this below).

[65] Hanushek and Woessman's splicing procedure implies that the same coefficient can be used for the regional tests used in the intermediate sample. In particular, the relevant standard error is the average of the standard deviations of Pisa science and math tests in Mexico, which is 80. Then we have 0.011/80 = 0.00014.

[66] This is based on Hanushek and Zhang (2009), who use the International Adult Literacy Survey (IALS) to estimate the return to cognitive skills in a set of 13 countries. The value of 0.002 is the one for the USA.

consideration is that there is considerable cross-country heterogeneity in the estimates, and that researchers often focus on estimates from the USA, which are often larger.[67, 68]

Figure 2.6. Human capital per worker relative to the US - baseline calibration



Source: Authors' calculations. *Notes*: Overall height: relative human capital per worker without cognitive-skill correction. Grey (Black) bars: relative human capital per worker with cognitive-skill correction based on regional (PISA) tests. Dashed line: average with no cognitive-skill correction. Light (heavy) solid line: average with regional-(PISA-) test correction.

On the other hand, Vogl's regressions are admittedly estimated via OLS, and there is a real concern with attenuation bias from measurement error. In order to gauge the sensitivity of my results to possibly excessively low values of the calibration parameters due to attenuation bias, I will also present results based on an " aggressive" calibration, which uses a Mincerian return of 0.10, Weil's 0.65 value for the mapping of the adult survival rate to human capital, and Hanushek and Woessman's 0.002 coefficient on the PISA test.[69]

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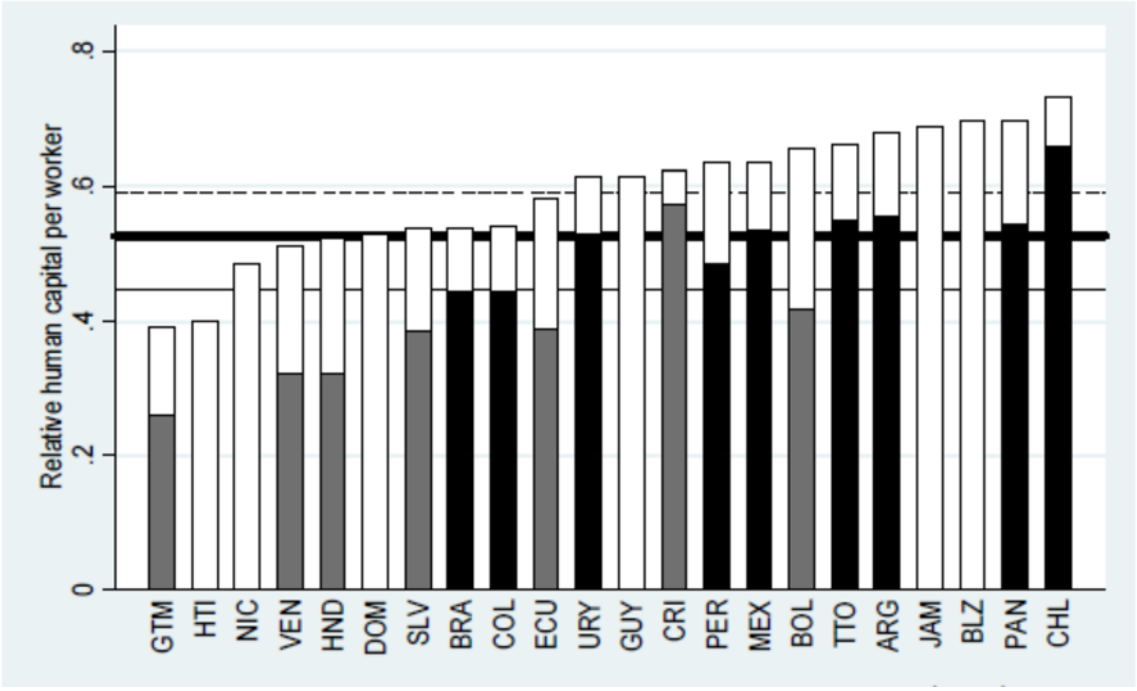
[67] For example, in Hanushek and Zhang (2009), the estimated market return to cognitive skills varies (from minimum to maximum) by a factor of 10! The estimate from the USA, which is used in Hanushek and Woessman (2012a) is the *maximum* of this distribution.

[68] This is actually an issue with the capital share α as well. However, the issue there is less severe as observed capital shares do not vary systematically with y, so it should be possible to ascribe the observed variation to measurement error. In other words the patterns of variation in α do not necessarily raise the issue of model misspecification.

[69] As described above the Hanushek and Zhang estimate for the US comes from a test d different from t. In order to go from their coefficient β_d to the coefficient of interest β_t we need to multiply the former by the ratio of the standard deviation of $d_{US,i}$ to the standard deviation of $t_{US,i}$. Since Hanushek and Zhang standardize the variable d, we just have to multiply by the inverse of the standard deviation of $t_{US,i}$. But in the test we are using this is just 0.98, so the correction would be immaterial use the same value both in the narrow and in the intermediate sample.

Figure 2.6 shows human-capital per worker estimates for Latin American countries relative to the US, h_i/h_{US}, under my baseline calibration. The full height of the bar shows the value of h_i/h_{US} when excluding cognitive skills, and is thus fully comparable across all countries in the figure. The solid bars are the values when including cognitive skills. Irrespective of sample and cognitive-skill correction the average Latin American worker is endowed with approximately 70 percent of the human capital of the average US worker.

Figure 2.7. Human capital per worker relative to the US - aggressive calibration



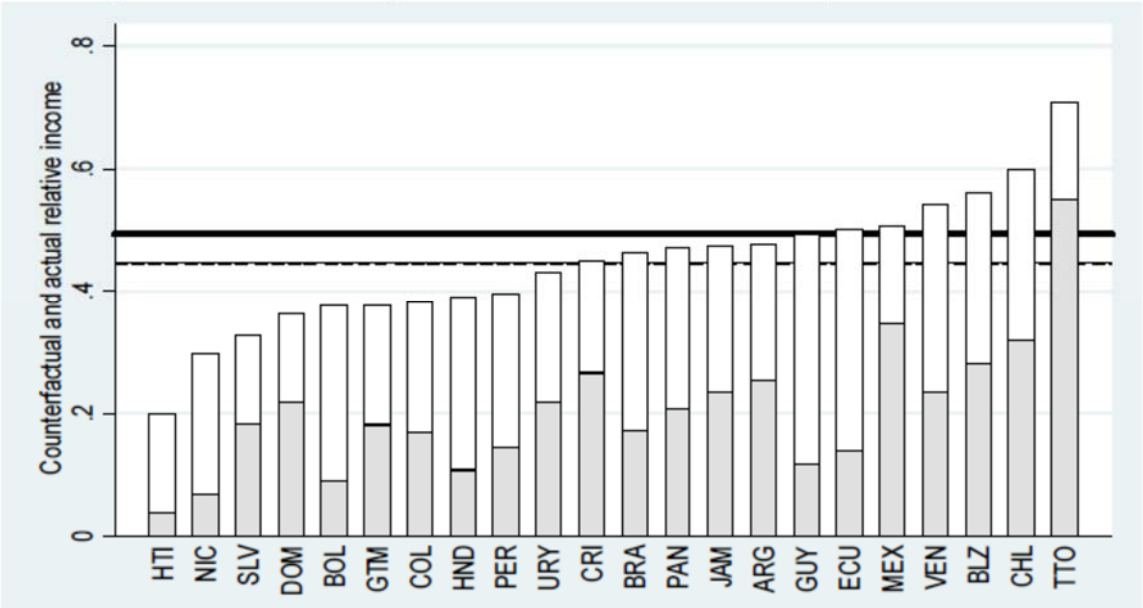
Source: Authors' calculations. *Notes*: Overall height: relative human capital per worker without cognitive-skill correction. Grey (Black) bars: relative human capital per worker with cognitive-skill correction based on regional (PISA) tests. Dashed line: average with no cognitive-skill correction. Light (heavy) solid line: average with regional-(PISA-)test correction.

Figure 2.7 is analogous to Figure 2.6 but shows the aggressive calibration instead**.** Not Surprisingly, using the aggressive calibration results in significantly lower relative human capital for Latin America, since the impact of differentials in schooling, health, and cognitive skills is magnified. Human capital gaps become particularly large when including the cognitive-skill corrections.

2. 5. Results

2.5.1. Baseline Calibration

Figure 2.8. Relative capital, baseline calibration, no cognitive-skill correction

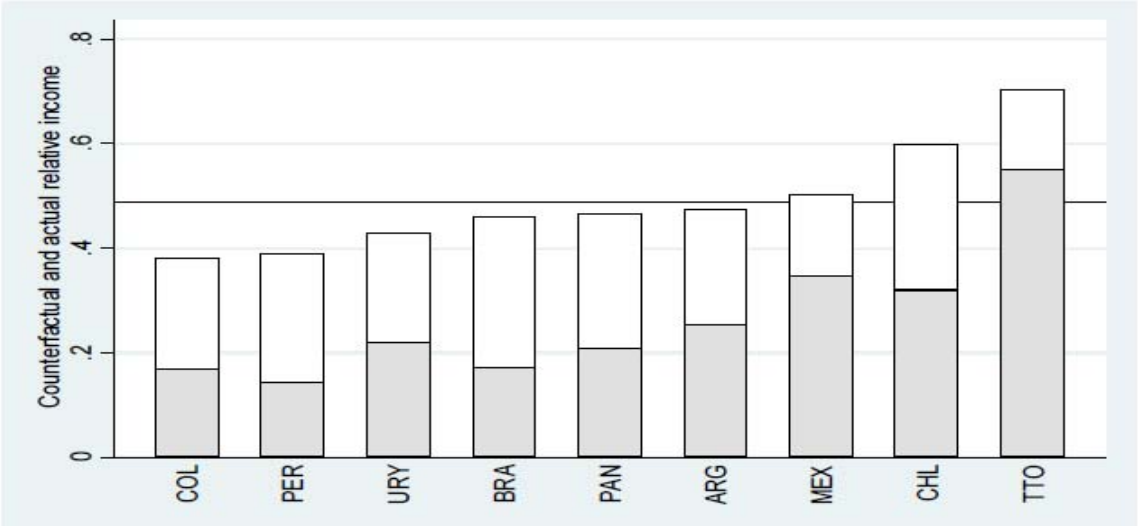


Source: Authors' calculations. *Notes*: Overall height: relative capital per worker. Grey bars: relative income per worker. Dashed line: broad sample mean. Light solid line: intermediate sample mean. Heavy solid line: narrow sample mean.

In the large sample we lack cognitive skill information for more than half of the countries, so we set $\beta_t = 0$. Figure 2.8 shows each country's counterfactual income relative to the US (relative capital) in 2005, $\tilde{y}_i/\tilde{y}_{US}$, as well as the relative incomes y_i/y_{US} already shown in Figure 2.1. In particular, for each country the overall height of the bar is relative capital, while the height of the shaded bar is relative income.

As is apparent, there is a lot of variation in relative capital, ranging from 20 percent to almost 70 percent. This reflects considerable heterogeneity in rates of physical and human-capital accumulation among Latin American countries, as seen above. Sample means are between 44 percent (broad and intermediate sample) and 49 percent (narrow sample). This means that observed distributions of physical and human capital are consistent with Latin American workers being between 44 and 49 percent as productive as USA ones. We can interpret this measure as a measure of the *capital gap* between Latin America and the US.

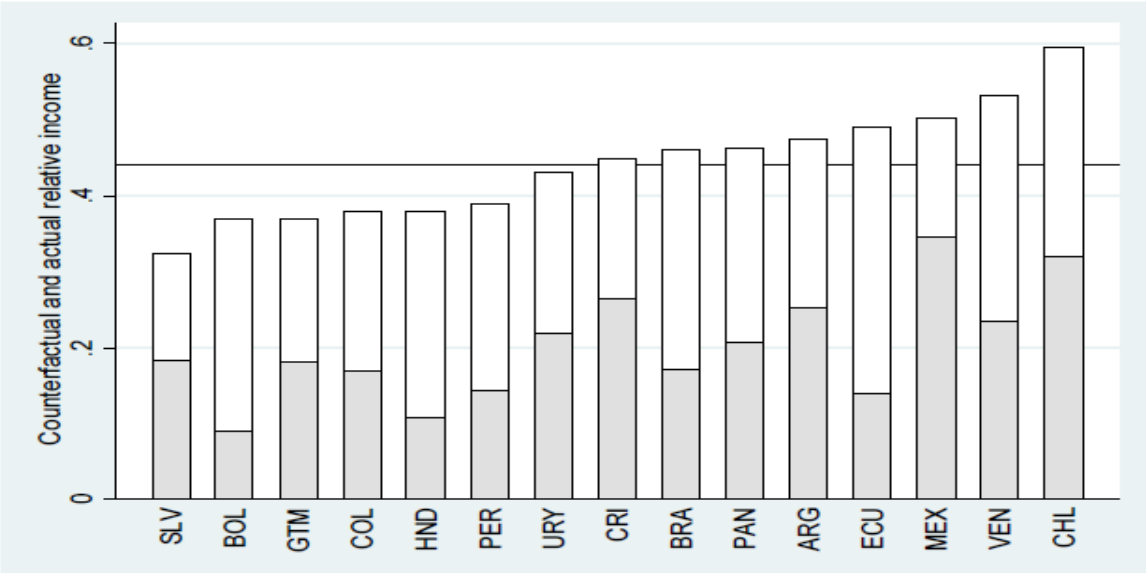
Figure 2.9. Relative capital, baseline calibration, PISA cognitve skills



Source: Authors' calculations. *Notes*: Overall height: relative capital per worker. Grey bars: relative income per worker. Solid line: mean.

In Figure 2.9 we extend our calculations to include information on cognitive skills based on worldwide PISA test scores. The sample size correspondingly drops to 9 countries. The effect of including cognitive skills under my baseline calibration is virtually nil: the mean remains unchanged at 0.49. This result is expected given the very small calibrated " loading" on cognitive skills implied by Vogl's estimates. Very similar patterns emerge when using the regional scores/intermediate sample, as seen in Figure 2.10.

Figure 2.10. Relative capital, baseline calibration, "regional-test" cognitive skills

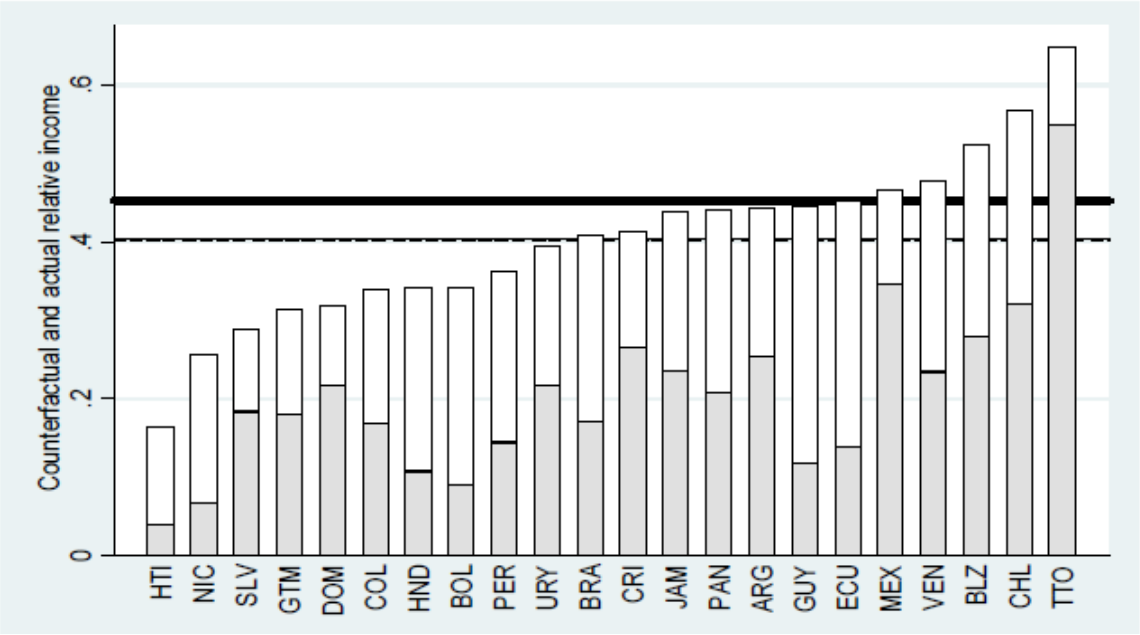


Source: Authors' calculations. *Notes* Overall height: relative capital per worker. Grey bars: relative income per worker. Solid line: mean.

2.5.2. "Aggressive" Calibration

My baseline calibration uses coefficients for mapping years of schooling, health, and cognitive skills into human capital that, taken individually, are lower than those presented in other contributions. In this section I explore the robustness to my results to more commonly-used values. Hence, I set $\beta_s = 0.10$, $\beta_r = 0.65$, and $\beta_t = 0.002$.

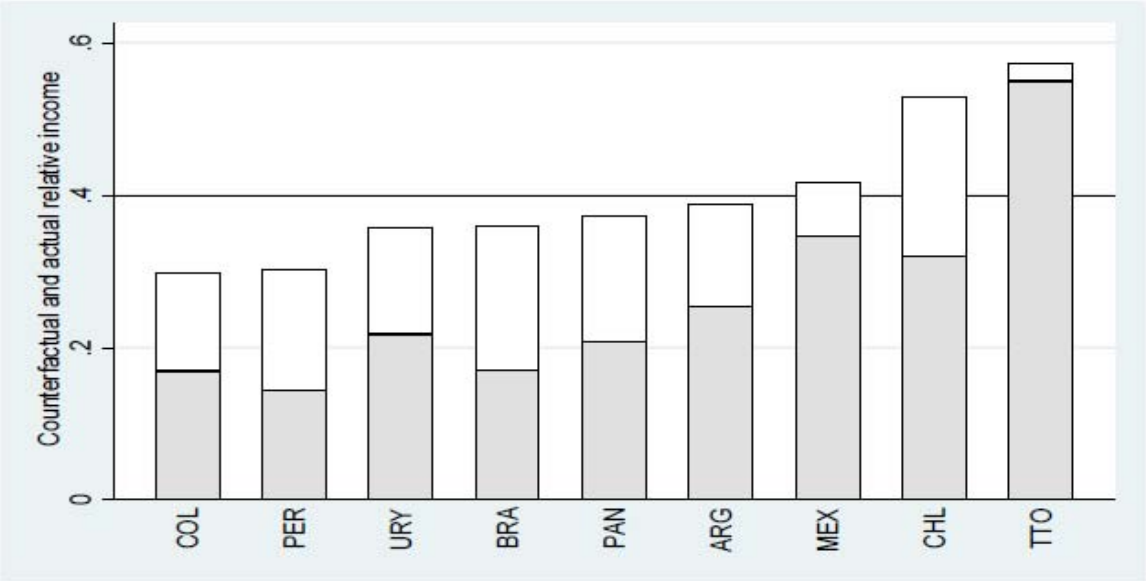
Figure 2.11. Relative capital, aggressive calibration, no cognitive-skill correction



Source: Authors' calculations. *Notes*: Overall height: relative capital per worker. Grey bars: relative income per worker. Dashed line: broad sample mean. Light solid line: intermediate sample mean. Heavy solid line: narrow sample mean.

Results from the large sample using this aggressive calibration are shown in Figure 2.11. Given the larger coefficients, counterfactual incomes are necessarily smaller than under the baseline calibration. Yet quantitatively the difference is not very large. Average relative capital drops to 40 percent, so still roughly double relative income.

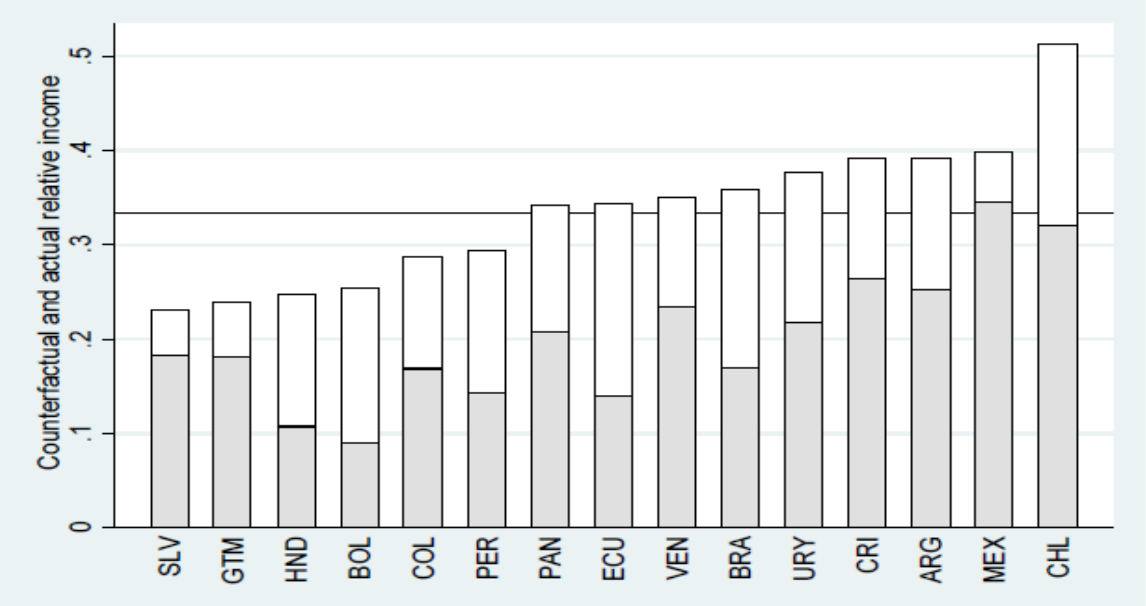
Figure 2.12. Relative capital, aggressive calibration, PISA cognitive skills



Source: Authors' calculations. *Notes*: Overall height: relative capital per worker. Grey bars: relative income per worker. Solid line: mean.

Figure 2.12 shows the results from the aggressive calibration using the PISA test scores. Including cognitive skills in the calculation of relative capital has a much bigger impact than under the baseline, because the coefficient on cognitive skills is an order of magnitude larger. The average counterfactual relative income falls to 40 percent, compared with 49 percent in the baseline calibration (within the same narrow sample). This is a large gain in explanatory power of observables. For many countries, the gap between relative income and relative capital shrinks considerably.

Figure 2.13. Relative capital, aggressive calibration, "regional-test" cognitive skills



Source: Authors' calculations. *Notes*: Overall height: relative capital per worker. Grey bars: relative income per worker. Solid line: mean.

Finally, Figure 2.13 reports the results from the aggressive calibration when using the regional test scores. Recall that these tests tend to show even larger cognitive gaps with the US. Correspondingly, using these tests in combination with the aggressive calibration leads to an even better alignment between relative capital and relative income.

2. 6. Implications for Efficiency Gaps

We have seen that, depending on cognitive skill correction, counterfactual income ratios (relative capital) in Latin America tend to be much larger than actual income ratios. This discrepancy implies that Latin America suffers from an *efficiency gap* as much as it suffers from a capital gap.

We can quantify efficiency gaps by noting, from (1) and (2), that

$$\frac{A_i}{A_{US}} = \frac{y_i/y_{US}}{\tilde{y}_i/\tilde{y}_{US}}.$$

Hence, Latin American efficiency gaps can be directly gleaned from Figures (2.8)-(2.13) by simply dividing the height of the shaded bars by the overall height of the bars.

In Table 2.1, I report the sample averages of the implied efficiency gaps, for the various cognitive skill correction - calibration combinations. For completeness I also report the corresponding averages for relative income and relative capital, as well as labor-force weighted means.

Table 2.1 Summary of Results

		Calibration			
		Baseline		Aggressive	
Sample/Cognitive Skill Measure	Relative GDP	Relative Capital	Relative Efficiency	Relative Capital	Relative Efficiency
Broad/None	**0.21**	**0.44**	**0.44**	**0.40**	**0.49**
	0.21	0.46	0.45	0.41	0.50
Narrow/PISA	**0.26**	**0.49**	**0.52**	**0.40**	**0.64**
	0.22	0.46	0.47	0.37	0.59
Intermediate/"Regional"	**0.20**	**0.44**	**0.45**	**0.33**	**0.60**
	0.22	0.46	0.46	0.36	0.60

Source: Authors' calculations. *Notes*: Bold entries are unweighted sample means. Plain entries are labor-force weighted sample means

Using the baseline calibration, average relative capital and average relative efficiency are almost identical, irrespective of sample/cognitive skill correction/weighting. One way to put this is that capital gaps and efficiency gaps contribute equally to Latin American income gaps. When using the aggressive calibration, the relative importance of capital gaps increases, particularly when adding the cognitive-skill corrections. Still, even under the most aggressive scenario average Latin American relative efficiency is only 60 percent of US efficiency.[70]

In order to fully appreciate the importance of these efficiency gaps it is crucial to note that, under almost any imaginable set of circumstances, physical (specifically, reproducible) and human capital accumulation respond to a country's level of efficiency. The higher A the higher the marginal productivity of capital, leading to enhanced incentives to invest in equipment and structure, schooling, etc. While quantifying this effect is difficult, most theoretical frameworks would lead one to expect it to be large. Hence, it is legitimate to conjecture that a significant fraction of the capital gap may be due to the efficiency gap.[71]

2. 7. Implications and Conclusions

There is a large gap in income per worker between Latin America and the USA: Latin American workers are only about one fifth as productive as workers from the United States. A development-accounting calculation reveals that both capital gaps and efficiency gaps contribute to this overall productivity gap. In particular, a Cobb-Douglas aggregate of observable physical and human capital per worker is roughly in the order of 40 percent on average of the corresponding US level (capital gap) – implying that the efficiency with which inputs are used in Latin America is in the order of 50 percent of US levels (efficiency gap). Reducing this efficiency gap would reduce the

[70] In the narrow sample it is probably best to focus on the labor-force weighted results, as the unweighted ones give disproportionate weight to Trinidad and Tobago.

[71] In principle, one might also argue for a reverse direction of causation, with larger physical and human-capital stocks leading to higher efficiency. In particular, this would be true if the model was misspecified, and there were large externalities. But as already mentioned the empirical literature has not to date uncovered significant evidence of externalities in physical and human capital.

overall productivity gap both directly, by allowing Latin America to reap greater benefits from its physical and human capital, and indirectly, since much of the capital gap is likely due to the efficiency gap itself: closing the efficiency gap would stimulate investment at rates potentially capable of closing the capital gap as well.

These conclusions are contingent on the quality of the underlying macroeconomic data. There is growing concern about the quality and reliability of the PPP national-account figures in the Penn World Tables and similar data sets [e.g. Johnson et al. (2013)]. Similar concerns apply, no doubt, to our proxies for human capital as well (as already discussed particularly in the context of cognitive skills). It is true that such concerns are most often voiced in the context of implied comparisons of changes, especially over short time spans: cross-country comparisons of *levels* reveal such gigantic differences (as seen above) that they seem unlikely to be entirely dominated by noise. Still, exclusive reliance on these macro data is highly inadvisable.

Fortunately, it is also increasingly unnecessary. The increasing availability of *firm level* data sets, particularly when matched with employee-level information (e.g. about schooling), provides an opportunity to supplement the macro picture with microeconomic productivity estimates comparable across countries.

The benefit of producing such micro productivity estimates is by no means limited to permitting to check the robustness of conclusions concerning average capital and efficiency gaps - though this benefit alone is sufficient to make such exercises worthwhile. An additional benefit is to uncover information on the within country *distribution* of physical capital, human capital, and efficiency. A relatively concentrated distribution would suggest that efficiency gaps are mostly due to aggregate, macroeconomic factors that affect all firms fairly equally (e.g. impediment to technology diffusion from other countries). A very dispersed distribution, with some firms close to the world technology frontier, would be more consistent with allocative frictions that prevent capital and labor to flow to the more efficient/talented managers.

More generally, firm-level data is likely to prove essential in the quest for the determinants of the large efficiency gaps revealed by the development-accounting calculation. After all, (in-)efficiency is – by definition – a firm-level phenomenon. Most of the most plausible possible explanations for the efficiency gap are microeconomic in nature – whether it is about firms unable to adapt technologies developed in more technologically-advanced countries, failures in the market for managers and/or capital, frictions in the matching process for workers, etc. It seems implausible that evidence for or against these mechanisms can be found in the macro data. Yet understanding the sources of the Latin American efficiency gap is unquestionably the most urgent task for those who want to design policies aimed at closing the Latin American income gap.

2. 8. Appendix: Alternative capital share

Expanding on previous work by Gollin (2002), Bernanke and Gurkaynak (2001) present estimates of the labor share in income for a cross-section of countries. Using the method which yields the largest number of observations, they produce estimates for 13 countries in Latin America and the Caribbean. In this group of 13, the average labor share is 0.62, implying a capital share of 0.38 - larger than the standard development-accounting benchmark. An alternative method, which Bernanke and Gurkaynak consider more accurate, yields estimates for 9 LATAC countries, averaging, 0.61.

These estimates prompt me to explore the robustness of the results to an alternative choice of α, namely 0.4. Before doing so, it is important to note that the US estimate of the capital share implied by the figures in Bernanke and Gurkaynak is actually 0.29. Hence, while using 0.4 may more accurately reflect the relative contributions of physical and human capital in Latin America, it greatly distorts their relative contributions in the benchmark country. Unfortunately, as discussed in footnote 4, I don't know of a method of doing development accounting that allows country-specific capital shares, and preserves the unit-invariance of the results to the measurement of capital. Perhaps 0.33 is a reasonable compromise, after all.

Another reason to be weary of the 0.4 figure is that deviations from perfect competition, both in labor and product markets, are likely to weigh more heavily in Latin American countries than in the USA. Both monopsonistic labor markets and monopolistic product markets are likely to result in a labor share in income that is less than the elasticity of output to labor, i.e. our technological parameter $1-\alpha$. Of course some of the difference with the USA may be due to true underlying technological differences, or to differences in the sectoral composition of the economy. But the presence of deviations from perfect competition should imply that 0.4 is too high an estimate of α even for Latin American countries.

With these caveats, Table 2.2 presents the results for relative capital and relative efficiency when using $\alpha = 0.4$ in the calibration. Compared to the case where $\alpha = 0.33$, capital gaps increase (i.e. relative capital falls) and efficiency gaps correspondingly shrink (the relative efficiency of Latin America goes up). The reason for this is that the gap in physical capital between Latin America and the US is larger than the gap in human capital. Hence, when more weight is given to physical capital, the overall capital stock of Latin America drops, decreasing the role for efficiency gaps in accounting for income differences. Even so, relative efficiency only increases by 4 or 5 percentage points, depending on calibration and sample. The big picture of large efficiency gaps remains unchanged.

Table A2.2 Summary of Results with α = 0.4

		Calibration			
		Baseline		Aggressive	
Sample/Cognitive Skill Measure	Relative GDP	Relative Capital	Relative Efficiency	Relative Capital	Relative Efficiency
Broad/None	**0.21**	**0.41**	**0.49**	**0.37**	**0.53**
	0.21	0.42	0.49	0.38	0.54
Narrow/PISA	**0.26**	**0.45**	**0.56**	**0.38**	**0.68**
	0.22	0.43	0.51	0.35	0.63
Intermediate/"Regional"	**0.20**	**0.40**	**0.50**	**0.31**	**0.64**
	0.22	0.42	0.50	0.34	0.63

Source: Authors' calculations. Note: Bold entries are unweighted sample means. Plain entries are labor-force weighted sample means.

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3. Reconciling Micro- and Macro-Based Estimates of Technology Adoption Lags in a Model of Endogenous Technology Adoption

Maya Eden and Ha Nguyen

3. 1. Introduction

There is a large and persistent income gap between countries in Latin America and the Caribbean (LAC) and the United States (US). In the year 2000, average income in LAC was only 23 percent of the average income in the US. Total Factor Productivity (TFP) is among the leading factors of the observed income gap. TFP in LAC, measured as the Solow residual after carefully accounting for inputs, is about half of that of the US (Caselli, 2013).

LAC's technology backwardness is being debated as one of the key factors that explain this large TFP gap. To explain to what extent technology backwardness matters, it is important to precisely estimate the technology adoption lags between LAC and the U.S.—the technology frontier. A slow adoption lag would indicate that technology backwardness is indeed the problem. On the other hand, a faster adoption lag would point to other factors, such as institutions and misallocation of resources (along the line of Hsieh and Klenow, 2009). The two sets of issues have fundamentally different policy implications. If technology adoption is key, the policy focus should be on removing barriers to technology adoption (such as increasing international integration or improving human capital). If institutions are more important, policies should aim to improve domestic institutions and correcting the misallocation of resources.

The literature currently offers conflicting views about the speed of technology adoption in Latin America. Micro-based evidence drawn from Comin and Hobijn (2010) suggests that adoption lags at the technology level between the U.S. and Latin America are long – 20 years on average. An adoption lag at the technology level is defined as the length of time between the invention and eventual adoption of the technology. On the other hand, macro-based evidence from the work of Akcigit, Alp, Eden and Nguyen (2014) (henceforth AAEN) suggests a much shorter lag. Based on the TFP time series data and the assumption that any shock to TFP growth in the US that affects the adopting countries (LAC) with a lag is a technology shock, they find that the lag is about only 8 years. Which number is right affects the debate about the role of technology adoption in LAC's convergence.

This paper argues that the two findings might be consistent, and for the purpose of explaining TFP gap, the macro-based number is more relevant. We reconcile the two findings with two insights. First, technologies tend to be adopted first in more productive firms. Since the first adopting firms tend to be more productive, the productivity gains from the first technology adopters are relatively larger than the productivity gains from later adopters. The macro-level adoption lag accounts for this, by weighting technology adoptions by their respective productivity gains. The micro-level adoption lag, in contrast, assigns equal weights to all adopters - thus, it is likely to be relatively longer than the macro-level lag. Second, more effective technologies are likely to be adopted faster. Technologies that improve productivity by more are likely to be adopted faster, as the return to adoption is higher. This implies shorter lags associated with technologies that are more productivity enhancing. The macro-level adoption lag focuses on aggregate productivity gains

from technology adoption, which is likely driven disproportionately by more productive technologies. In contrast, the micro-level adoption lag weighs technologies equally, and is thus likely to be longer. We discuss this disparity in a model with endogenous technology adoption, in which (a) the most productivity-enhancing technologies are adopted first, and (b) production units who have the largest productivity gains from adopting new technologies are the first to adopt. We illustrate that reasonable parameters can generate the observed differences between the micro- and macro-based estimates of technology adoption lags.

The model suggests that the macro-based estimate by AAEN can be consistent with the micro-based estimate by Comin and Hobijn (2010). However, when it comes to explaining the TFP gap, the macro estimate is more appropriate because it works directly on the TFP. AAEN's result therefore is relevant to argue that technology adoption lags at the TFP level are short—about 8 years. AAEN's result implies that other factors such as institutions remain the sticking points for lack of convergence between LAC and the U.S.'s income.

The paper is organized as follows: section 3.2 revisits in details the micro and macro-based evidence. Section 3.3 lays out a model to reconcile the two estimates. Section 3.4 is a numerical illustration of the model. Section 3.5 concludes.

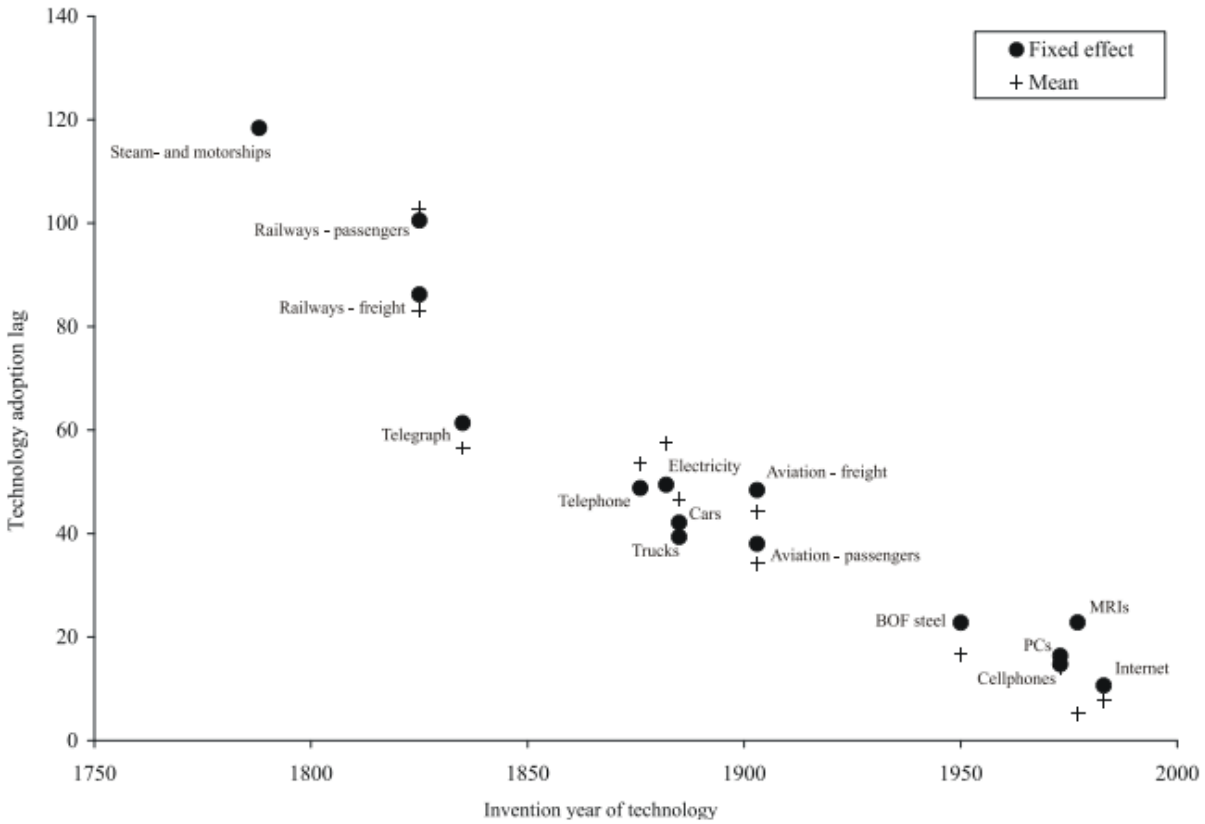
3. 2. Micro- and macro-based technology adoption lags in Latin America

In this section, we discuss the details of the micro and macro-based evidence for the technology adoption lags in Latin America. In particular, we analyze the CHAT dataset constructed by Comin and Hobjin (2009) for the micro-based evidence, and go into details the results obtained by AAEN for the macro-based evidence.

3. 2. 1. Micro-based Evidence from the CHAT dataset

Comin and Hobijn (2010) estimate the diffusion of 15 technologies in 166 countries over the last two centuries to show that in general, countries take a long time to adopt new technologies: on average, countries have adopted technologies 45 years after their invention. However there is a substantial variation across technologies. Recent technologies are adopted faster than old ones. Figure 3.1 is borrowed from Comin and Hobijn (2010) to illustrate this fact.

Figure 3.1. Technology adoption lags decrease for later invention



Source: Comin and Hobijn (2010).

We replicate Comin and Hobijn (2010)'s adoption lags for the U.S. and Latin America. Table 3.1 shows the average adoption lags -- the length of time between the invention and the eventual adoption of the technologies-- for the U.S., Latin America. On average, the U.S. takes about 19.8 years to fully adopt a new technology, while Latin America takes about 40 years. This means that Latin America is about 21 years behind the U.S. in adopting new technologies.

For older technologies, Latin America lags quite far behind the U.S. in adoption. For example, for Cars and Electricity, Latin America is 23 and 31 years behind the U.S. respectively. However, for more recent technologies, such as personal computers (PCs) or internet, the adoption lag gaps are much smaller. Latin America is 7.8 and 4.3 years behind the U.S. for the two technologies, respectively.

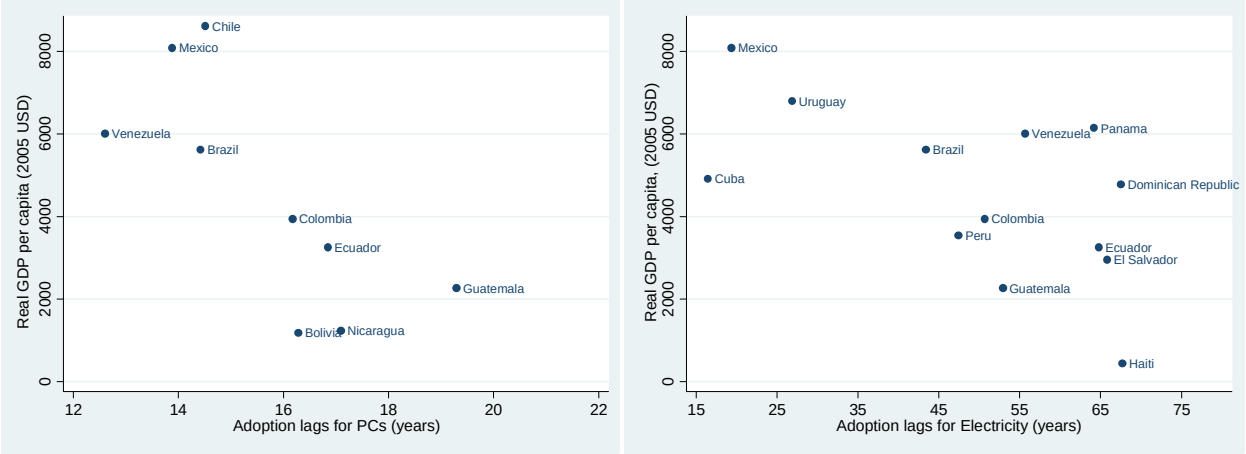
Table 3.1 Adoption lags (years) for the U.S. and Latin America

Technology name	U.S.	Latin America	All countries
Aviation freight	24.39	32.62	43.48
Aviation passengers	26.16	28.94	33.89
Cars	14.23	37.67	43.68
Cellphones	9.80	16.78	14.61
Electricity	19.40	51.67	56.36
Internet	4.40	8.68	7.79
MRI	2.92	.	5.30
PCs	7.66	15.53	13.96
Ships	29.71	111.07	120.45
Telegraph	31.85	53.27	45.61
Telephone	-0.31	40.35	51.45
Trucks	18.34	29.81	39.13
Blast oxygen steel	8.83	17.09	16.31
Railway freight	43.93	85.23	79.59
Railway passengers	55.81	98.36	97.32
TOTAL	19.81	42.08	45.48

Source: Comin and Hobijn (2010) and Authors' calculations.

How do adoption lags vary between Latin American countries? Table A3.2 in the appendix shows the adoption lags for individual Latin American countries and for individual technologies. Within each technology, the adoption lags do vary across countries. It is expected that there is a negative association between adoption lags and countries' levels of development. The association can go both ways. Richer countries might have less obstacles and higher incentives that encourage technology adoptions, hence shorter adoption lags for them. On the other hand, faster technology adoptions enable the countries to grow faster and reach a higher level of development. We pick the most two arguably influential technologies-- electricity and personal computers-- to check if there are significant relationships between the level of development and adoption lags. Indeed, this is the case (see Figure 3.2).

Figure 3.2. GDP per capita and adoption lags for PCs and Electricity



Source: Authors' calculations.

3. 2. 2. Macro-based Evidence from AAEN

AAEN develop a methodology to estimate the adoption lags between a technology frontier and subsequent technology adopters, based on aggregate macro data such as TFP and output. An advantage of this approach is that it can be agnostic about which technologies are important. Unlike the approach based on micro data that has to necessarily assume a mapping between the prevalence of specific technologies and aggregate productivity, the macro approach does not to make a stance about which technology should be the focus. They find that Latin America's technology adoption is about 8 years behind the U.S.

The identifying assumption is that any shock to productivity growth in the frontier country (the US) that affects the adopting countries (LAC) with a lag is a technology shock. The technological component is then used to study the effects of a technology shock on TFP growth in LAC, both in terms of timing and in terms of magnitude. In other words, while non-technology shocks (e.g., demand shocks) may be contemporaneously correlated across countries, technology shocks are likely to have a lagged effect on TFP growth in the adopting countries.

In particular, the framework used in AAEN (2014) is as follows. Denote $A_{i,t}$ as a country's TFP at time t. $A_{i,t}$ consists of a technology component $X_{i,t}$ and a non-technology component $Z_{i.t}$:

$$A_{i,t} = X_{i,t} Z_{i,t}$$

The non-technology component, $Z_{i.t}$ is a catch-all phrase that includes all aspects of the economy that affect measured TFP, excluding technology. For example, $Z_{i,t}$ includes misallocation, competition, as well as policies that may distort the efficient use of factors. In log forms, TFP is written as follows:

$$a_{i,t} = x_{i,t} + z_{i,t}$$

There is one country that is identified as the frontier, and the rest of the countries are identified as adopters. We will denote the frontier economy *us* and the adopting countries *lac*. Technology growth in the frontier represents the growth of the frontier technology. In adopting countries, a technological innovation may affect TFP growth with some lag, reflecting the possibility of learning and adoption frictions. Thus, current technology growth in adopting countries is a function of current and lagged values of the technological progress in the frontier (e.g., growth in LAC today may reflect technological innovation in the US several years ago, as the technology is adopted with some delay). They assume that this function takes the following linear form:

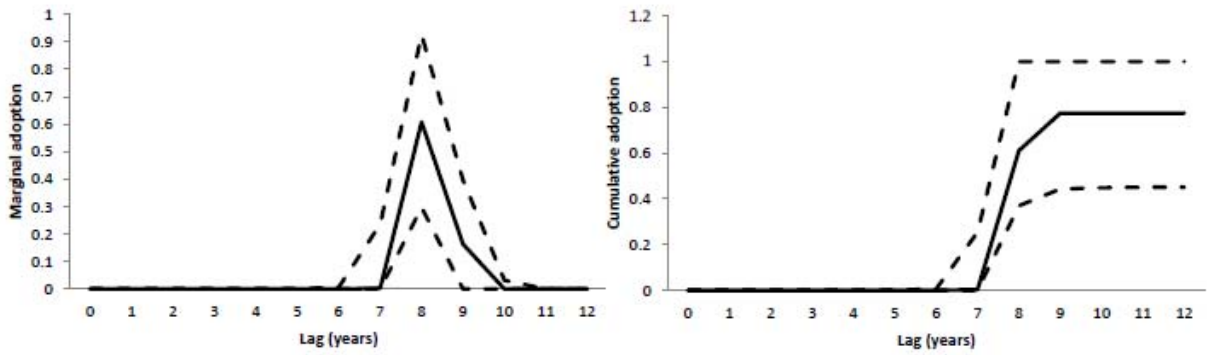
$$x_{lac,t} = \sum_{j=0}^{\infty} \lambda_j x_{us,t-j}$$

Note that the sum $\sum_{j=0}^{\infty} \lambda_j$ has the interpretation of the long-run adoption rate: an innovation in the technological frontier today will have a contemporaneous effect of λ_0, an effect of λ_1 in the

next period, and so on. For further details about the estimation, please refer to AAEN (2014). Here we will show the results only.

The left panel of Figure 3.3 represents the estimated marginal adoption rates (λj), and the right panel represents the estimated cumulative adoption rates ($\sum_{j=0}^{\infty} \lambda_j$). The estimation suggests that the bulk of technology adoption happens at an 8 year lag. The point estimate suggests that technological innovations in the frontier have a somewhat smaller effect on productivity in LAC: the point estimate of the infinite sum $\sum_{j=0}^{\infty} \lambda_j$ is about 0.8, suggesting that a 1 percent improvement in technology in the US increases long-run productivity in LAC by only 0.8 percent. However, it is important to note that the 90 percent confidence interval cannot reject full adoption in the long run (and in fact, after 8 years). In this case, technological innovations in the US have the same effect on TFP in LAC, with an 8 year lag.

Figure 3.3. Estimated marginal and cumulative adoption rates – LAC Aggregate

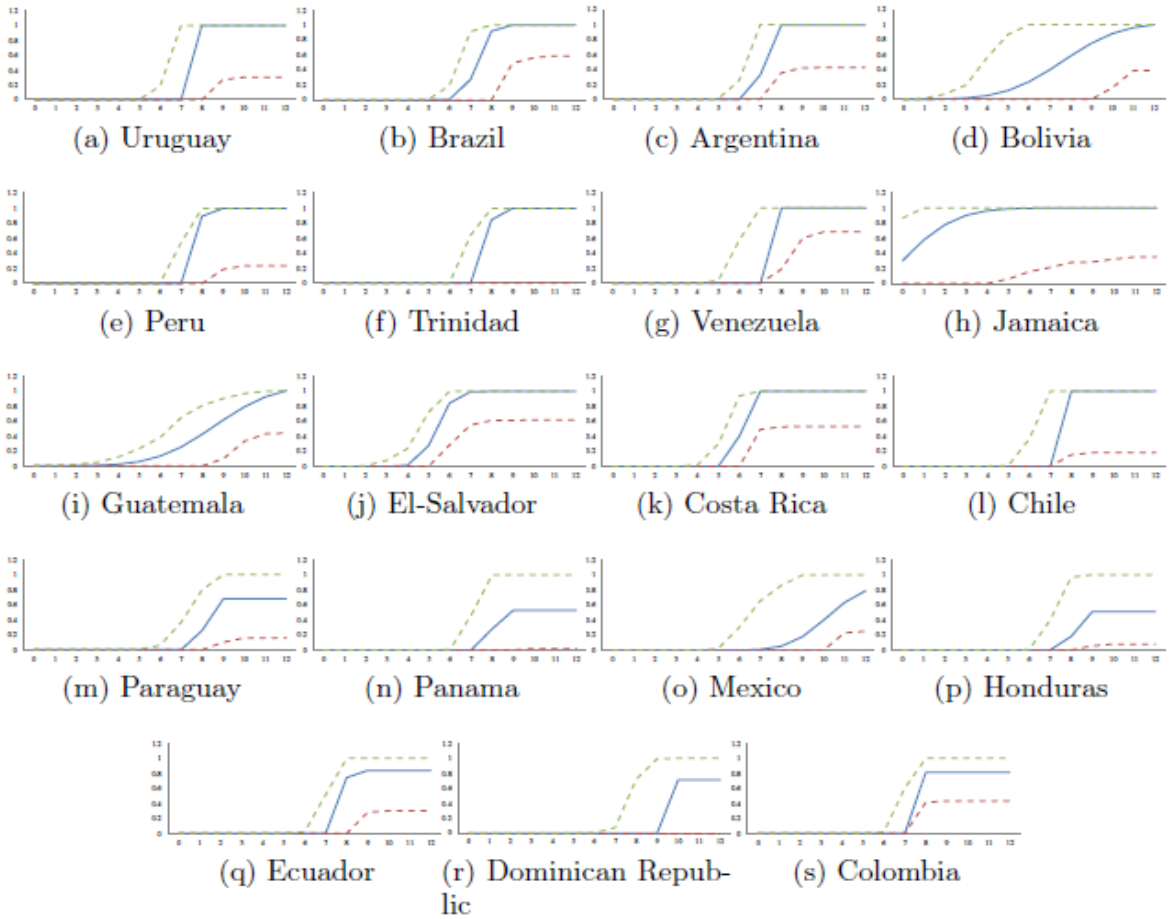


(a) Marginal adoption rates (b) Cumulative adoption

Source: Authors' calculations. *Notes*: Dotted lines represent the bounds of the 90 percent confidence intervals

They also conduct the analysis by (a) including each country in LAC as a separate adopting country, and (b) estimating the marginal adoption rates by industry. These extensions allow for the sequence of marginal adoption rates to differ across countries and across industries. However, while there is some variation in the results, they broadly confirm the findings on the aggregate level.

Figure 3.4. Estimated cumulative adoption rates – Individual LAC Countries



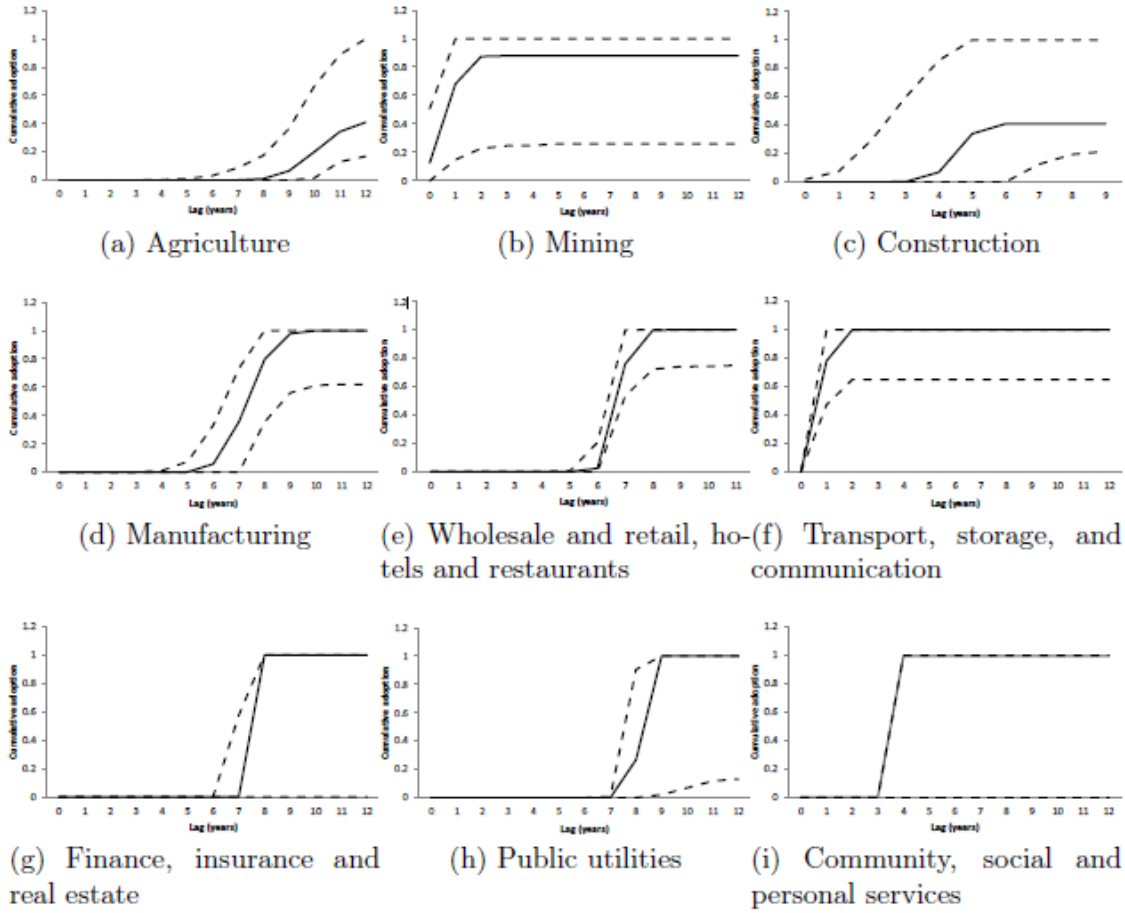
Source: Authors' calculations. *Notes*: Dotted lines represent the bounds of the 90 percent confidence intervals

The results are presented in Figure 3.4. The results are highly consistent with those obtained with the LAC aggregate. For most countries in LAC (12 out of 19), the point estimates suggest full adoption of technologies after 8 years at most. While there is some variations across countries, the variation is not statistically significant in the sense that full adoption after 8 years is within the 90 percent confidence interval for all countries in our sample.

At the industry level, they proxy measured productivity growth with growth in value added per worker by industry, using the value added in constant prices from the Groningen Growth and Development Centre 10-sector database for LAC countries and the US. Note that for LAC countries, only 9 sectors are available. Data is available from 1950- 2005. They estimate for each industry separately, using a LAC weighted average in which weights are given by real value added in each industry. The results are presented in Figure 3.5. Broadly, the results at the aggregate level are consistent with the industry-level results, in the sense that full adoption within 12 years (as well as 0.8 long-run adoption) fall within the confidence intervals of each of the industry-level results.

However, there is some interesting variation across industries, both in the point estimates and in the confidence intervals. For example, manufacturing - a sector which is widely viewed as a "fast" adopter - delivers point estimates suggesting full adoption after 8 years, with a relatively tight confidence interval. Mining, a sector with significant foreign presence, seems to exhibit faster adoption, with the bulk of adoption occurring at a 1 year lag (however, it should be noted that the magnitude of long-run adoption is rather imprecisely estimated, though statistically significant). On the other hand, agriculture sees longer adoption lags.

Figure 3.5. Estimated cumulative adoption rates – Individual Industries



Source: Authors' calculations.

The differences between the micro evidence and macro evidence are quite clear. The micro evidence suggests an average of 21 years lags between LAC and the U.S. in terms of technology adoption, while the macro evidence is quite consistent at 8 years. There is a strong variation across LAC countries from the micro evidence, but it is not as clear from the macro evidence. On the other hand, both macro evidence and micro evidence point to some adoption heterogeneities across sectors and technologies.

3. 3. Model

In this section we present a model to reconcile the two findings. We consider a simplified model in which capital is the only input of production. The economy is endowed with a unit measure of production units, each with a single unit of capital; for simplicity, we abstract away from capital accumulation.

Production units are heterogeneous with respect to the extent that they can benefit from technology. Denoting the stock of technology in production unit x by Tx, the output of production unit x is given by:

$$y_x(T_x, k_x) = x \min\{T_x, k_x\}$$

Note that, by assumption, $kx=1$ for all x. Technology and capital are strongly complementary; thus, the amount of technology demanded by the firm is bounded by the amount of its capital. In this formulation, production units with higher levels of x are those who benefit more from technology.

Technology adoption is costly. For simplicity, it will be useful to think of this cost as a "user fee" (that may include, for example, royalties for the inventor of the technology). The cost of adopting a unit of technology is p. The firm's profits are therefore given by:

$$\pi_x = y_x(T_x, k_x) - pT_x$$

The production unit's optimization problem is:

$$\max_{T_x} \pi_x$$

The solution to the production unit's problem is trivial: if $p>x$, it is optimal to choose $Tx=0$. If $p< x$, it is optimal to choose $Tx=1$.

The distribution of production units is given by a pdf $f(x)$, with support in $[0,\infty)$ (in other words, it is assumed that all production units weakly benefit from technology).

Note that the distribution $f(x)$ is a joint characteristic of production units and the technology. It captures the extent to which a specific technology improves productivity in a specific firm. Thus, different technologies will typically be associated with different distributions of x.

Dynamics. Time evolves continuously and is indexed t. There are two countries: a "frontier" country (f) and an adopting country (a). At $t=0$, there is are two technological innovations, indexed 1 and 2, associated with distributions f_1 and f_2 respectively. It will be useful to assume that technology 1 is more effective than technology 2, in the sense that the distribution f_1 stochastically dominates the distribution f_2. In other words, the productivity gains from adopting technology 1 are greater, on average, than the productivity gains from adopting technology 2. We will assume for simplicity that the adoption costs p are the same across technologies.

In the frontier country, it is costless to adopt technologies, and $p_{f,t}=0$ for all t; thus all production units adopt the technology instantaneously. In the adopting country, the price of adoption, p, falls over time according to:

$$p_{a,t} = p_t = \exp(-\lambda t)$$

For some $\lambda>0$. In the frontier country, the price of adoption is always 0; thus all production units in the frontier country immediately adopt the technology. To abstract away from strategic delays in adoption (due to the anticipation of a falling price), it is convenient to assume that the adoption cost p must be paid in each period that the technology is used.

Equilibrium. At any time t, all production units with $x> p_t$ purchase the technology. Aggregate output is therefore given by:

$$Y_t = \int_0^\infty f_1(x)y_x(T_x,k_x)dx + \int_0^\infty f_2(x)y_x(T_x,k_x) = \int_{p_t}^\infty (f_1(x)+f_2(x))xdx$$

Micro and macro adoption lags. Of course, in this framework, technologies are never fully adopted in finite time, since there are always some production units (with x close to 0) for which adoption is too costly. It is therefore useful to define adoption lags with respect to almost-full adoption rather than full adoption. Specifically, we will consider some small $\varepsilon>0$ and define adoption lags as follows. The technology-specific micro-level adoption lag, l^{micro}, is defined as the time elapsed until the difference between the technology stock in the adopting country and the technology stock in the frontier country (which is always 1) is less than ε. The technology-specific micro adoption lag is then:

$$x_\epsilon = p_{l^{micro}} = \exp(-\lambda l^{micro}) \Rightarrow l^{micro} = -\frac{\ln(x_\epsilon)}{\lambda}$$

Let l_1^{micro} and l_2^{macro} be the technology-specific micro-adoption lags associated with technologies 1 and 2, respectively. The (aggregate) micro-level adoption lag, L^{micro}, is then defined as the simple average of the technology-specific micro adoption lags:

$$L^{micro} = \frac{1}{2}(l_1^{micro} + l_2^{micro})$$

Note that, in this framework, aggregate output is the same as aggregate productivity, since capital is the only input of production and is in fixed supply. Thus, the macro-level adoption lag is defined as the elapsed time necessary for the output difference between the adopting country and the frontier country to be less than ε. Formally, define $\hat{x}_\epsilon$ as:

$$\int_{\hat{x}_\epsilon}^\infty (f_1(x)+f_2(x))xdx = (1-\epsilon)\int_0^\infty (f_1(x)+f_2(x))xdx$$

The macro adoption lag is the time elapsed until a production unit with $x = \hat{x}_\epsilon$ finds it optimal to adopt the technology:

$$\hat{x}_\epsilon = p_L = \exp(-\lambda L^{macro}) \Rightarrow L^{macro} = -\frac{\ln(\hat{x}_\epsilon)}{\lambda}$$

Note that the micro-level adoption lag and the macro-level adoption lag may be very different, depending on the distribution of firms. Specifically, the macro lag is typically shorter than the micro lag, for two reasons:

1. Technologies are adopted first in production units in which they are relatively more effective. Thus, the productivity gains from the first technology adoptions are relatively larger relative to the productivity gains from later adoptions. The macro-level adoption lag accounts for this, by weighting technology adoptions by their respective productivity gains. The micro-level adoption lag, in contrast, assigns equal weights to all adoptions - thus, it is likely to be relatively longer than the macro-level lag.

2. More effective technologies are likely to be adopted faster. Technologies that improve productivity by more are likely to be adopted faster, as production units are more willing to pay the adoption costs. This implies shorter lags associated with technologies that are more productivity enhancing. The macro-level adoption lag focuses on aggregate productivity gains from technology adoption, which is likely driven disproportionately by more productive technologies. In contrast, the micro-level adoption lag weighs technologies equally, and is thus likely to be longer.

This framework illustrates that, when technology adoption is costly and the decision to adopt technology is related to its effectiveness, macro-level adoption lags will tend to be shorter than micro-level adoption lags. The next section offers a simple numerical illustration of this principle, with parameters chosen to match key features of micro- and macro-level adoption lags in LAC.

3. 4. A numerical illustration

This section proposes a simple numerical illustration of the model that admits to the following features which are roughly consistent with the patterns of technology adoption in LAC:

1. A 20 year (aggregate) micro-level adoption lag
2. Some technologies adopted within approximately 10 years (e.g., Internet) and some technologies adopted within approximately 30 years (e.g., electricity)
3. An 8 year macro-level adoption lag
4. No adoption within the first 8 years, and almost-full adoption after 8 years

Consider an economy with two technologies, 1 and 2, and the following distributions of technology effectiveness. There are two types of production units. A measure δ_i of production units have a value of upper bar x_i, and the remaining measure 1-δi have a value of x_i<bar(x_i).

The adoption patterns do not uniquely pin down δ_i and x_i. In what follows, we present two examples: one in which the difference between micro- and macro-adoption lags is driven entirely by differences in technology effectiveness across technologies, and one in which the difference is driven entirely by differences in technology effectiveness across production units.

Example 1: differences across technologies. As a first example, consider an environment in which there is no heterogeneity across production units. For technology *i* to be adopted after *ti* years, it must be the case that:

$$\bar{x}_i = \exp(-\lambda t_i)$$

Thus, to match the micro adoption lags, we need to match:

$$\bar{x}_1 = \exp(-10\lambda)$$

$$\bar{x}_2 = \exp(-30\lambda)$$

Note that the micro-level adoption lag is the average of 10 and 30, which is 20. For the macro level adoption lag to be 10, *t* must be the case that the productivity gains from technology 2 are negligible:

$$\bar{x}_1 \geq (1-\epsilon)(\bar{x}_1 + \bar{x}_2) \Rightarrow \frac{\epsilon}{1-\epsilon}\bar{x}_1 \geq \bar{x}_2$$

Choosing ε=0.001, the above holds, for example, for $x1=0.5x2$:

$$\bar{x}_1 = \exp(-10\lambda)$$

$$0.5\bar{x}_1 = \exp(-30\lambda)$$

Solving for λ:

$$0.5\exp(-10\lambda) = \exp(-30\lambda) \Rightarrow \exp(-20\lambda) = 0.5 \Rightarrow \lambda = -\frac{\ln(0.5)}{20} \approx 0.035$$

Substituting in yields $x_1= 0.7$ and $x_2=0.35$.

We have thus constructed an example in which heterogeneity across technologies in terms of the productivity gains that they generate resulted in a difference between micro and macro adoption lags that is consistent with the experience of LAC.

Example 2: differences across production units. In this second example, we focus on the role of heterogeneity across production units in generating a difference between the micro- and macro technology adoption lag. For this purpose, we abstract away from differences across technologies and simplify by assuming a single technology that has a micro adoption lag of L^{micro}=20 and a macro adoption lag of L^{macro}=10.

To construct this example, note that the following conditions must hold:

$$(1-\delta) > \epsilon$$

$$\delta\bar{x} \geq (1-\epsilon)(\delta\bar{x} + (1-\delta)\underline{x})$$

$$\bar{x} = \exp(-10\lambda)$$

$$\underline{x} = \exp(-20\lambda)$$

The first equation states that the micro-adoption lag is given by the time elapsed until all production units adopt the technology. The second equation states that the macro-adoption lag is given by the time elapsed until the first δ production units adopt the technology; thus, the macro-adoption lag is driven by the most productive uses of the technology, while the micro-adoption lag is driven by the least productive use of the technology. The third and fourth equations state that the adoption lags of the first δ adopters and the last 1- δ adopters should be 10 and 20 years, respectively, consistent with the pre-specified micro- and macro-level adoption lags.

Note that, given ε=0.001, these equations have four unknowns: δ, λ, $\bar{x}$ and $\underline{x}$. Thus, since the first two equations are inequality constraints, there may be infinite solutions. We will focus on one possible solution. We will assume that the first inequality constraint holds with equality, and thus δ =1-ε=0.999. Further, we will assume that $\underline{x}=0.5\,\bar{x}$, and verify that the second constraint holds:

$$0.999\bar{x} \geq 0.999(0.999\bar{x} + 0.001 \cdot 0.5\bar{x}) \Leftrightarrow 0.999 \geq 0.999(0.999 + 0.0005)$$

Note that the inequality on the right hand side holds, because 0.999+0.0005<1 (in fact, it is easy to see that this inequality would hold for any $\underline{x}<bar(x)$). Thus, we can proceed in solving for λ by imposing:

$$0.5\exp(-10\lambda) = \exp(-20\lambda) \Rightarrow 0.5 = \exp(-10\lambda) \Rightarrow \lambda = -\frac{\ln(0.5)}{10} \approx 0.07$$

Yielding λ= 0.07, $\bar{x}$ = 0.5 and $\underline{x}$= 0.25.

These examples illustrate that the observed differences between micro- and macro-level adoption lags can be generated with reasonable heterogeneity across technologies or production units in technology effectiveness, and that it is actually quite easy to reconcile the two estimates. However, absent further data on the prices of technology adoption (that pins down λ) or the distribution of technology effectiveness (that governs *f*), the parameters of the model are not uniquely pinned down, and therefore the quantitative relevance of the model remains an open question.

3. 5. Conclusion

This paper proposes that endogenous technology adoption may account for the difference between micro-level adoption lags - defined as the cross country differences in technology prevalence rates

- and macro-level adoption lags, defined as the productivity gap attributed to differences in technology. When technology adoption is endogenous, the most effective technologies are adopted first, and by their most effective users. Thus differences in technology prevalence rates tend to overstate the differences in total factor productivity.

We illustrate numerically that, in a model with endogenous technology adoption, it is easy to generate the observed disparity between micro-level adoption lags estimated by Comin and Hobijn (2010), Comin and Mestieri (2014) and macro-level technology adoption lags estimated by AAEN. This suggests that the two estimations are not inconsistent with one another; however, assessing the consistency of the two estimates requires a better understanding of (a) the rate at which technology adoption costs diminish over time and (b) the distribution of technology effectiveness across production units. We hope to pursue this question further in future work.

3. 6. Appendix

Table A3.2 Adoption lags for individual Latin American countries

	aviation passengers	cars	cell phones	electricity	internet	pcs	ships	telegraph	tele phone	trucks	blast oxy steel	rail passengers
Argentina	31.72		15.60		8.79	14.21	64.28	27.53			10.32	101.23
Belize												
Bolivia		41.63	17.59			16.28						116.67
Brazil	28.74	37.56	16.88	43.41	7.69	14.42	75.99	36.29	24.05	31.86	17.28	90.62
Chile	27.03		15.45		8.59	14.52	62.58			6.84	23.14	96.21
Colombia	24.46	28.03		50.67	7.73	16.17	140.89	68.46	30.11	16.86	16.56	
Costa Rica		29.80	17.49		8.94				27.93	28.24		
Cuba			15.93	16.47			134.07					111.37
Dominican Rep		55.51	16.06	67.52					65.88	48.97		
Ecuador	39.56	47.38		64.77	8.04	16.85	177.48		54.29	46.14		
El Salvador		27.25	19.41	65.80						31.03		
Guatemala		20.52	16.48	52.92		19.30			19.61	5.93		
Mexico	25.47	29.63	14.69	19.35	7.56	13.88	96.80	53.18	23.18	26.24	18.13	92.47
Nicaragua		24.28	19.28			17.09				26.99		
Panama		50.80		64.20	10.73		155.85		67.54	41.38		
Peru			16.31	47.42	10.77		91.17	58.51				81.94
Puerto Rico		58.89	18.16	66.52					56.65	41.83		
Uruguay			18.12	26.84				52.41				96.40
Venezuela	25.65	38.49	14.32	55.66	8.04	12.61	111.58	76.55	34.20	35.22		

Source: Authors' calculations.

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4. Structural change in Latin America: Does the allocation of resources across sectors, products, and technologies explain the region's slow productivity growth?

Marc Schiffbauer, Hania Sahnoun, and Jorge Thompson Araujo

The objective of this study is to assess the role of structural change in explaining the persistent productivity gap between countries in Latin America and high income countries. Recent contributions by Pages (2010) and McMillian and Rodrik (2011) find that labor flows between sectors reduced aggregate labor productivity growth in several Latin American countries between 1990 and 2005. Against this background, this paper documents in detail the evolution of employment, productivity, and technologies across sectors in Latin American and several benchmark countries between 1960 and 2005 and uses newly available data to analyze the robustness of the findings.

Theories of structural change show that the reallocation of activity across sectors accompanying generalized balanced growth can originate from income effects generated by non-homothetic preferences for different consumption goods (Pasinetti 1981, Kongsamut et al., 2001), changes in relative prices due to technological progress that differs across sectors (Baumol, 1967; Ngai and Pissarides, 2007), or changes in relative prices due to differences in capital intensities or elasticities of substitution in production across sectors (Herrendorf et al., 2013a). In the following, we take the source of structural change as given and analyze to which extent the sectoral reallocation associated with structural change affected aggregate labor productivity growth in Latin America. We note that structural change does not affect aggregate labor productivity growth in a neoclassical closed economy framework assuming for instance perfect competition in output and factor markets. In this framework, wages and labor flows between sectors fully adjust (e.g., after a sector specific technology shock) equating marginal labor productivities across sectors.

In the presence of market failures, distortions, and rigidities (e.g., due to product or labor market regulations) wages and labor flows do not fully adjust driving a wedge between marginal productivities across sectors. While the impact of these distortions is difficult to measure, it is likely that they are more severe in developing countries. For instance, Herrendorf and Valentinyi (2012) find large sectoral TFP differences relative to the U.S. in agriculture, manufacturing, and services. Moreover, the sectoral TFP gaps relative to the U.S. are larger in agriculture and services than in manufacturing; the latter is consistent with Rodrik (2013) who finds unconditional convergence in labor productivity in manufacturing despite the absence of aggregate convergence. These findings imply that aggregate labor productivity is affected by the sectoral composition of the economy (Duarte and Restuccia, 2010; Herrendorf et al., 2013b).

Echevarria (1997) and Duarte and Restuccia (2010) show that sectoral reallocation associated with structural change can explain most of the cross-country differences in aggregate productivity growth if countries are at different stages of the process of structural change. In particular, Duarte and Restuccia (2010) reveal that during the process of structural change, the reallocation of labor from agriculture to manufacturing leads to a catch up of aggregate productivity relative to the U.S., and the reallocation from manufacturing to services leads to a falling behind. Their results are based on a three sector model whereby they do not distinguish between the large potential

differences in productivity and tradability across different service sub-sectors. In the following, we also account for differences in labor productivity levels across different service sectors using the Groningen ten-sector database.

Our findings show that the contribution of sectoral reallocation associated with structural change to aggregate labor productivity growth in Latin America was relatively small and even negative in some countries. In contrast, for some countries, within sector labor productivity growth was as high as in East Asian countries. We also find substantial heterogeneity in both effects across Latin American countries. The results suggest that it is important to account for differences in labor flows and productivity across different service sub-sectors. For instance, we find that the employment-intensive retail & wholesale trade sector expanded in all Latin American countries. However, the performance of the sector, i.e. its relative level of productivity in the economy, differed widely across countries. As a result, the reallocation of labor tended to increase aggregate productivity growth in countries with a good sector performance (relative to other sector in the economy) and tended to reduce growth in countries with relatively low levels of retail & wholesale trade productivity.

Moreover, we find that employment shares in manufacturing declined in most Latin American countries. This trend potentially slows down the region's speed of convergence as it counterweights the aggregate impact of unconditional convergence of labor productivity in manufacturing with the rest of the world (Duarte and Restuccia, 2010; Rodrik, 2013). This finding warrants a more detailed analysis of the evolution of manufacturing production structures across Latin America countries. Against this background, we use the product space approach to compare the patterns of specialization within manufacturing in Latin America and the Caribbean with other regions of the world, especially East Asia. Despite limitations in the analysis[72], it remains a relevant analytical approach to capture differences in the evolution of manufacturing across regions over the past 30 years. We find a lack of formation of production clusters among related manufacturing products or industries relative to other regions. Finally, we analyze if manufacturing firms in Latin American countries tend to be specialized in resource intensive, idiosyncratic production technologies that are unrelated to processes or technologies applied in large employment or technology intensive manufacturing clusters. Therefore, we apply the recently developed "knowledge applicability" measure (Cai and Li, 2013) which captures the scope for technology spillovers embodied in the technological specialization of firms in a given country. In contrast to East Asian economies, we find that manufacturing firms in Latin America tend to be specialized in idiosyncratic instead of general purpose technologies limiting the scope for the adoption of foreign technologies and integration into global value chains.

4. 1. Labor Productivity and Structural Change in Latin America

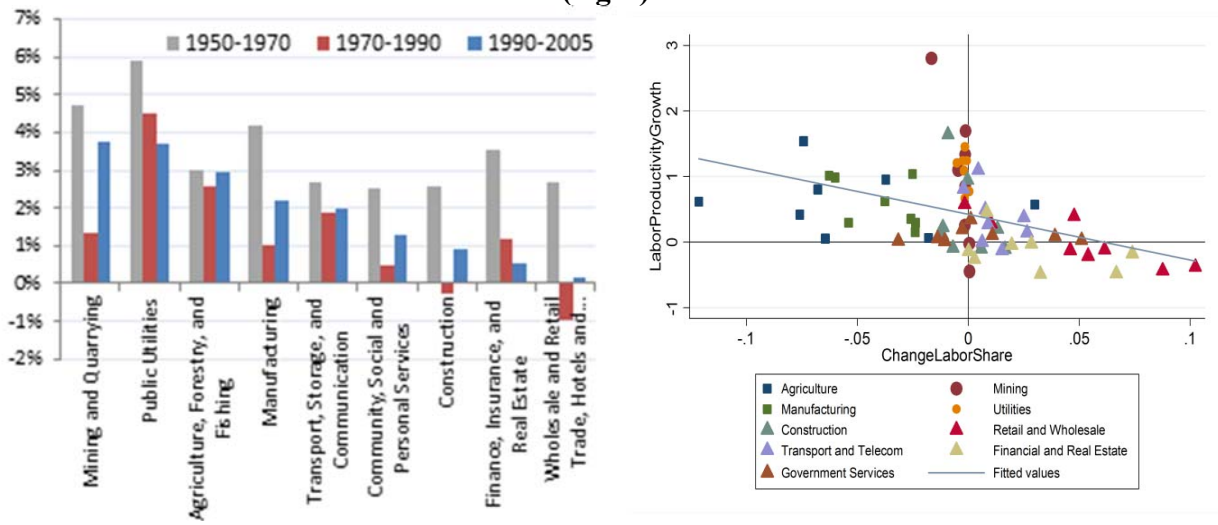
Are there large productivity differences across sectors within Latin American countries?

Productivity growth in Latin America differed significantly between sectors of the economy. Figure 4.1 (left) shows that productivity growth in service sectors was lagging behind agriculture and manufacturing. Since 1970 labor productivity in agriculture, public utilities, and mining grew

[72] Trade data is only a proxy for the productive structure of an economy, and in some cases can substantially deviate from actual sectoral contributions to GDP.

faster than in other sectors of the economy. After the period of import substitution policies and the debt crisis, labor productivity in 1990-2005 grew in the manufacturing sector by about two percent annually. However, regional labor productivity in services stagnated during the same period and even declined in several countries. Figure 4.1 (right) illustrates that among the large sectors in terms of employment,[73] the highest labor productivity growth was observed in agriculture, manufacturing, and transportation. However, labor moved from agriculture and manufacturing to the services sectors with the lowest productivity growth such as retail & wholesale trade, government services, and finance, real estate & business services.

Figure 4.1. Labor productivity growth by sector (left), versus change in employment share (right)



Source: staff calculations on Timmer and de Vries (2009).

The distribution of productivity growth across sectors does not appear to reflect a process of convergence in productivity levels between sectors. Among others, McMillian and Rodrik (2011) or Herrendorf and Valentinyi (2012) find stark differences in productivity levels across sectors in developing countries while productivity levels across sectors in high income countries are typically minor reflecting the outcome of past structural change. That is, the latter has been interpreted to signify an equilibrium balanced growth path in high income countries whereby initial productivity differences across sectors have been marginalized over time as labor moved to the sectors with the highest marginal productivity equalizing productivity levels.[74] Thus, market forces in developing countries should re-allocate resources to the sectors with the highest marginal productivity. Instead, the distribution of productivity growth across sectors in Figure 4.1 suggests that the forces of labor reallocations across sectors are imperfect in the region implying the prevalence of market failures and distortions: retail trade, construction, and government services, which are typically relatively low productivity sectors in developing countries, had the lowest productivity growth rates since 1970 but increased their employment shares significantly in most

[73] That is, excluding mining and utilities sectors which also suffer from methodological issues related to their capital intensity. See footnote on page 5 for more detailed notes on methodology.
[74] Structural change can be regarded as a convergence concept towards a long term equilibrium with comparable marginal productivity levels across sectors.

countries. This is counterbalanced, however, by strong productivity growth and declining labor shares in agriculture which is often the sector with the lowest labor productivity level. In line with Pages (2010), Herrendorf and Valentinyi (2012) and others, the evidence indicates that there exist substantial differences in labor productivity levels and growth across sectors within Latin American countries.[75]

The increase in the employment shares of lower productivity sectors can potentially explain Latin America's low aggregate productivity growth. Structural change is defined as the reallocation of input factors between sectors with different productivity.[76] In practice, the analysis is reduced to the re-allocation of labor since time series data of capital stocks at the more detailed sector level are typically not available for developing countries.[77] Given the relatively large differences in productivity levels across sectors within countries in the region, the increase in employment shares of lower productivity sectors can help explain low aggregate productivity growth and hence the lack of income convergence despite the successful technological catch-up of individual firms or industries in Latin America.[78] Therefore, we aim to extent the work of McMillian and Rodrik (2011) documenting in detail the evolution of employment and productivity across sectors in nine Latin American and several benchmark countries between 1960 and 2005. In particular, we decompose labor productivity into a *within* component measuring changes in sector level productivity and a *structural change* component measuring changes arising from a re-allocation of labor between sectors as follows:

$$\Delta Y_t = \sum_{i=n} s_{i,t-k}\, \Delta y_{it} + \sum_{i=n} y_{i,t}\, \Delta s_{it} \qquad (1)$$

where ΔY_t is the change in aggregate labor productivity between *t* and *t-k*, s_{it} is the employment share in sector *i* at time *t* and y_{it} is the productivity level in sector *i* at time *t*. The first term is the "within" component and the second term is the "structural change" component.

[75] It is possible that these differences in labor productivity growth are mostly entirely stemming from differences in capital-labor ratios across sectors implying that total factors productivity is similar across sectors. However, Herrendorf and Valentinyi (2012) show that this is not the case for broader sector definitions. For services sub-sectors, we cannot directly test this hypothesis given the absence of sectoral time series capital stock data (see paragraph on data limitations below). Nevertheless, we argue that it is unlikely that differences in capital intensities alone can explain the large differences in labor productivity levels and growth across services sub-sectors within Latin American countries.

[76] The definition of structural change is consistent with Duarte and Restuccia (2010), McMillian and Rodrik (2011) and others. Alternatively Hausman and Klinger (2006) use exports as a proxy for production to analyze structural change within the manufacturing sector only.

[77] At the aggregate level, previous analysis was typically limited to measure the reallocation of labor across three broad sectors only: agriculture, manufacturing, and services. The recent availability of new data sets such as the Groningen 10 sector database and the UNIDO sector data provide more detailed international time series sector data for value added and employment that ensure a certain degree of consistent in cross-country sector definitions making it possibly to refine the previous approaches.

[78] We emphasize that aggregate GDP growth does of course not only depend on aggregate labor productivity growth but also on changes in the aggregate labor input and demographics. For example, if a redundant worker with zero productivity is laid off in agriculture and drops out of the labor force labor productivity in agriculture increases, the contribution of the labor input to GDP growth declines while structural change and aggregate GDP growth remain the same.

Data limitations in the analysis require a number of assumptions. Previous studies using the same data sources have been criticized for several empirical shortcomings. First, aggregate productivity must not always lead to higher aggregate welfare (at least in a static setting abstracting from dynamic productivity or technology spillovers a la Aghion and Howitt, 1992, or Romer, 1990). For example, productivity may be higher in sectors with monopoly power. A reallocation of labor to these sectors would contribute positively to structural change but would not necessarily enhance welfare. Moreover, differences in the coverage of the informal sector (in terms of GDP and employment) across countries can bias the results. Most importantly, however, previous studies such as Pages (2010) and McMillian and Rodrik (2011) measure differences in the average instead of the marginal rates of labor productivity across sectors; under perfect competition in input and output markets, however, labor should move to the sector with the highest marginal productivity (i.e., wage) equalizing marginal rates across sectors over time. In fact, under a Cobb-Douglas production function specification, the marginal productivity of labor is the average productivity multiplied by the share of labor in GDP. Thus, large differences in labor shares, i.e. in capital intensities across sectors, drive a wedge between marginal and average labor productivity levels. For instance, among the sectors above, public utilities and mining are likely to have higher capital intensities potentially overstating their measured marginal productivities when approximated with averages. McMillian and Rodrik (2011) argue, however, that in the case of the other sectors, which employ most labor, it is not clear that there is a significant bias.[79] Thus, we assume in the following that large gaps in average productivity across sectors within a country are positively correlated with the underlying unobservable gaps in marginal productivities across sectors.[80] Moreover, we provide a robustness test by approximating the marginal productivity of labor with the estimated labor share of income in the Appendix. Using World Bank I2D2 data, we calculate the income share of labor using wage data for Peru and Chile.[81] We find that gaps in marginal productivities measured by average wages across sectors are smaller than gaps measured by value added per worker, but sectoral differences remain significant.[82]

Do changes in the allocation of labor across sectors explain the region's laggard aggregate productivity growth?

Aggregate productivity growth in Latin American countries between 1960 and 2005 was well below that of East Asian peers during the same period. Figure 4.2 illustrates that average annual aggregate productivity growth ranged between 2.5 and 4.5 percent in Taiwan, Thailand, Malaysia, Indonesia, and India. In contrast, average annual productivity growth was about 1.8 percent between 1960 and 2005 in Brazil and Chile and around 1 percent for all other Latin American countries, apart from Venezuela where it was negative. The only East Asian country with available data and similar productivity growth around 1 percent are the Philippines.

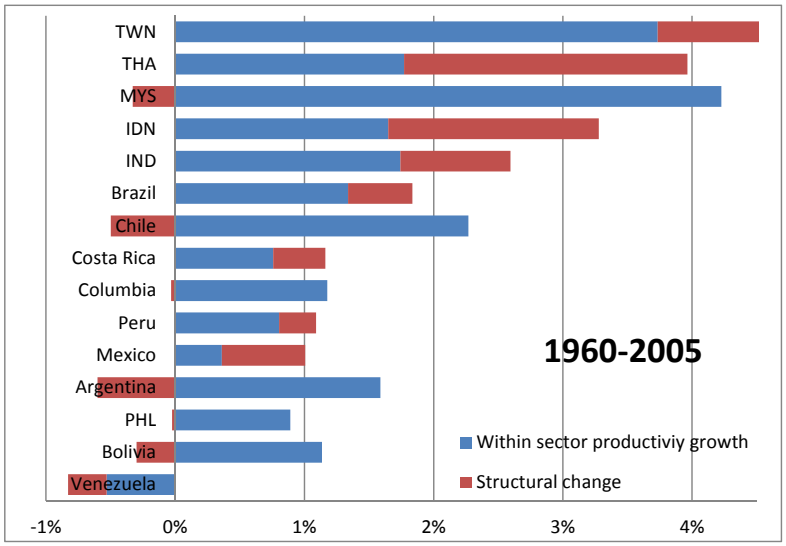
[79] McMillian and Rodrik (2011) refer, for instance, to Mundlak et al (2008) who show that it is not clear that the labor share in agriculture is significantly lower than in manufacturing once the share of land is taken into account.
[80] See Hsieh and Olken (2014) for a detailed discussion under which conditions the average and the marginal products of capital and labor move together.
[81] These two countries have the most reliable wage data in the I2D2 in the region. To eliminate biases arising from unobserved heterogeneity, the data is narrowed down to a sub-set of workers. The marginal labor productivities are calculated for single males aged 30-34 years with elementary education. The wage data is adjusted for the rural-urban price differential.
[82] McMillian and Rodrik (2012) come to similar conclusions using a comparable approach for Mexico.

Within sector productivity growth in Argentina and Chile between 1960 and 2005 was comparable or higher than in East Asian countries but the labor shares of higher productivity sectors declined in both countries reducing aggregate productivity growth. Within sector productivity growth in Argentina was as high as in India or Indonesia; however, the relative decline in employment in higher productivity sectors reduced aggregate productivity growth in Argentina from 1.6 to 1 percent annually while increasing labor shares in these sectors raised aggregate productivity growth in India and Indonesia to 2.6 and 3.3, respectively. Likewise, within sector growth in Chile was even 0.5 percent higher than in Thailand but the declining labor shares in higher productivity sectors reduced annual aggregate growth to 1.8 percent Chile while increasing labor shares in these sectors raised it to 4 percent in Thailand between 1960 and 2005, respectively. Thus, while structural change accounted for -61 and -28 percent of aggregate productivity growth in Argentina and Chile, it accounted for 55 and 50 percent in Indonesia and Thailand, respectively. Overall, a decline in the labor share of higher productivity sectors contributed negatively to aggregate productivity growth in five out of nine Latin American countries. In contrast, increasing labor shares in these sectors contributed positively to aggregate productivity growth (between 26 and 64 percent) in Brazil, Mexico, Costa Rica, and Peru; the within sector component, however, was relatively weak (around 1 percent) in these four Latin American countries.

The changes in aggregate productivity growth between 1990 and 2005 mirror these long term trends. Between 1990 and 2005, aggregate productivity growth stagnated in most Latin American countries apart from Peru, Chile, and to some extent Argentina where it was comparable to East Asian countries except from China. Aggregate productivity in China grew by 8.8 percent annually from 1990-2005 outperforming the second highest growth country (India) by 4.6 percent annually. Aggregate productivity also grew strongly in Peru and Chile, at comparable rates to Thailand, Turkey, and Indonesia during that period.

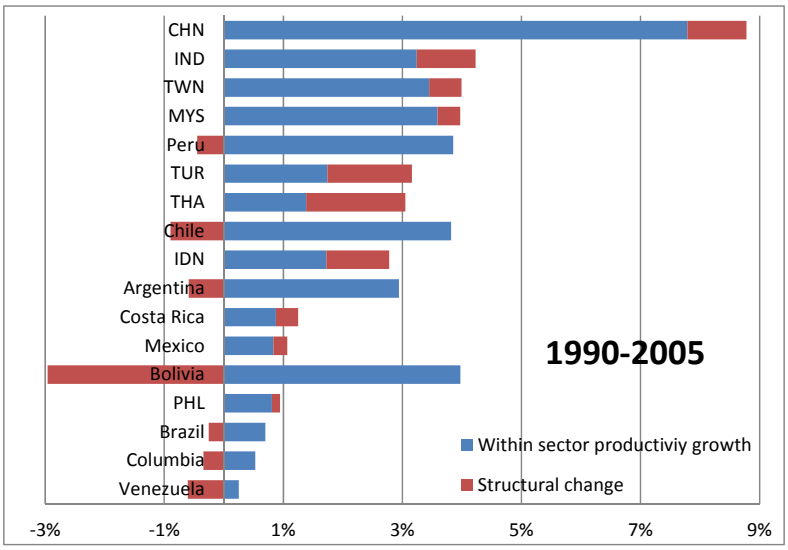
The labor shares of higher productivity sectors declined in seven out of nine Latin American countries from 1990-2005 but slightly increased in Mexico and Costa Rica. Within sector growth was about 4 percent in Chile, Peru, and Bolivia, second only to China. However, declining labor shares in higher productivity sectors reduced aggregate productivity by 0.4, 0.9, and 3 percent in Peru, Chile, and Bolivia, respectively, while the relative increase in employment in these sectors has raised aggregate productivity growth in the East Asian peer countries. Overall, the structural change component was strongest in Thailand, Turkey, Indonesia, India, and China where it contributed between 1 and 2 percent to aggregate annual productivity growth.

Figure 4.2. Decomposition of labor productivity growth (un-weighted averages): 1960-2005



Source: Authors' calculations.

Figure 4.3. Decomposition of labor productivity growth (un-weighted averages): 1990-2005



Source: Authors' calculations.

Overall, these findings show that reallocations of labor across sectors were pivotal in many Latin American countries to explain their inferior aggregate productivity growth performance during the past 50 years relative to East Asian peers. This trend was even more pronounced in the more recent sub-period between 1990 and 2005. What are the major trends in sector employment shares causing this slow structural change in Latin American countries? To answer this question, we analyze the changes in employment shares by sector in Latin American countries between 1990 and 2005 in more detail in Figure 4.4 and Figure 4.5.

In most Latin American economies, labor shares of manufacturing and agriculture declined between 1990 and 2005 while labor moved to various services sectors. Where these services

sectors were more productive, labor reallocation associated with structural change made a positive contribution to overall productivity growth (Figure 4.4 and Figure 4.5). For example, in Costa Rica, labor reallocation increased aggregate productivity growth, showing movement of labor from agriculture to transport & telecommunication, finance, real estate & business services, as well as wholesale & retail. Notably, wholesale & retail trade in Costa Rica has a relatively high average labor productivity which contrasts with all other Latin American countries in the sample apart from Mexico. Apart from this overall finding, five additional observations are salient.

First, the productivity level of the wholesale & retail trade sector is pivotal to explain the contribution of structural change to aggregate productivity growth among Latin American countries. Figure 4.4 and Figure 4.5 demonstrate that a significant share of the labor force is working in wholesale & retail trade; the sector's employment shares yet increased in all Latin America countries (apart from Peru) between 1990 and 2005. The sector had relatively high productivity levels in Mexico and Costa Rica contributing to aggregate productivity growth in these countries. In contrast, productivity levels of wholesale & retail trade were low in all other Latin American countries reducing aggregate growth; notably, the sector's relative productivity level was the lowest among all sectors in Brazil, Chile, and Columbia. The latter suggests that in many Latin American countries redundant labor from other sectors often ends up working in unproductive small scale activities (e.g., street vendors) in the retail trade sector which typically hosts a large share of informal labor. In contrast, the relatively high productivity levels in Mexico and Costa Rica might indicate a higher degree of formalization in the sector possibly due to the past entry of a large number foreign (U.S.) wholesale and retail trade franchises in both countries.

The finding implies that case studies analyzing differences in the performance of specific service sectors across different Latin American countries can help understand the underlying causes of cross-country differences in aggregate productivity growth. For instance, the World Bank database on service trade restrictions provides comparable information across 103 countries for five key service sectors (Borchert, Gootiiz, and Mattoo, 2012). The indicators focus on policies and regulations discriminating against the entry of foreign service providers. The data show significant variations in services trade restrictions across Latin American countries.

Second, the share of labor working in manufacturing sectors declined in all Latin American countries (apart from Bolivia). The manufacturing sector is among the most productive sectors in all countries. In Argentina and Peru, it was the sector with the strongest labor share decline (stronger than agriculture). This trend slowed down aggregate productivity growth. In particular, aggregate productivity growth would have been higher if a larger share of new labor market entrants or redundant labor from agriculture and the government sector would have been absorbed by manufacturing instead of the lower productivity (partially informal) retailed & wholesale trade sector. The decline in the size of the manufacturing sector was particularly notable in Argentina, Brazil, Chile, Peru, and Venezuela. Our findings are consistent with Duarte and Restuccia (2010).

Third, the employment share in the relatively low productivity agriculture sector typically declined contributing positively to aggregate productivity growth. The contribution was especially high in Brazil, Costa Rica, Columbia, and Mexico due to the strong decline of the

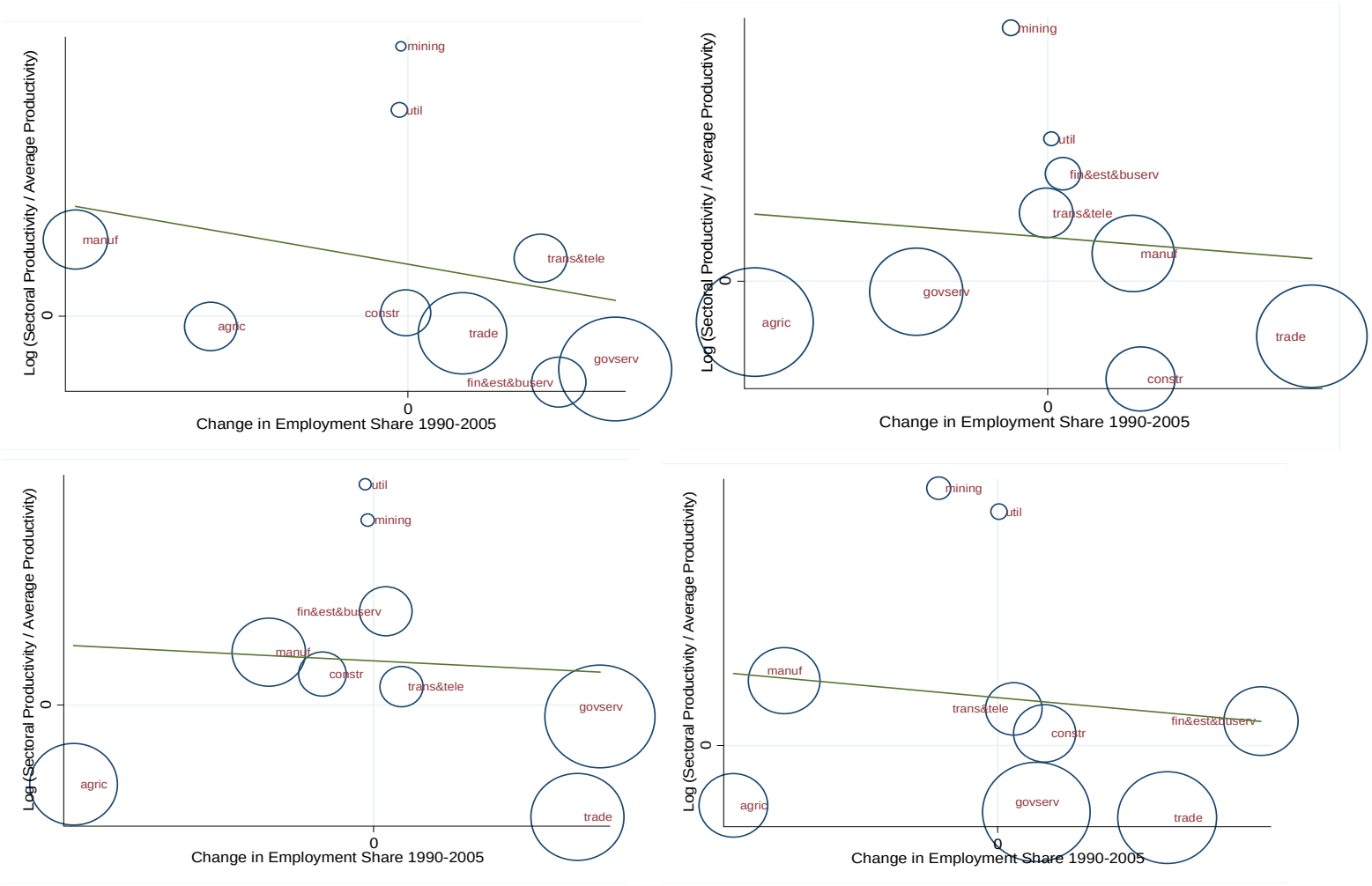
relatively high initial employment shares of agriculture in these countries. The only Latin American country in the sample where the labor share in agriculture increased is Peru.

Fourth, increases in the public sector employment share between 1990 and 2005 slowed down aggregate productivity growth in Argentina and to some degree also in Brazil. The government service sector is the largest employer in Argentina, Brazil, Chile, and Mexico. For instance, in Argentina and Brazil labor moved primarily from agriculture and manufacturing to lower productivity wholesale & retail trade as well as government services.

Fifth, increases in the labor shares of finance, real estate, & business services sectors contributed positively to aggregate productivity growth in Chile, Columbia, Costa Rica, and Mexico. These relatively high productivity sectors employ only a relatively small share of labor in some Latin American countries; e.g., Bolivia, Peru, or Venezuela. In contrast, they are a relatively large employer as well as fast-expanding in Chile, Columbia, Costa Rica, and Mexico. The measured productivity levels of the sector also vary noticeable across countries; while it is above average in most countries, productivity is particularly low in Argentina and Peru. The sector includes finance as well as professional services which often have major restrictions to foreign entry in Latin America. Borchert, Gootiiz, and Mattoo (2012) show that both sectors have low restrictions to service trade in Columbia and Costa Rica, labeled as virtually open to foreign entry in both countries.

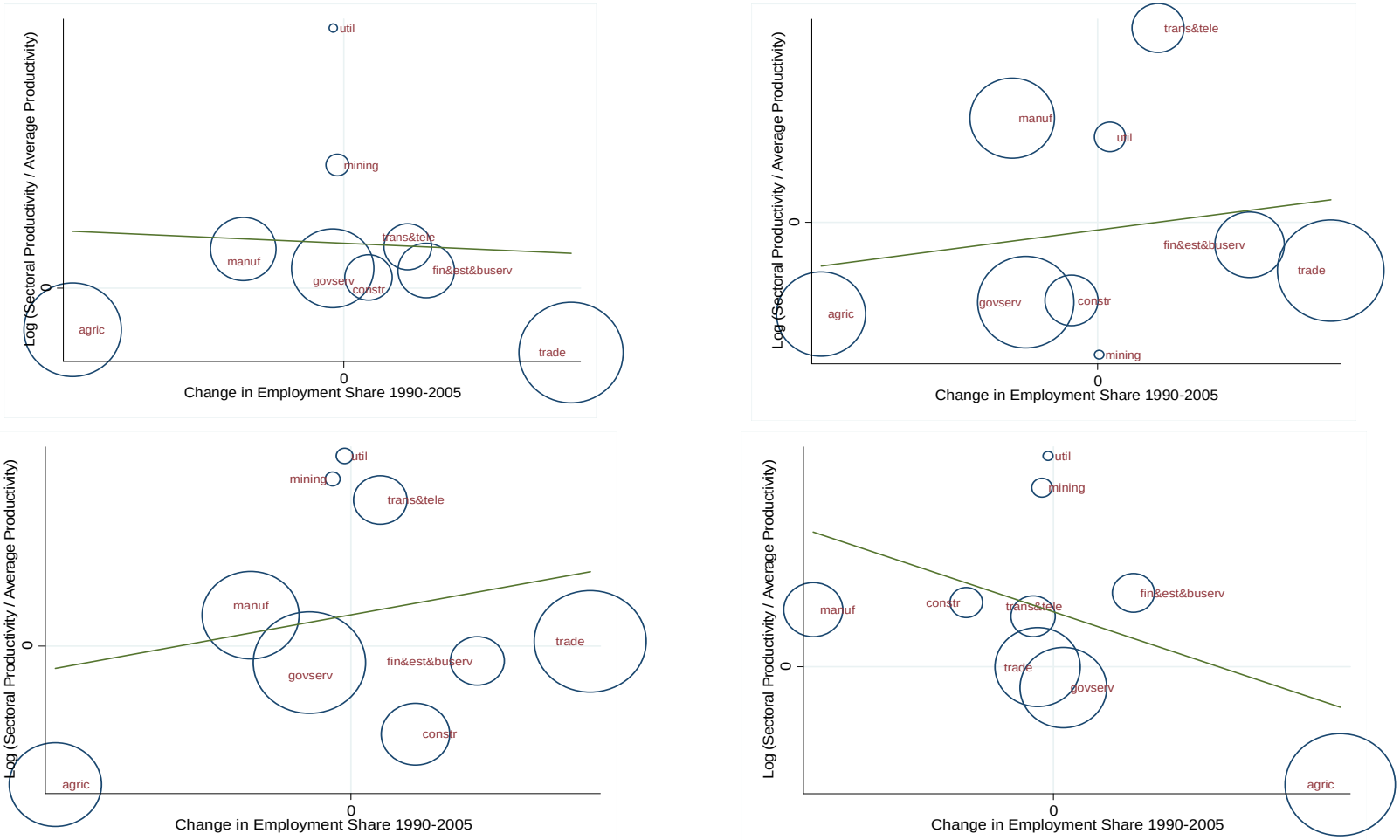
The above findings suggest several promising directions to deepen the analysis in order to help explain slow aggregate productivity growth in Latin American countries. One striking feature is certainly the decline of the size of manufacturing sectors in almost all countries. Given that manufacturing productivity appears to be substantially higher relative to most other sectors, its decline contributed to lower aggregate productivity growth in the region. Moreover, it has been argued that manufacturing activities, which are usually freely tradable and more internationally mobile, embody aggregate growth externalities. That is, their exposure to trade and the integration of global value chains potentially facilitate international knowledge transfers or lead to more competitive market structures.

Figure 4.4. Structural change 1990-2005: Argentina (upper-left), Bolivia (upper-right), Brazil (lower-left) and Chile (lower-right)



Source: Timmer and de Vries (2009), McMillan and Rodrik (2011) and staff calculations.
Note: Figures plots logarithm of sectoral value added per worker (relative to the average across all sectors) and the change in the employment share for 9 sectors of an economy between 1990 and 2005. The size of the circle reflects the employment share in 2005. On the vertical axis, sectors above zero are relatively more productive compared to an average sector in an economy. On the x-axis, sectors to the right from zero have had increases in their employment shares.

Figure 4.5. Structural change 1990-2005: Columbia (upper-left), Costa Rica (upper-right), Mexico (lower-left) and Peru (lower-right)



Source: Timmer and de Vries (2009), McMillan and Rodrik (2011) and staff calculations. Note: Figures plots logarithm of sectoral value added per worker (relative to the average across all sectors) and the change in the employment share for 9 sectors of an economy between 1990 and 2005. The size of the circle reflects the employment share in 2005. On the vertical axis, sectors above zero are relatively more productive compared to an average sector in an economy. On the x-axis, sectors to the right from zero have had increases in their employment shares.

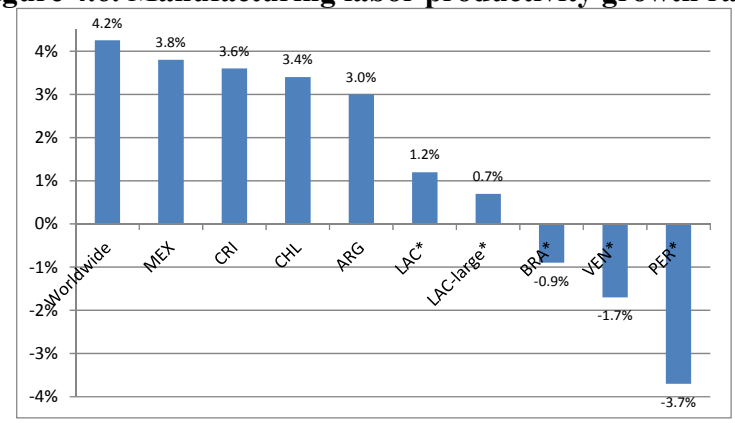
Is manufacturing labor productivity in Latin America catching up with high income countries? Is the convergence rate in the region different from other developing regions?

Recent academic findings suggest that the declining share of labor working in Latin America's manufacturing sector might have particular consequences for the region's (speed of) convergence. Rodrik (2013) reveals the empirically robust stylized fact of *unconditional convergence* in manufacturing labor productivity across countries. That is, manufacturing labor productivity in poorer countries is catching up (on average) with manufacturing labor productivity in high income countries independent of developing countries' policies, qualities of institutions, education, or other growth determinants. Arguably, his findings are also valid for tradable service sectors but data limitations limit the scope of the analysis to manufacturing. The author used recently constructed UN data (INDSTAT) that allow for robust empirical analysis covering a large sample consisting of 23 manufacturing sub-sectors from most countries in the world over several decades. The manufacturing labor shares are often very low (5-10 percent) as the data mostly cover formal employment. Rodrik (2013) also shows that convergence in manufacturing productivity does not imply aggregate convergence because of the low and often declining manufacturing labor shares in developing countries. While the article includes a battery of empirical robustness checks across different time periods and levels of sector aggregation, it does not report testing for potential differences in the convergence rate in manufacturing labor productivity across specific developing regions.

Against this background, we test if the finding of *unconditional convergence* in manufacturing productivity also holds among Latin American countries and if convergence rates differ across the region. In other words, we test if there are Latin America specific factors holding back manufacturing productivity that are fundamentally different from the rest of the world? If it is the case, the declining size of manufacturing sectors in Latin America is a potential concern for policymakers. In other words, policymakers should focus on removing product and labor market constraints (i) preventing manufacturing firms from expanding (potential entrepreneurs from entering) and/or (ii) holding back employment and labor productivity growth in tradable service sectors.

Manufacturing productivity growth in Latin America was significantly lower than the worldwide average; however, there were substantial growth differences across Latin American countries. Figure 4.6 illustrates the (compound) average annual labor productivity growth rate across 23 manufacturing sectors for the latest decade with available data (post 1990). The growth rate is measured net of year-industry specific effects and the sample corresponds to Rodrik's baseline post 1990 specification. Accordingly, manufacturing labor productivity growth (net of year-industry specific effects) amounted to 4.2 percent across all 104 countries with available data. In contrast, average growth among Latin American countries is only 1.2 percent. The difference in growth rates is statistically significant (5 percent level as indicated by the "asterisk"). The average growth rate is even lower among large Latin American countries including Argentina, Brazil, Chile, Colombia, Mexico, and Peru. However, it conceals a substantial degree of heterogeneity among these countries. Manufacturing productivity growth in Mexico, Costa Rica, Chile, and Argentina was not statistically significantly different from the worldwide average. In contrast, growth in Brazil, Venezuela, and Peru was even negative statistically significantly different (at the 1 percent level).

Figure 4.6. Manufacturing labor productivity growth rates



Source: Authors' calculations.

Each bar corresponds to the average annual labor productivity growth rate across 2-digit manufacturing sectors in the Latin American region for the latest decade with available data (post 1990). The sample corresponds to a baseline specification in Rodrik (2013). The growth rate is measured net of year-industry specific effects. The "worldwide" bar measures the average annual growth rate across all countries and 2-digit manufacturing industries over a decade. An "asterisk" indicates that the growth rate in the region or country was statistically significantly different from the worldwide manufacturing labor productivity growth rate (i.e., from 4.2 percent). "LAC-large" corresponds to Argentina, Brazil, Chile, Colombia, Mexico, and Peru. "LAC" excludes small island states (less than 200,000 people), Belize, Guyana, Suriname, and French Guyana.

Manufacturing labor productivity in the Latin American region overall is converging unconditionally (independent of policies, institutions, or educational levels) with the same convergence rate as the rest of the world. Table 4.1 shows to which extent Latin American countries catch up in manufacturing productivity with high income countries. It reports the three main estimation specifications from Rodrik (2013).[83] In all cases the dependent variable is the (compound annual) growth rate of labor productivity for 2-digit manufacturing industries. The regressors are the log of initial labor productivity and industry-year fixed effects. The baseline estimation specification consists of a pooled sample that combines the latest ten-year period for each country maximizing the number of countries covered (118). Since each country enters with around 20 industries, the total number of observations is 2,122. The second specification restricts the sample to post 1990 10-year periods while the third is a pure cross-section for 1995-2005. The second column replicates Rodrik's findings of a convergence rate of 2.9 percent implying that industries that are a tenth of the way to the technology frontier (roughly the bottom 20 percent of industries in the sample) experience a convergence boost in their labor productivity growth of 6.7 percentage points per annum. In columns 5-15 of Table 4.1, we test if the convergence rate was different in Latin America; i.e., we include a region dummy and its interaction term with log initial labor productivity in the corresponding estimation specifications. The coefficient of the interaction term measures if the convergence rate was differed from the convergence rate across all other countries. Table 4.1 only reports cases in which the convergence rate was statistically significantly different

[83] We would like to thank Danny Rodrik for sharing the original data and Stata codes of Rodrik (2013) with the authors. We added regression specifications to test for differences in the speed of unconditional manufacturing convergence in Latin America. All potential errors are the responsibility of the authors.

from the rest of the world (the t-statistic of the interaction term is reported in brackets below). The results show that the convergence rate in the Latin American region overall was the same as in the rest of the world.[84] The results for the region overall conceal a substantial heterogeneity across countries.

Manufacturing labor productivity in Brazil, Peru, and Chile did not catch up (unconditionally) with high productivity countries. The last three columns of Table 4.1 show that the convergence rate in Brazil, Peru, and Chile was (statistically) significantly lower than in the rest of the world. The actual convergence rate (-2.9 percent plus the coefficient of the interaction term) was close to zero and even diverging in Chile (not statistically different from zero though). For all other larger Latin American countries in the sample apart from Mexico, the speed of convergence was not (statistically) different from the convergence rate in the rest of the world.

The convergence rate of manufacturing labor productivity in Mexico was significantly higher than in the rest of the world. The yearly convergence rate for manufacturing productivity in Mexico amounted to 4.8 percent between 1993 and 2003 (last year with available data) which is two-third larger than in the rest of the world. The Mexican manufacturing convergence rate is (statistically) different from the rate in the rest of the world (at a 10 percent level). Thus, manufacturing firms in Mexico were able to catch up in terms of productivity with high productivity countries (the U.S.) between 1993 and 2003.

Table 4.1 Is the convergence rate in manufacturing labor productivity different in Latin America?

	Rodrik (2013)			*Is the speed of convergence in manufacturing labor productivity different in LAC?*										
	All countries	countr	obs	LAC	LAC-large	MEX	ARG	URU	VEN	CRI	COL	PER	BRA	CHL
Baseline	**-0.029*** **	118	2,122	*same*	*same*	-0.048*	*same*	*same*	*same*	*same*	*same*	0.000***	-0.001**	0.016*
	(-6.95)					(-1.86)						(3.32)	(2.28)	(1.83)
post-1990	**-0.029*** **	104	1,861	*same*	*same*	-0.048*	*same*	*same*	*same*	*same*	*same*	0.000***	-0.001**	0.016*
	(-7.14)					(-1.92)						(3.45)	(2.37)	(1.90)
1995–2005	**-0.024*** **	58	955	*same*	-0.001**			*same*			0.006***	0.000***	*same*	0.004***
	(-6.17)				(2.18)						(3.51)	(3.33)		(3.08)

Source: Authors' calculations.

Columns 2-4 replicate the baseline finding of Rodrik (2013). Columns 4-12 show if the convergence rate in manufacturing labor productivity differed among (groups of) Latin American countries. Each cell is based on a regression of growth on initial productivity including year-industry dummies (analog to Rodrik, 2013) and a region dummy as well as the interaction term of the region dummy with initial productivity.[1)] The coefficients show the compound convergence coefficient (baseline-coefficient + coefficient interaction term) while the t-statistics tests if convergence coefficient is statistically different from the convergence coefficient in the full sample, i.e. across all counties (e.g., -0.029). Standard errors are clustered at the country level in all specifications.

Why did unconditional convergence in manufacturing for most Latin American countries not translate into higher manufacturing productivity growth?

[84] We find a lack of unconditional convergence in manufacturing labor productivity among the large Latin American countries for the 1995-2000 cross sections (the convergence rate of 0.1 percent corresponds to the convergence coefficient in the rest of the world -2.4 percent plus the coefficient of the interaction term of -2.3 percent which is not reported explicitly here). It is probably due to the fact that data for Mexico, Argentina, Venezuela, and Costa Rica are not available for the 1995-2005 cross section.

Rodrik (2013) shows that unconditional convergence in (formal) manufacturing does not translate into aggregate convergence due to low (sometimes declining) manufacturing labor shares. The author derives the following decomposition of aggregate productivity growth into a manufacturing convergence term and a reallocation term measuring the potentially negative effect of labor reallocating from the manufacturing sector to less productivity non-manufacturing sectors:

$$\Delta Y = g + [\alpha\theta_m\beta(lny^* - lny_m)] + [(\theta_m - \theta_n)\Delta\alpha] \qquad (2)$$

where aggregate labor productivity $Y = \alpha y_m - (1-\alpha)y_n$ is the weighted average of labor productivity in these two activities, α is the share of the economy's labor force employed in manufacturing, ΔY is the aggregate labor productivity growth rate, g is the long-term balanced growth rate of the economy, $\theta_m = y_m / y$ and $\theta_n = y_n / y$ are the productivity premium/discounts for the manufacturing and non-manufacturing sectors, $\beta = 2\%$ is the convergence rate estimated for the full sample from 1995-2005 which is applied to all countries, and y^* is the productivity frontier in manufacturing. Rodrik (2013) quantifies equation (2) by combining the INDSTAT manufacturing data with data for aggregated GDP per worker from the Penn World tables (non-manufacturing productivity being the difference between the two for each country). Table A4.5 in the appendix shows the details for the different convergence terms in equation (2) for the Latin American countries with available data.[85] It shows that aggregate productivity convergence was lagging in the region due to (i) small initial manufacturing labor shares (α), (ii) declining manufacturing labor shares over time ($\Delta\alpha$), (iii) small productivity differentials relative to the rest of the economy (θ_m), or (iv) smaller productivity gaps relative to the world productivity frontier in manufacturing ($lny^* - lny_m$). Moreover, we emphasize that tradable service sectors arguably have similar characteristics as manufacturing but sufficiently detailed cross country data for these services sub-sectors are not available limiting the scope of the analysis to unconditional convergence in manufacturing.

To which extent do patterns of specialization within manufacturing help explain the declining labor shares and slower manufacturing productivity convergence in some countries in the region?

4. 2. Changing Production Structures in Manufacturing

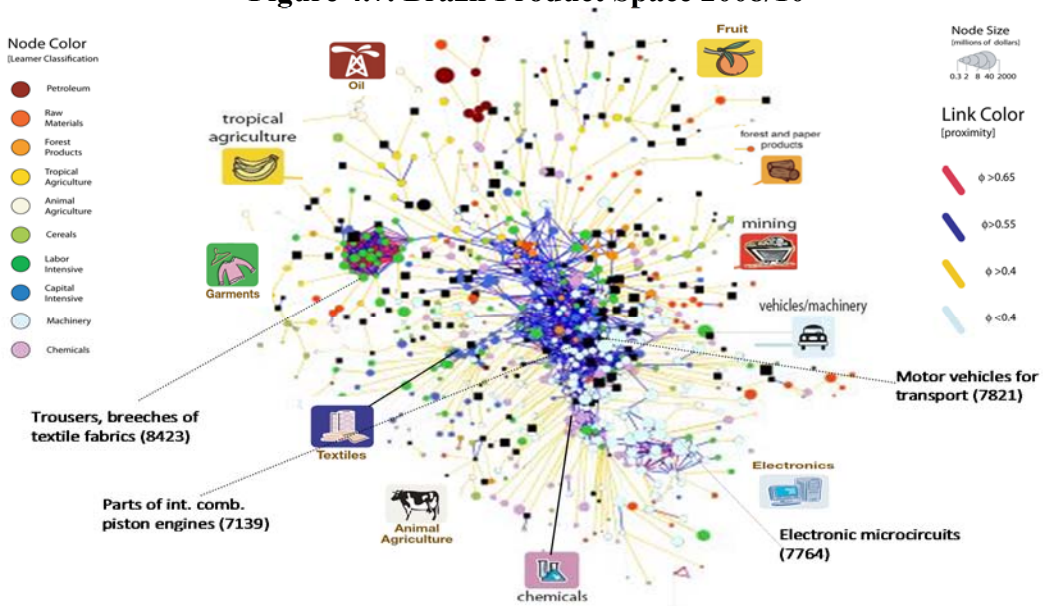
In the following, we evaluate in detail the patterns of specialization within manufacturing observed in Latin American countries. These help explain country-specific specialization trends potentially leading to either declining labor shares or slow productivity growth.

The structural transformation that took place in Latin America's manufacturing sector is analyzed in detail through the lens of analyzing the evolution of export specialization patterns. We use the product space to capture the evolution of Latin America's manufacturing. Despite some

[85] We note that Peru, Chile, and Brazil are estimated to have benefitted from manufacturing convergence since we assumed the same convergence rate of 2 percent for all countries. Table 4.1**Error! Reference source not found.** shows, however, that this assumption is rejected in the data for these three countries. Accordingly, manufacturing convergence terms should have amounted to zero instead ($\beta = 0$ cannot be rejected in the data for these three countries). In turn, Table 4.1**Error! Reference source not found.** shows that the actual speed of manufacturing convergence is estimated to have been higher in Mexico.

notable limitations of the product space analysis (Hidalgo et al., 2007)[86], it is a relevant analytical tool to study the dynamics of the manufacturing sector over the past 15-30 years. The "product space" methodology measures a potential relatedness between production structures among 775 4-digit SITC products. The analysis is based on export data at the 4-digit product level from the Comtrade database. The data are pooled for the corresponding three year periods (e.g., 2008-2010) to minimize the impact of yearly outliers in export values. The product space is a graphical representation of the relatedness between every pair of the 775 4-digit SITC manufacturing products whereby distances between two products represent the similarity between their production structures. Figure 4.7 illustrates the product space for Brazil.

Figure 4.7. Brazil Product Space 2008/10



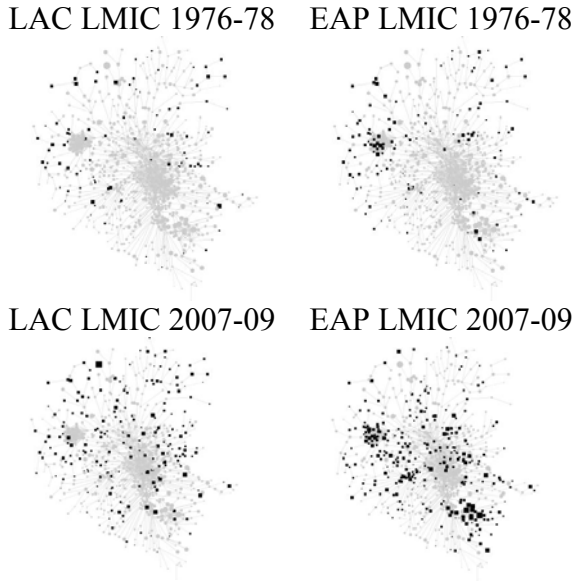
Source: Authors' calculations.

The comparison with the evolution of the production structures in East Asia reveals a lack of cluster formation among related manufacturing products or industries in Latin America. The findings are summarized in Figure 4.8. which illustrates the product space among lower middle income countries (LMIC) of Latin America and East Asia Pacific (EAP) today and 30 years ago. In particular, the product space reveals the existence of a densely connected industrial core (center) and several peripheral clusters, e.g., garments (left), textiles, or electronics (lower right). Modern manufacturing clusters are typically located in the core (e.g., vehicles, machinery, or chemicals) or the bottom (electronics cluster). Products in which a country has a (revealed) comparative advantage (in exporting) are depicted as "black squares". Figure 4.8. shows that LMIC countries in Latin America succeeded in developing a relatively diversified manufacturing base over the last 30 years. Nevertheless, peripheral agricultural and natural resource related products still make up the majority of revealed comparative advantages. Moreover, Figure 4.8. suggests that Latin America did not

[86] The product space analysis depends on a number of limiting assumptions. Trade data is only a proxy for the productive structure of an economy, and in some cases can substantially deviate from actual sectoral contributions to GDP. In addition, Lederman and Maloney (2012) highlight that there can be a substantial degree of heterogeneity in technology content of products even at the 4-digit level.

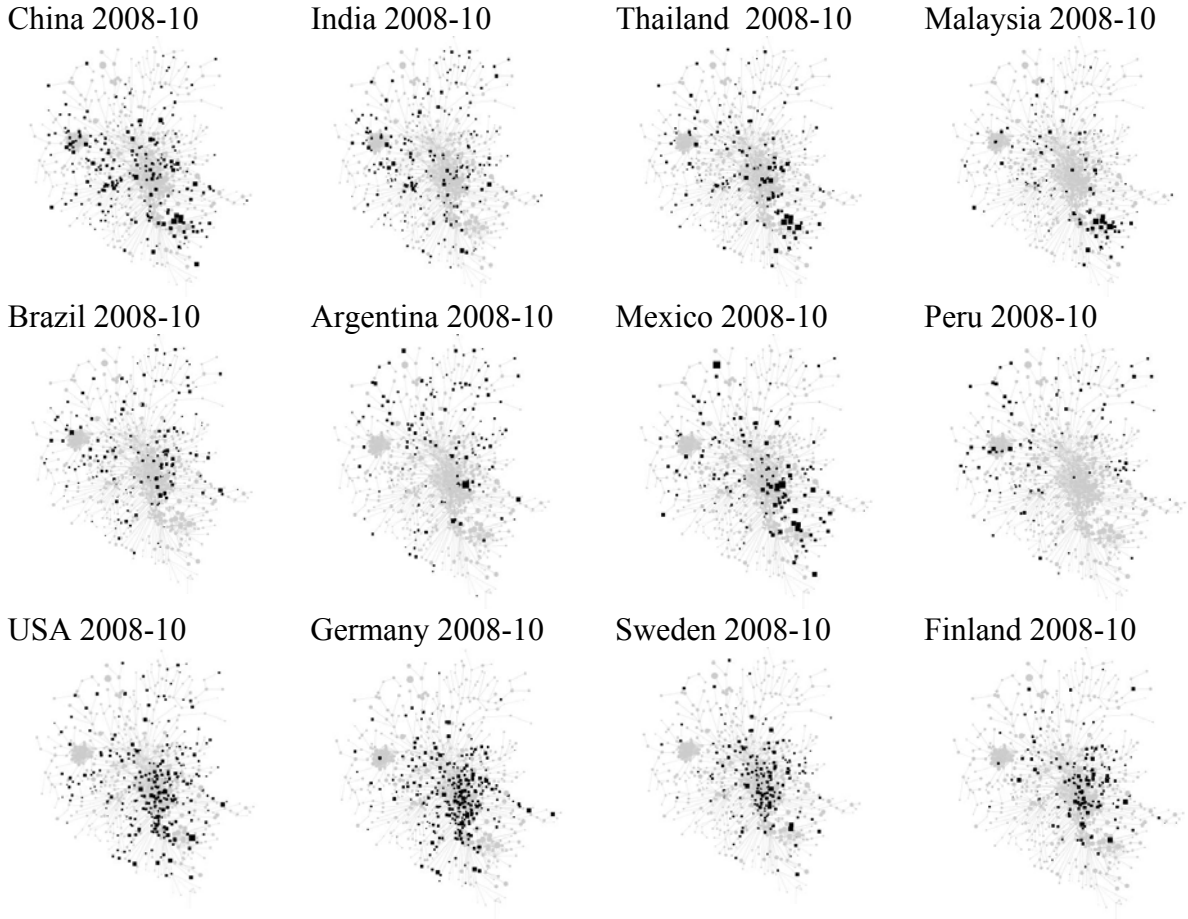
develop major industrial manufacturing clusters at this aggregate regional level. This contrasts with the development of electronics, machinery, or car parts clusters in East Asia. Figure 4.9 confirms the lack of cluster formation among related products or manufacturing sub-sectors for the largest Latin American countries; however, Mexico appears to differ from this pattern. In the following, we analyze the evolution of manufacturing production clusters in detail for selected Latin American countries.

Figure 4.8. **Product Space for Latin America and East Asia, 1976-78/2007-09**



Source: Authors' calculations.

Figure 4.9. Product Space for selected emerging Asian economies, Latin America and selected high income countries, 2008-10

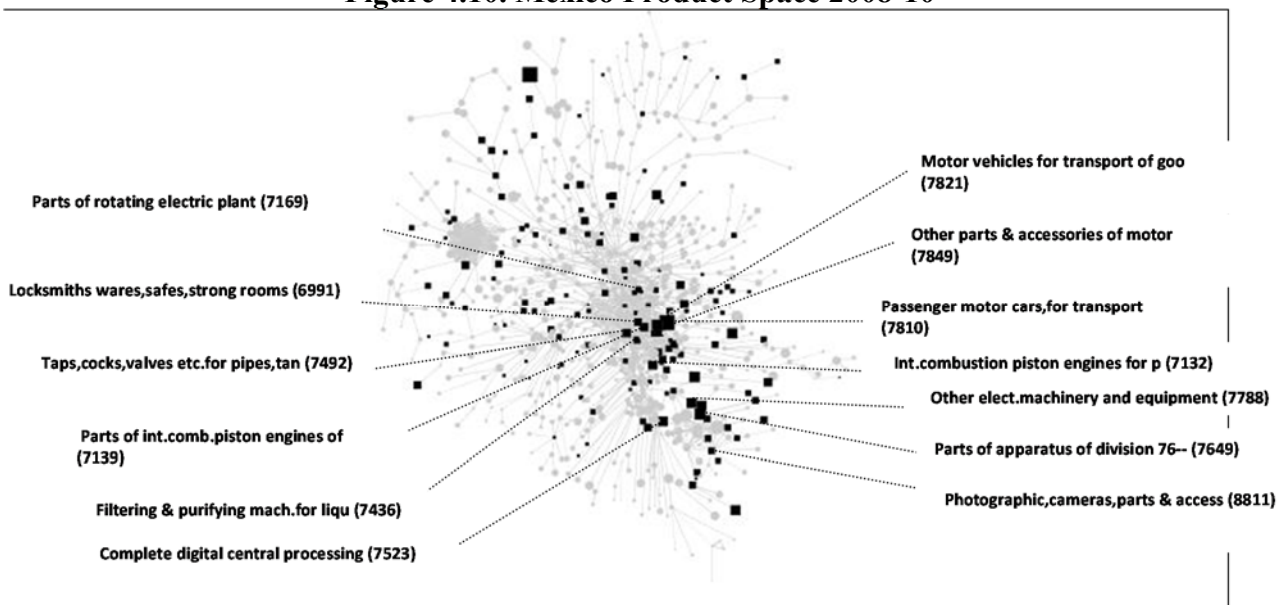


Source: Authors' calculations.

The product space for Mexico reveals the formation of automobile as well as machinery and transport equipment industrial clusters (i.e., car parts). Mexico gained competitiveness in the machinery and transport equipment industry. As of 2008-10, Mexico has a revealed comparative advantage in a number of product classes in the core of the product space (Figure 4.10) such as the machinery and transport equipment industry and the electronics (52 RCAs). Those are mostly medium technology engineering products (MT3, based on a classification from Lall, see Table 4.2) and electronics (HT1); in addition, the country displays a significant comparative advantage for automotive products (MT1) such as *passenger motor cars* (7810) and *motor vehicles for transport of goods* (7821). Many of the products in the core, which Mexico successfully exports, are also successfully exported by the US (or at least closely related to products with RCA in the US). This suggests that some of the products with RCA in Mexico in potentially higher technology sectors such as automobiles and electronics could be merely assembled in Mexico and re-exported to the US. In fact, the formation of automobile and electronics clusters in Mexico is closely related to FDI of several U.S. electronics companies as well as major car producers from the U.S. or Germany producing in Mexico. Nevertheless, Figure 4.10 suggests that Mexico developed a domestic car parts industry supplying intermediate goods ranging from tires to motor parts to foreign multinationals (MNEs) operating in the country. That is, once domestic producers manage to satisfy the quality

standards of MNEs in Mexico, they are automatically obtained the accreditation to sell to their intermediate products to all other production facilities of that MNE around the world. As a consequence, Mexico gained revealed comparative advantages in exporting machinery and transport equipment to the rest of the world. Notably, Argentina also developed an export cluster in *passenger motor cars* (7810). However, Figure 4.9 illustrates that Argentina did not develop similar production clusters in related upstream supplying industries so far.[87]

Figure 4.10. Mexico Product Space 2008-10



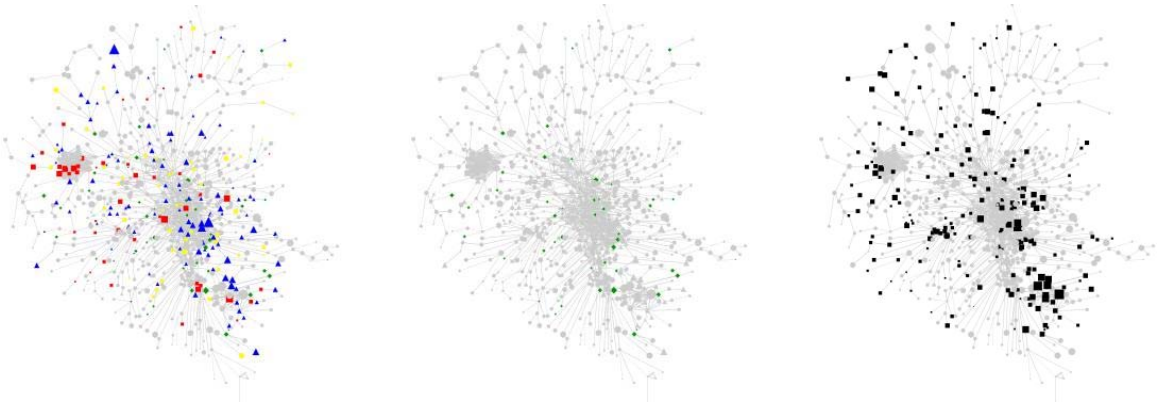
Source: Authors' calculations.

The dynamic representation of the product space (Figure 4.11) reveals that Mexico already successfully exported automobiles, electronics, and several machinery and transport equipment products in 2000/02 while several new export successes emerged in these clusters until 2008/10. Figure 4.11 shows the dynamic representation of Mexico's product space over the last decade. We distinguish between four different categories of products. First, "classics" refer to products that have RCA in 2000-02 as well as 2008-10 and are represented by a "blue triangle". Second, "disappearing" reflect a RCA in 2000-02 but not in 2008-10; red square. Third, "Emerging" shows RCA in 2008-10 but not 2000-02; green diamond. Finally, "marginals" reflect products where Mexico has not yet acquired a RCA (0.5<RCA<1) but experienced positive export growth (of 10 percent or higher) since 2000-02; yellow pentagon. Figure 4.11 (left) reveals that Mexico lost export competitiveness in several products in the garments cluster. At the same time, the country maintained RCAs in exporting automobiles, electronics, and several machinery and transport equipment products. Moreover, Figure 4.11 (middle) highlights that additional export successes emerged among in related products within these product classes (in the core of the product space) since 2000-02 including *complete digital central processing* (7523) or *internal combustion piston engines* (7132). Although, the long term picture points to a successful structural transformation of Mexico's

[87] However, Argentina recently gained RCA in exporting radio-broadcast receivers for motor vehicles (7621). Other recent export successes emerged In Argentina in the densely connected core of the product space include dairy machinery (7213), agricultural & horticulture machinery (7211), polyamides (5824), chemical products and preparations (5989), transmission, conveyor/elevator belt (6282), or photographic film (8822).

manufacturing productive capabilities from resource-based products to automobiles and machinery, the picture relativizes when comparing Mexico's product space with Thailand (Figure 4.11, right). That is, Thailand developed twice as many new RCAs than Mexico since 2000/02. In particular, Thailand managed to successfully expand the number of new products with RCAs in the electronics cluster while Mexico lost some competitiveness in electronics (as indicated by the red squares). Overall, however, the strong export growth of manufacturing clusters in the core of the product space in Mexico is consistent with the findings in section 4.1 which revealed a higher manufacturing convergence rate than in the rest of the world.

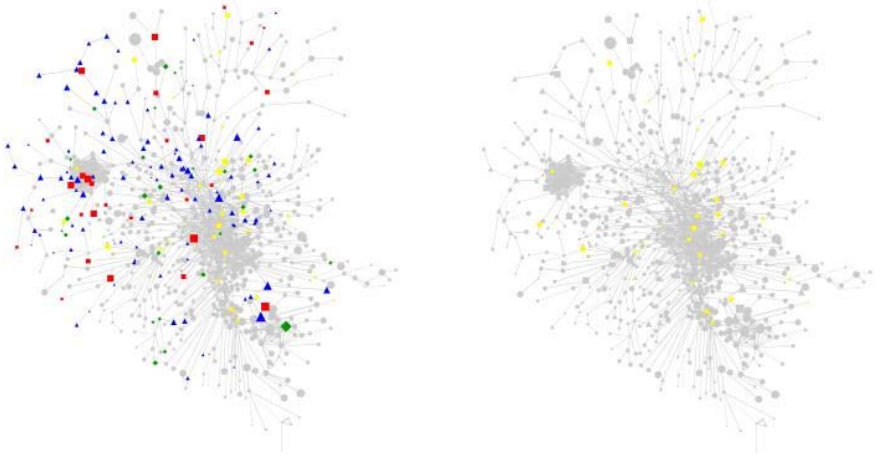
Figure 4.11. Mexico Dynamic Illustration 2000-10 (left), Emerging 2000-10 (middle), Thailand 2008-10 (right)



Source: Authors' calculations.

Costa Rica's economy is fairly diversified with export successes ranging from garments, food, or base metal products to car parts, chemicals, or electronics. Figure 4.12 illustrates that Costa Rica has RCAs in several products in the densely connected core of the product space including *medicaments* (5417), *varnishes and lacquers* (5334), *tires* (6251), *internal combustion piston engines* (7131), *parts for office machines* (7599), or *electronic microcircuits* (7764). The strong export growth in the latter two electronic products emerged over the last 20 years and has been triggered by the substantial investment of a foreign MNE (Intel). Moreover, Figure 4.12 shows Costa Rica lost some competitiveness in garments as well as two major products located in the core of the product space (*miscellaneous articles of materials*, 8939 and *other electrical machinery & equipment*, 7788) over the past decade. Figure 4.12 also reveals a large number of marginals; i.e., products with strong export growth since 2000 for which Costa Rica is close in achieving a RCA.

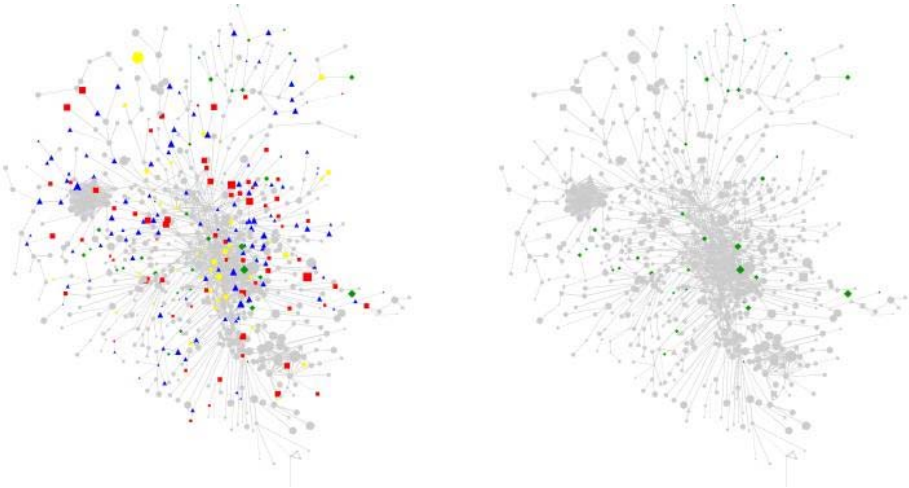
Figure 4.12. Costa Rica, Dynamic Illustration 2000-10 (left), Marginals (right)



Source: Authors' calculations.

The dynamic representation of the product space (Figure 4.13) reveals that Brazil's export basket has shifted over time, but not significantly. Figure 4.13 (left) reveals that Brazil lost export competitiveness in products of various industries located in the core of the product space since 2000-02 including *photographic film* (8822), *television tubes* (7761), *radio receivers of cars* (7621), *cast, rolled, drawn or blown glass* (6644), *optical glass* (6642), *transmission shafts* (7493), *refractory bricks* (6623), *natural or artificial abrasive powder* (6632), *cut to size paper and paperboard* (6424), or *other furniture* (8219). On the other hand, Figure 4.13 (right) highlights the following emerging products in the core of the product space since 2000-02: *motor vehicles for transport* (7821), *road tractors & semi-trailors* (7832), *machinery for sorting, screening & separating* (7283), *larger aircrafts* (7924), or *printing & writing par* (6412). While declining and emerging product categories are scattered across various industries, the recent decline of Brazil's television & photographic as well as glass manufacturing is evident. In contrast, emerging products in automotive and machinery suggest that these industry clusters are expanding and gaining international competitiveness.

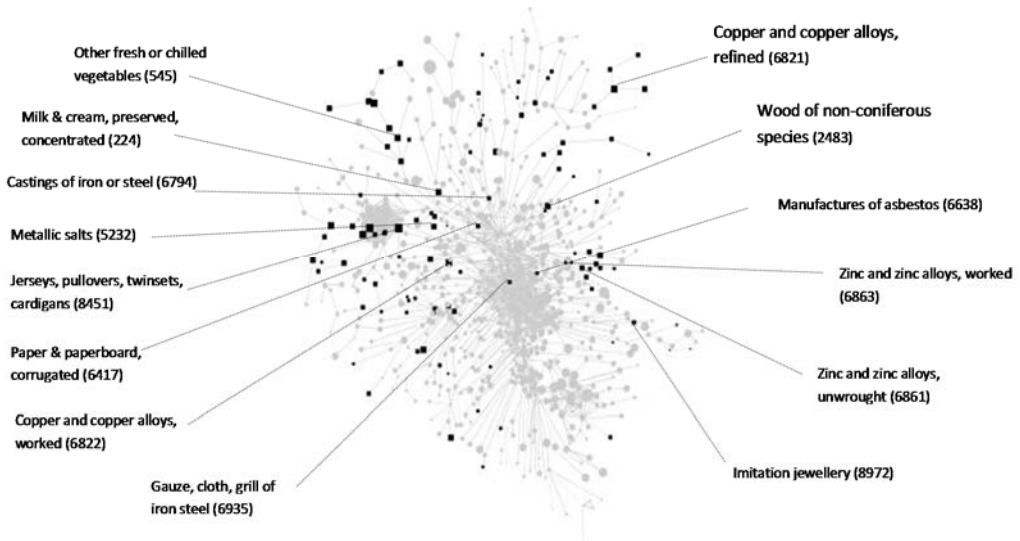
Figure 4.13. Brazil Product Space Dynamic Illustration 2000-10 (left) Emerging 2000-10 (right)



Source: Authors' calculations.

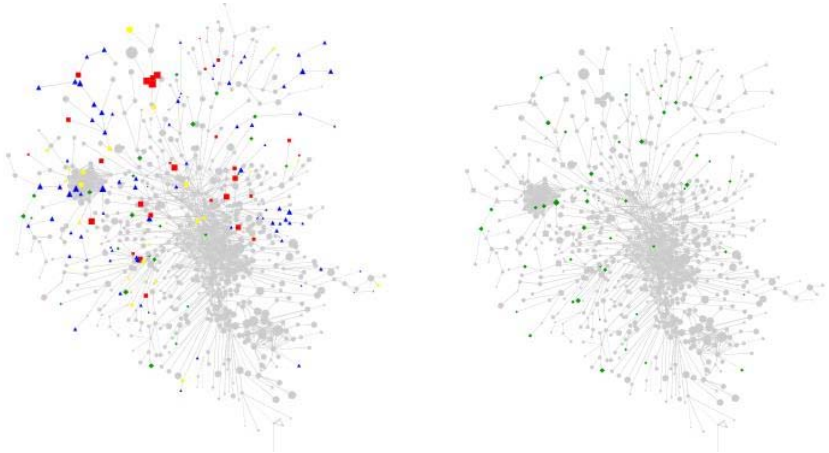
Peru primarily specialized in agricultural, mining, and some garment products. Figure 4.14 illustrates that Peru has RCA in many agricultural and mining based products including *fresh or chilled vegetables* (545), *copper or zinc alloys, metallic salts* (5232), or *manufacturers of asbestos* (6638). The dynamic representation of the product space in Figure 4.15 shows that the export successes in garments emerged in the 1990s. Overall, however, hardly any new products emerged over the past ten years.

Figure 4.14. Peru Product Space RCAs only 2008/10



Source: Authors' calculations.

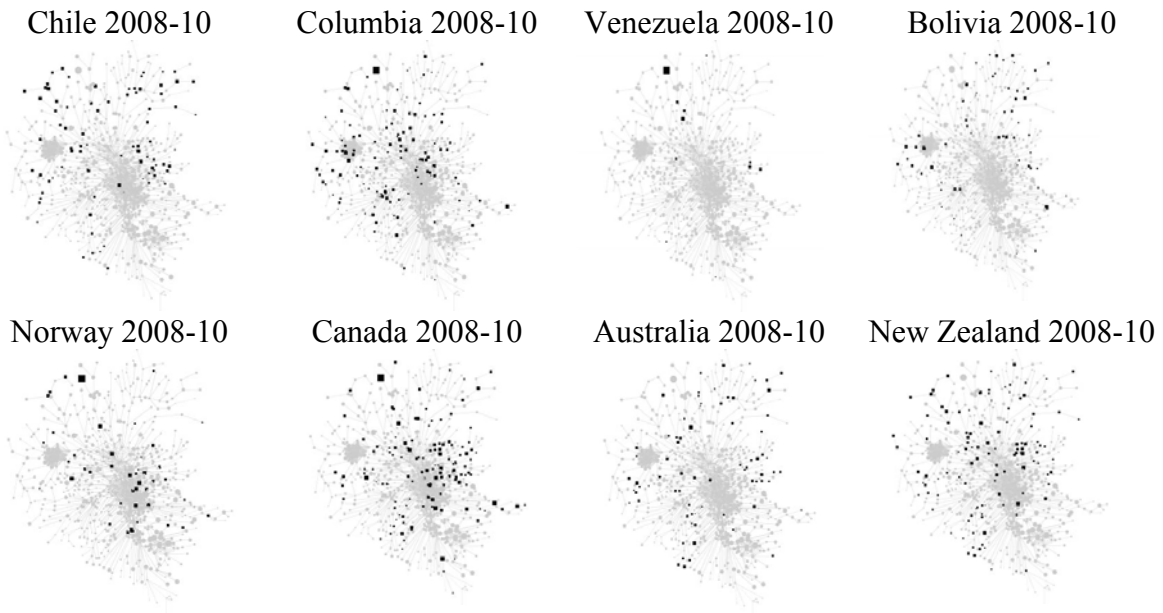
Figure 4.15. Peru Product Space Dynamic Illustration 2000-10 (left), Emerging 1990-10 (right)



Source: Authors' calculations.

Except for Chile, natural resource rich countries in Latin America performed worse in terms of economic growth than other countries that are resource rich in other parts of the world. For example, the product space of Venezuela reflects the dominance of natural resources, in particular petroleum and crude oils. Venezuela's economy is highly concentrated with RCA only in 12 products. While part of the decline in other manufacturing products might stem from a Dutch disease type of effect, a comparison with Norway, Canada, or New Zealand (Figure 4.16.) suggests that other forces might have played a more important role. That is, Norway, Canada, and New Zealand are major exporters of mining products but nevertheless developed a sound manufacturing base.

Figure 4.16. **Natural resource leverage, selected economies, 2008-10**



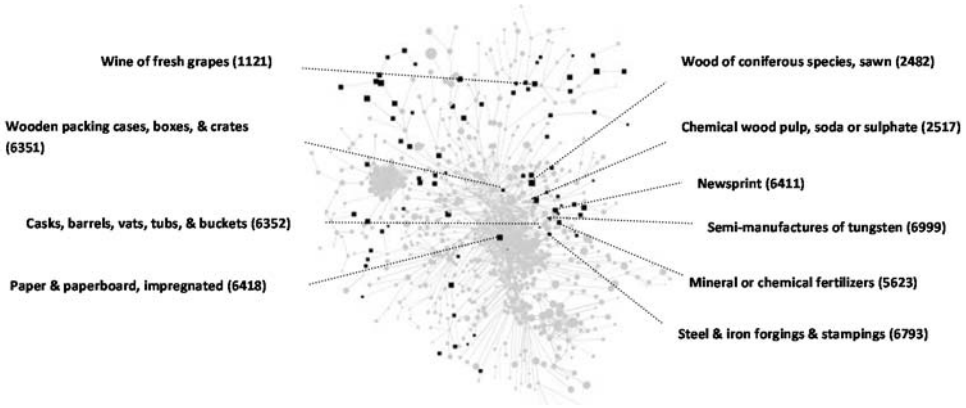
Source: Authors' calculations.

However, it should be stressed that the product space methodology does not imply that sustained growth necessarily requires an expanding manufacturing sector. Chile specialized in products which are typically not in the core of the product space (food processing and mining), having revealed comparative advantage in many agricultural and mining based products. Chile's export basket has barely shifted over the past decade. Moreover, Chile lost comparative advantage in a few manufactured products while hardly any new products emerged which is consistent with the decline in the manufacturing labor share as well as the stagnant productivity growth in Chile identified in Section 4.1. These developments, however, did not preclude strong economic growth over the last decade, suggesting an example of advancement from low to (higher) middle income levels without a strong manufacturing base in the core of the product space. This means that there is not necessarily a "unique" economic structure suitable for growth. In addition, the historical experience of Canada, Sweden and Finland shows that diversification into non-resource industries from a strong resource base is possible.[88] Similarly, Columbia's manufacturing sector is concentrated in natural resource-based products (e.g., crude oil, paper products) and several

[88]Lederman, D. and W. Maloney (2012).

garments & textile products; over the last 20 years, however, the country started to successfully export some chemicals as well as car parts.

Figure 4.17. Chile Product Space 2008-10



Source: Authors' calculations.

Primary and resources- based products are still dominating Latin America's exports. We use the classification of Lall (2000), presented in Table 4.2 to classify countries' exports into primary, resources-based, low, medium, and high technology products. Table 4.3 (classics category) shows that exports of primary and resources-based products account for the lion share of manufacturing exports among Latin American countries. In fact, their importance has been increasing between 2005 and 2009 (see emerging category, Table 4.3). For instance, 60 percent of all products in which Brazil has a RCA are primary and resource-based products (Table 4.3). The products in which Latin American countries are about to gain a RCA (i.e., marginal category) is populated by products that are either primary, resource-based, or low technology except for Costa Rica.

Table 4.2. Commodity Technology Classification

PP		**Primary Products**
RB		**Resource-based Manufactures**
	RB1	Resource-based Manufactures: Agro-Based
	RB2	Resource-based Manufactures: Other
LT		**Low Technology Manufactures**
	LT1	Low Technology Manufactures: Textiles, Garment and Footwear
	LT2	Low Technology Manufactures: Other Products
MT		**Medium Technology Manufactures**
	MT1	Medium Technology Manufactures: Automotive
	MT2	Medium Technology Manufactures: Process
	MT3	Medium Technology Manufactures: Engineering
HT		**High Technology Manufactures**
	HT1	High Technology Manufactures: Electronic and Electrical
	HT2	High Technology Manufactures: Other

Source: Authors' calculations.

Table 4.3. PRODY[89], PATH and Technological Sophistication

	TOTAL	PP	RB1	RB2	LT1	LT2	MT1	MT2	MT3	HT1	HT2	Average Prody 0509	Average Path 0509	export share 2009 (in percent)
CLASSICS				(RCA05>=1, RCA09>=1)										
Argentina	134	54	33	14	6	2	2	17	2		1	13,112	124	70.1
Brazil	137	36	29	17	8	8	4	18	12	2	3	12,874	122	67.1
Chile	75	28	23	12		4		7				13,010	118	89.8
Colombia	87	14	11	12	15	12		15	3	1		12,674	131	80.5
Costa Rica	95	19	24	4	8	15		12	7	3	2	13,007	133	88.0
Mexico	117	17	8	10	7	19	4	10	25	13	3	15,094	134	73.2
Peru	91	36	11	18	11	7		7				10,075	119	89.4
Venezuela	11	3		2		3		3				12,820	111	96.6
EMERGING				(RCA05<1, RCA09>=1)										
Argentina	16	2	4	1			2	2	4		1	18,222	132	9.9
Brazil	20	9		3	1	1		2	3	1		13,060	127	3.6
Chile	12	5	3	3								12,703	120	1.1
Colombia	31	9		6	7	3		2	3		1	14,155	135	4.7
Costa Rica	18	7	3	2	1	3		1		1		13,349	126	2.0
Mexico	32	6	6	4	1	2		3	6	2		15,074	130	6.6
Peru	17	4	2	2	5	2		1				11,421	116	1.4
Venezuela	4	1		1		1		1				16,329	124	0.4
MARGINALS				(RCA05<1 or RCA05=. , 0.5<RCA09<1 and RCAgrowth>= 10 percent)										
Argentina	9	2	2	1	1				2	1		16,339	140	0.3
Brazil	12	5	1	1		1		1	2	1		17,592	125	7.5
Chile	12	3	2		2	3		1	1			12,353	134	0.4
Colombia	13	3	2	1		2		1	4			14,225	124	1.4
Costa Rica	9		1	2	1				3		2	19,468	132	0.3
Mexico	24	3	5	3	2	3	1	5	2			13,828	120	1.2
Peru	14	2	3	1	1	4		2	1			12,914	132	0.8
Venezuela	2	1		1								6,967	95	0.4
DISAPPEARING				(RCA05>1, RCA09<1)										
Argentina	27	2	5	5	2	4	1	4	2	1	1	15,170	125	2.4
Brazil	58	8	10	8	3	7	2	6	11	3		15,806	123	5.8
Chile	16	4	3	2	1			2	4			13,201	120	0.5
Colombia	41	12	8	1	6	5		4	1			11,046	130	2.9
Costa Rica	37	6	6	3	8		3	3	5	2	1	12,582	125	1.7
Mexico	44	2	5	3	11	5		4	2	10	2	14,155	128	5.2
Peru	17	2	2	4	2	3		2	1			12,352	129	1.3
Venezuela	19	3	3	5	1	3		3	1			15,702	118	0.9

Source: Authors' calculations.

Does the lack of specialization away from primary or resource-based manufacturing products in many Latin American countries matter?

4. 3. Export quality and Knowledge Spillovers

[89] PRODY is used as a proxy for the capabilities embedded in a product. However, there are some limitations to using PRODY since High income countries export natural resources resulting in high PRODY values for certain goods not necessarily representative of the capabilities required for production.

"How" goods are produced can often matter more for economy-wide productivity than in which sectors they are produced (Lederman and Maloney, 2012). Identical goods can be produced at very different levels of sophistication and with very distinct long-term impacts on growth. That is, within each industry, the sophistication and novelty of the production process and potential for productivity growth matter.[90] For example, while South Korea and Mexico have reached a similar degree in manufacturing export sophistication, the manufacturing share of value-added in Mexico was declining until recently, while it has been rising continuously in South Korea.[91] Moreover, the lack of technology absorption capacity in Chile at the turn of last century did not allow its copper industry to increase productivity to the degree it did in the US, with wide-ranging externalities to the rest of the economy.[92]

The following analysis suggests that "what" and "how" countries' produce might be correlated. The scope for learning and foreign knowledge and technology spillovers might itself depend on the specific product or industry. In fact, Cai and Li (2012) show that production technologies differ in the extent to which they are more or less widely applicable across products or industries. That is, some knowledge can be more readily adapted to be used in related production processes while other knowledge is limited in its scope of application. The authors find that U.S. firms using more applicable technologies are more likely to innovate. Thus, products or industries embodying more applicable technologies also embody a larger scope for knowledge spillovers. Primary and resource-based products might in fact embody less scope for knowledge spillovers as their production processes and embodied technologies are more idiosyncratic and thus less widely applicable. In the following, we analyze if Latin American countries tend to be specialized in less widely applicable technologies and production processes using a quantitative measure of the "knowledge applicability" developed by Cai and Li (2013). The measure is based on patent citation data and can be aggregated to the country level measuring a country's knowledge composition.

Latin America as a region appears to be less specialized in industries with high knowledge applicability. Cai and Li (2013) developed for each industry a quantitative measure of *knowledge applicability*. The authors use the 2006 patent citation database, provided by U.S. Patent and Trade Office (USPTO), to trace the direction and intensity of knowledge flows within and across technological classes which allows constructing indices of knowledge applicability for each industry. This measure is aggregated to the country level based on using countries' export structure to create industry weights. Cai and Li (2013) find that countries with a higher knowledge applicability index experience higher subsequent economic growth.[93] Figure 4.18 summarizes one

[90] Lederman and Maloney (2012) also highlight that there can be a substantial degree of heterogeneity in technology content of products even at the 4-digit level. For instance, a country that successfully exports microchips might host high-tech firms engaging in R&D and product design or low tech firms simply assembling the microchips without adding much value. Therefore, detailed sector case studies or value chain analysis would be necessary to supplement the analysis.

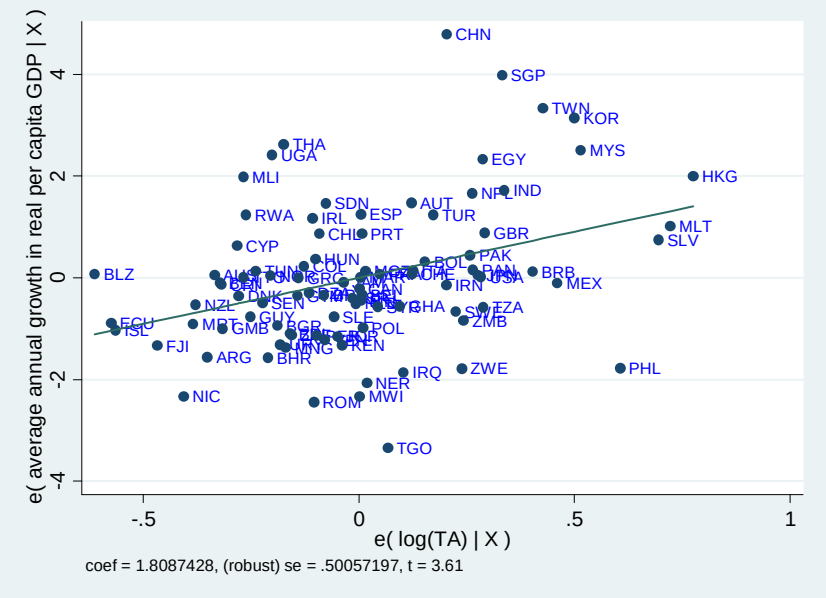
[91] See Jankowska, Nagengast and Perea (2012).

[92] See Wright and Czelusta (2006).

[93] The applicability of a country's knowledge portfolio (revealed through its exports) indeed predicts its subsequent growth. Cai and Li (2013) find that the coefficients on log (TA) are always positive and highly significant across all specifications, suggesting that specializing in sectors with large knowledge spillovers brings growth in the future. The size of the estimated effect is large. The estimated coefficients vary from 1.1 to 4.7, implying that a ten percent increase in log (TA0), which is approximately what Thailand achieved between 1975 and 1980, on average enhances a country's subsequent growth by 1/4 percent per year. In addition, all the other initial control variables have the correct signs.

of their main finings. It demonstrates that countries that initially specialize on exporting goods that embody highly applicable knowledge experience higher subsequent growth.

Figure 4.18. Average annual per capita GDP growth and log (TA).



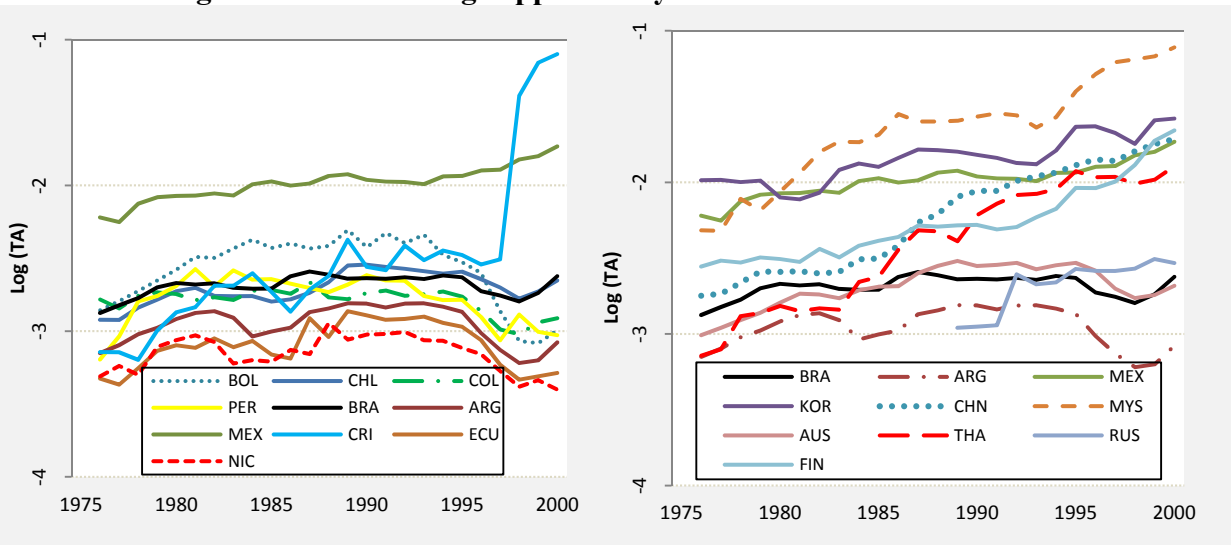
Source: Authors' calculations.

Despite substantial heterogeneity across countries, production structures in most countries in Latin America imply low knowledge applicability. Figure 4.19 represents the time trends for the knowledge applicability indices (*log(TA)*) for a sample of 17 countries. It shows that China's and Thailand's export knowledge applicability has been growing steadily, rapidly converging to the index levels for South Korea and the U.S. over the past decades. In contrast, the exports baskets of most Latin American countries imply lower knowledge applicability in their embodied technologies. Thus, they are less specialized in sectors with high knowledge applicability. The exceptions are Mexico and Costa Rica (due to the strong growth of electronics exports after the entry of Intel in the mid-1990s). Both countries' knowledge applicability of their production structures are relatively high and have been rising since 1990. This finding is consistent with our results in Section 1 showing that manufacturing labor productivity converged unconditionally in both countries. Moreover, Section 2 showed that both countries are the least specialized in primary and resource-based goods in the region. In contrast, Nicaragua, Ecuador, Argentina, Peru, and Columbia, which are all specialized in primary and resource-based goods, have the lowest knowledge applicability index. Noteworthy, the knowledge applicability embodied in Chile's export basket has been rising until late 1990s and is higher than that of most other Latin American countries.[94]

Notably, initial investment to GDP ratio, export diversification and openness do not seem to enter in a robustly significant way, and including institutional quality does not affect much the significance of log initial TA either.

[94] This result is quite different from the measure of export sophistication developed in Hausman et al. (2007).

Figure 4.19. Knowledge applicability over time for selected countries



Source: The Composition of Knowledge and Long-Run Growth In a Path-dependent World, Jie Cai and Nan Li (2013).

4. 4. Conclusions and Potential Policy Implications

The findings of this paper suggest that structural change in LAC has often been accompanied by some degree of resource misallocation or inefficient resource use. Three distinct, but related phenomena affecting countries in the region deserve particular attention: (i) structural change accompanied by decreased economy-wide value-added per worker; (ii) manufacturing productivity growth below the world average; and (iii) the presence of idiosyncratic production structures.

First, in contrast to East Asia, the contribution of structural change to growth in value-added per worker in Latin America has been small and even negative in some countries. More specifically, an increase in the employment shares of lower productivity sectors seems to have been the prevalent pattern across the LAC countries in recent decades. This phenomenon may be one factor behind the limited income convergence observed with respect to richer countries.[95] It should be borne in mind, however, that in many instances high "within sector" value-added per worker growth compensates for the adverse structural change effect.

Second, average manufacturing productivity growth in Latin America was significantly lower than the worldwide average. Therefore, the region seems to have benefited less than others from the phenomenon of unconditional convergence in manufacturing. Two caveats are in order, however: (i) there is significant variation across countries in the region; and (ii) some service sub-sectors are acquiring manufacturing-like characteristics, which may propel them to display unconditional convergence properties as well. Thus, it is not all about manufacturing, but rather "modern" economic activities which are subject to the forces of competition and exposed to incentives to innovate.

[95] Silva and Ferreira (2013) argue that low growth in the tertiary sector explain much of the divergence between LAC and the US after 1980.

Third, idiosyncratic production structures may be limiting Latin American firms' ability to absorb or imitate more productive foreign technologies. That is, the region appears to have specialized in technologies that are not well connected or "idiosyncratic". This can be seen through the analysis of both the product spaces and the knowledge applicability of a country's technology. However, there is not a one-to-one relationship between the results of the two methodologies: while Chile shows a lack of specialization in products within the core of the product space, its degree of knowledge applicability is among the highest in the region.

Those findings highlight the difficulty in clearly separating the effects of two competing explanations of low TFP growth in Latin America: resource misallocation versus delays in technology adoption. At the sector level, structural change may be related to inefficiencies in the allocation and reallocation of resources in many of Latin Americas' economies. At a more disaggregated level (e.g., through the product space and knowledge applicability analyses), technology adoption patterns emerge as a potentially important explanatory factor. Ultimately, it might not be possible to completely disentangle misallocation effects from technology adoption effects since the misallocation of resources may itself be affecting the pace of technological diffusion in the region.

Whereas manufacturing has some special characteristics, it does not follow that reversing the decline of manufacturing labor shares should be a development policy goal. To jump from the empirically observed phenomenon of unconditional convergence in manufacturing to an assertion that deindustrialization would have to be reversed somehow is a *non sequitur*. The reason is twofold. First, reversing the decline in manufacturing is not costless. Not only the potential benefits, but also the costs, of undertaking this kind of economic reengineering would need to be assessed. Second, as mentioned above, certain subsectors within the services sector are becoming tradable and as such are potentially also subject to unconditional convergence.

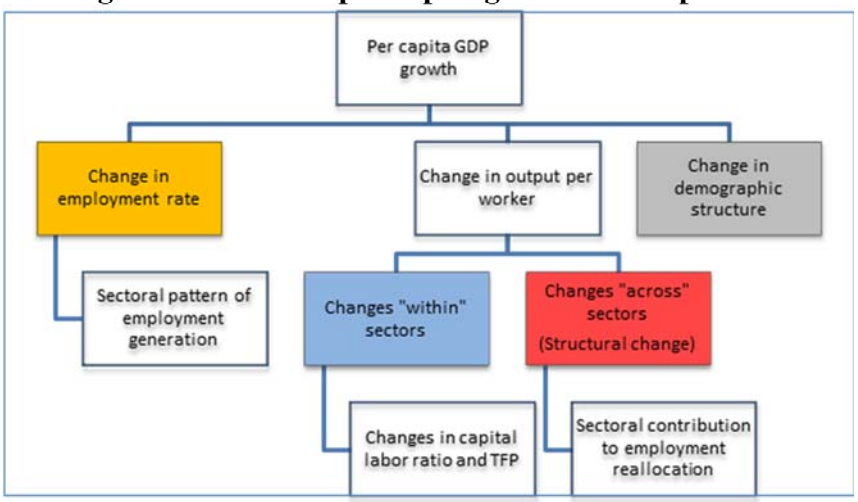
Perhaps the main implication from the results reported here is that searching for an "optimal economic structure" is futile and that a more sensible approach would be to look for productivity growth opportunities across different sectors. In other words, instead of attempting to unduly protect existing manufacturing activities and preventing it from shedding labor, the key policy goals should involve (i) lifting productivity levels in lagging sectors that are absorbing labor; and (ii) upgrading skills across the board so that newly-unemployed workers can find jobs in more productive sectors that could potentially absorb labor.

4. 5. Appendix

4. 5. 1. Structural change

GDP per capita growth can be decomposed into the following components as illustrated in Figure A4.20.: a) change in employment rate, b) change in demographic structure and c) change in labor productivity.

Figure A4.20. GDP per capita growth decomposition



Source: Authors' calculations.

Labor productivity can be further decomposed into two additional components: changes in sector level productivity ("within" component) and changes arising from a re-allocation of labor between sectors ("structural change" component). Following Pages (2010) and McMillian and Rodrik (2011) this can be written as:

$$\Delta Y_t = \sum_{i=n} s_{i,t-k}\, \Delta y_{it} + \sum_{i=n} y_{i,t}\, \Delta s_{it} \qquad \text{(A.1)}$$

where ΔY_t is the change in aggregate labor productivity between *t* and *t-k*, s_{it} is the employment share in sector *i* at time *t* and y_{it} is the productivity level in sector *i* at time *t*. The first term is the "within" component and the second term the "structural change" component. Alternatively, the decomposition can be conducted using the Shapley decomposition as follow:

$$\Delta y_t = \sum_{i=n} \frac{s_{i,t}+s_{i,t-k}}{2} \Delta y_{it} + \sum_{i=n} \frac{y_{i,t}+y_{i,t-k}}{2} \Delta s_{it} \qquad \text{(A.2)}$$

whereby the main difference is that the Shapley decomposition assigns to each factor the average marginal contribution rather than the contribution of a specific year.

4. 5. 2. Marginal productivity of labor

The above analysis of structural change has been based on average productivity. To pass judgment on whether this change was welfare improving and growth promoting, however, would

require a more in-depth analysis.[96] One important step in this direction is to look at marginal productivity across sectors. Under perfect competition, marginal labor productivity – not average productivity – should be equalized across sector. Assuming a constant returns production function, since labor share are not necessarily negatively correlated with average productivity, large gaps in average productivity may reflect large gaps in marginal labor productivity. There are some caveats though. For example, high average labor productivity in capital-intensive sectors, such as mining, may simply reflect that the labor share is low.

The marginal productivity of labor can be calculated by estimating the labor share of income. Using World Bank I2D2 data, we calculated the income share of labor using wage data for Peru and Chile, the only two countries with reliable wage data.[97] In a perfectly competitive market, wages equal the marginal product of labor. Labor markets are often not perfectly competitive, for example, in the presence of unionization or indexed contracts. Moreover, in many developing countries some workers, such as those in the agricultural sector household employees are only paid partially in wages. Finally, using wages to calculate labor's share of income automatically leads to an exclusion of self-employed. To eliminate biases arising from unobserved heterogeneity, the data is narrowed down to a sub-set of workers. The marginal labor productivities are calculated for single males aged 30-34 years with elementary education. The wage data is adjusted for the rural-urban price differential.

Gaps in marginal productivities measured by average wages across sectors are smaller than gaps measured by value added per worker, but sectoral differences remain significant. In Chile in 1990, the gap between the highest productivity sector (public utilities) and the lowest productivity sector (agriculture) was twelve, while the difference in raw wages between the minimum (agriculture) and maximum (public utilities and finance) wage was three. The difference becomes even smaller when controlling for individual characteristics, shrinking to 1.8. This gap has remained almost constant in Chile between 1990 and 2003. That is, in 2003, an individual with the same characteristics and education would have earned nearly 1.7 half times more if she would have moved from community services (the lowest wage sector) to mining (the highest wages sector). In Peru in 1999, the gap between the highest productivity sector (public utilities) and the lowest productivity sector (agriculture) was 23, while the difference in wages after controlling for individual characteristics between the minimum (community services) and maximum (mining) wage was 2.8. In 2005, the difference in wages after controlling for individual characteristics between the minimum (agriculture) and maximum (mining) sector increased slightly to 2.9.

[96] Not all structural change is good. For example, productivity may be higher in sectors with monopoly power. A reallocation to these sectors would contribute positively to structural change but would not necessarily promote growth or enhance welfare (for a more detailed discussion, see Maloney 2012).

[97] See also McMillan (2013) "Measuring the Impact of Structural Change on Labor's Share of Income," unpublished manuscript.

Table A4.4. Estimates of Labor's Share and Marginal Productivities using harmonized household survey data from the World Bank (I2D2)

				Value added per capita		Average wages (raw differences)[3]		Average wages (controlling for individual characteristics)[1, 3]		Average wages (controlling for individual characteristics)[2, 3]		
Country	Year	Sector	Code	In 2005 PPP dollars	Employment Share	In 2005 PPP dollars	Implied Labor Share	In 2005 PPP dollars	Implied Labor Share	In 2005 PPP dollars	Implied Labor Share	% of Labor force in paid employment
Chile	1990	Agriculture	agr	5,546	18.1%	2,837	51.2%	2,716	58.0%	2,699	58.0%	66.4%
		Mining	min	37,973	3.0%	7,329	19.3%	4,097	21.1%	4,096	21.1%	87.9%
		Manufacturing	man	17,688	17.5%	4,476	25.3%	2,965	27.1%	2,943	27.1%	79.0%
		Public utilities	pu	68,697	0.6%	8,322	12.1%	3,526	14.4%	3,509	14.4%	97.4%
		Construction	con	19,918	7.4%	4,479	22.5%	3,033	24.3%	3,011	24.3%	69.6%
		Commerce	wrt	9,226	17.1%	3,913	42.4%	2,528	44.7%	2,511	44.8%	51.7%
		Transports and communications	tsc	13,610	6.8%	5,013	36.8%	2,877	38.8%	2,861	38.9%	72.2%
		Financial and business-oriented services	fire	31,700	4.9%	8,334	26.3%	3,718	32.0%	3,687	32.0%	81.7%
		Community and family-oriented services	cspsgs	12,159	24.8%	5,304	43.6%	2,309	49.2%	2,293	49.2%	90.3%
	2003	Agriculture	agr	12,484	11.2%	3,539	28.4%	2,897	33.4%	3,028	33.3%	68.0%
		Mining	min	147,720	1.3%	11,637	7.9%	4,848	9.5%	5,076	9.5%	92.5%
		Manufacturing	man	30,341	12.4%	5,664	18.7%	3,092	22.1%	3,236	22.1%	75.5%
		Public utilities	pu	111,641	0.6%	7,864	7.0%	3,626	8.2%	3,788	8.1%	95.6%
		Construction	con	22,529	8.5%	5,655	25.1%	3,254	30.0%	3,407	30.0%	68.4%
		Commerce	wrt	11,795	21.7%	4,819	40.9%	2,896	61.3%	3,031	61.4%	58.3%
		Transports and communications	tsc	25,043	7.6%	6,033	24.1%	3,077	28.2%	3,218	28.2%	71.6%
		Financial and business-oriented services	fire	26,428	11.4%	8,132	30.8%	3,347	40.0%	3,501	40.0%	81.0%
		Community and family-oriented services	cspsgs	13,438	25.3%	7,525	56.0%	2,797	65.1%	2,925	65.1%	90.8%
Peru	1999	Agriculture	agr	3,807	33.0%	2,087	54.8%	2,990	93.7%	3,100	93.8%	17.6%
		Mining	min	80,849	0.9%	7,746	9.6%	6,462	10.0%	6,707	10.0%	90.1%
		Manufacturing	man	19,622	10.2%	3,518	17.9%	3,075	19.8%	3,172	19.7%	52.9%
		Public utilities	pu	89,894	0.3%	5,390	6.0%	3,062	8.0%	3,164	7.9%	81.1%
		Construction	con	25,209	3.0%	4,120	16.3%	3,546	19.8%	3,661	19.8%	67.0%
		Commerce	wrt	11,770	21.3%	3,352	28.5%	3,014	30.5%	3,114	30.5%	25.2%
		Transports and communications	tsc	19,610	5.6%	6,052	30.9%	4,389	36.2%	4,572	36.4%	44.1%
		Financial and business-oriented services	fire	27,718	4.9%	5,917	21.3%	3,334	27.9%	3,450	28.0%	66.1%
		Community and family-oriented services	cspsgs	10,225	20.7%	4,809	47.0%	2,287	48.5%	2,366	48.5%	79.9%
	2005	Agriculture	agr	4,347	34.1%	1,587	36.5%	2,107	50.5%	2,223	50.7%	17.4%
		Mining	min	90,987	1.2%	8,217	9.0%	6,070	10.0%	6,362	10.0%	89.3%
		Manufacturing	man	26,104	9.7%	3,512	13.5%	3,037	13.9%	3,208	13.9%	55.2%
		Public utilities	pu	125,931	0.3%	7,095	5.6%	4,079	6.4%	4,286	6.4%	96.8%
		Construction	con	28,100	2.9%	3,185	11.3%	2,800	13.4%	2,954	13.4%	65.7%
		Commerce	wrt	14,504	20.4%	3,101	21.4%	2,770	20.6%	2,922	20.5%	26.0%
		Transports and communications	tsc	24,351	5.5%	4,002	16.4%	2,965	18.0%	3,124	17.9%	40.4%
		Financial and business-oriented services	fire	30,910	4.9%	5,605	18.1%	3,491	22.0%	3,683	21.9%	71.8%
		Community and family-oriented services	cspsgs	11,721	21.0%	4,306	36.7%	2,304	38.4%	2,431	38.4%	82.2%

Source: I2D2.

Notes: * Regression results controlling for urban location, gender, age (6-year intervals), marital status, occupation and education level (no education, primary, secondary and post-secondary). ** Adds household size and number of working members to the previous controls.

4. 5. 3. Manufacturing convergence and reallocation effects

Table A4.5. Predicted aggregate growth rates based on manufacturing convergence and reallocation effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	α	θ_m	$(\ln y^* - \ln y_m)$	Manufacturing growth [βx(3)]	Aggregate convergence term (1)x(2)x(4)	Δ	Predicted aggregate growth (5)+(6)
Brazil	0.0662	3.9088	0.7826	1.58%	0.41%	-0.03%	0.38%
Peru	0.0346	7.2648	0.971	1.96%	0.49%	0.38%	0.87%
Columbia	0.0441	3.7566	1.4963	3.02%	0.50%	-0.79%	-0.29%
Urugay	0.1196	2.3889	1.6237	3.27%	0.94%	-0.57%	0.36%
Ecuador	0.032	3.3488	1.9056	3.84%	0.41%	-0.15%	0.26%
Chile	0.0599	4.3842	0.8962	1.81%	0.47%	0.18%	0.65%
Costa Rica	0.1173	1.123	2.3018	4.64%	0.61%	-0.22%	0.39%
Mexico	0.0398	2.244	1.2578	2.54%	0.23%	0.31%	0.53%
Trinidad	0.0658	0.1877	3.6921	7.44%	0.09%	-0.69%	-0.60%
Argentina	0.0684	3.2578	1.0709	2.16%	0.48%	-0.21%	0.27%
Bolivia	0.0129	11.0363	1.5602	3.15%	0.45%	0.00%	0.45%
China	0.0814	2.7279	3.745	7.55%	1.68%	0.04%	1.72%
India	0.0229	3.2179	3.0258	6.10%	0.45%	-0.08%	0.37%
Malaysia	0.1226	1.6098	1.8863	3.80%	0.75%	0.16%	0.91%
Thailand	0.0555	5.8818	1.5038	3.03%	0.99%	0.63%	1.62%
Turkey	0.046	3.2232	0.889	1.79%	0.27%	0.04%	0.30%

Source: Authors' calculations.

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5. Productivity Convergence at Firm Level: New Evidence from Americas

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5. 1. Introduction

Since 2003, Latin America has experienced a period of economic resurgence, with strong output growth and generally favorable macroeconomic conditions (Sosa et al. (2013)). Growth in the LAC region reached an average of 4.2 percent per year from 2003 to 2012; after a slow down in 2013 (2.75 percent) and 2014 (projected at 2.25 percent), growth is expected to pick up again in 2015 (3 percent, IMF (2014)). These outcomes stand in contrast the cronic low rates of economic growth registered in most Latin American countries in the last fifty years in particular, whereby the ratio of average income per capita in Latin America and US decreased from one fourth in 1960 to one sixth in the early 2000s (IADB (2010)).The analysis of the roots of such underperformance highlighted the role of low productivity growth in the region, despite not negligible rates of investment in physical and human capital in the region. However, the positive aggregate performance in recent year was found to be disproportionately due factor accumulation rather than increases in factor productivity (Sosa et al. (2013)), which marked a clear distinction between Latin America and emerging Asia. As a consequence, there is general consensus that faster productivity growth in the region needs to be achieved in order for output growth to be sustainable in the future.

Adopting a micro-economic lens, this paper explores the reasons why LAC countries have been lagging behind in their rate of productivity growth. Recent economic literature has linked low aggregate productivity growth to either the performance of firms or to that of markets. Specifically (Hsieh and Klenow (2009), Bartelsman et al. (2013a), for instance) have highlighted two distinct channels driving cross-country differences in productivity: the capacity of markets to allocate resources efficiently among firms, and the evolution of firm productivity itself. In other words, differences in growth rates of aggregate productivity can been pinned down to changes in the average firm level productivity, and changes in the relative importance of firms in their sector or market. In presence of distortion to the efficient allocation of resources across firms and to the process of entry and exit from the market, more productive firms may fail to grow and be limited in their share, thus reducing aggregate productivity. This paper investigates both channels of aggregate productivity growth using firm level data from the manufacturing sector in four Latin American countries (i.e. Mexico, Colombia, Chile and Uruguay) and United States in the last decade.[102] We find that the allocation of employment in productive firms has improved in the aggregate manufacturing sector during the 2000's period, but that this aggregate picture hides notable heterogeneity across industries and even more firm-level heterogeneity. This heterogeneity is evident from Figure 5.1, where the distribution of the growth rate of labor productivity at the firm level is more widespread than at the industry level.[103]

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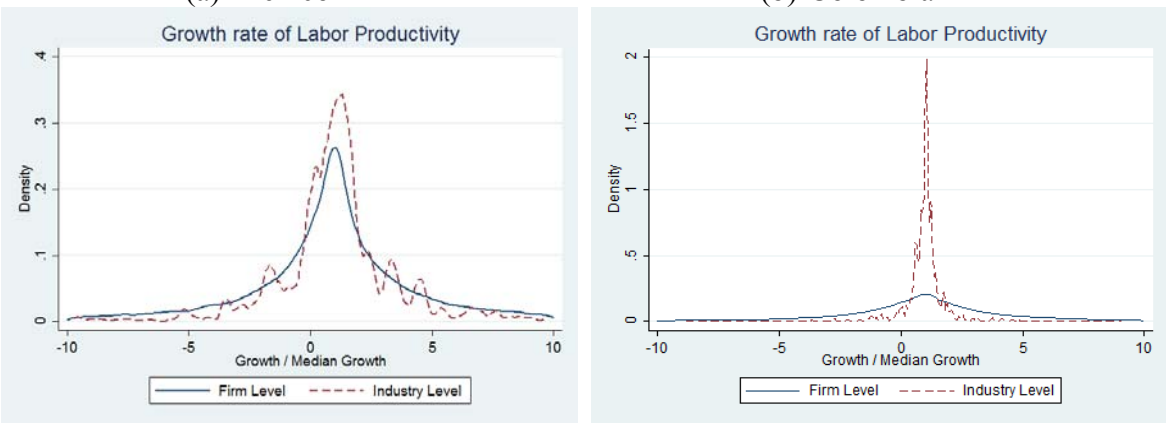
[102] This preliminary version only includes results for Mexico and Colombia.
[103] At the firm level, we graph the ratio between the plant's growth rate in a year, over the median growth rate of all plants in the same four-digit sector. At the industry level we graph the ratio between the median growth rate in the four-digit sector over the median growth rate in the economy.

Figure 5.1. Density of Industry and Firm level Productivity Growth

(a) Mexico (b) Colombia



Source: Authors' calculations.

In our analysis we decompose productivity growth and confirm the predominance of within-firm productivity in determining overall aggregate productivity. For this reason, we further investigate the process of productivity growth at the plant level, by analyzing the determinants of productivity converge. More importantly, we distinguish between convergence with domestic frontier versus convergence with "global" frontier.[104] In a second stage, we explore what factors influence the speed of convergence at the plant level. Our results suggest both in Colombia and Mexico, as well as in US, evidence of productivity convergence, but this is only the case for convergence with domestic frontier.[105] We also find that the degree of "integration" of the plant with the global economy does not influence speed of convergence for Colombia and Mexico, but we find it does increase the speed of convergence with local frontier for US companies. Additionally, we find that for all countries analyzed the most important determinant of productivity convergence at the firm level is innovation effort measured as the firm-level expenditure shares in innovation and investment in capital equipment. We also find that faster growth in the domestic frontier is also translating in higher productivity growth at the plant level, which suggests the existence of productivity spillovers. However, these spillovers appear to be weaker for those firms that are far away from the frontier which is consistent with the idea that firms lacking absorptive capabilities are less able to take advantage of potential knowledge spillovers.

Our paper is divided into four main sections aside from introduction and conclusion. In the first section we present the most important economic literature which inspired the current paper. In the second section, we present the data at hand, the first descriptive evidence of the catch up in firm labor productivity, and the results of the productivity decomposition. This is followed by the discussion of our estimation strategy (section 3) and of the results of the econometric analysis (section 4). A data appendix completes the study.

[104] We use the US productivity frontier as our measure for the global frontier.
[105] This latter result is not relevant for the US for which we don't have a "global frontier

5. 2. Literature

Aggregate productivity growth is normally estimated as the part of GDP growth which cannot be explained by the growth in the inputs of production (employment, physical and human capital). This unexplained component measures the country's efficiency in using inputs to produce one unit of output. Recent analyses, on the other hand, have investigated aggregate productivity as the result of firm level processes, where firms are assumed to be heterogeneous in their productivity even within narrowly defined sectors (Syverson (2004), Bartelsman et al. (2004, 2009), Foster et al. (2008)). This heterogeneity in firm level productivity can reflect misallocation of resources across firms: as low productivity firms have lower survival than high productivity ones, aggregate (industry) productivity can improve by reallocating resources among incumbents with different productivity levels, or between incumbents and firms entering or exiting the market (see, for a recent survey of this literature, Restuccia and Rogerson (2013)). Moreover, cross country differences in output per capita can be at least partially explained by the extent of such misallocation (Banerjee and Duflo (2005), Restuccia and Rogerson (2008), Hsieh and Klenow (2009)).

The availability of micro level data now permits to investigate the extent of such differences in the link between misallocation and productivity at the cross country level (Bartelsman et al. (2004, 2013b)). In this paper we do so for various Latin American countries (i.e. Mexico, Colombia, Chile and Uruguay) and compare it with US, exploiting the industry level productivity decomposition proposed by Olley and Pakes (1996) (henceforth, OP). This decomposition divides aggregate productivity into an unweighted average of firm-level productivity in the sector, and a covariance term picturing the joint distribution of firm's productivity and market share. The extent of resource misallocation would is inferred by the covariance term, larger positive value indicate that more productive firms use higher industry inputs shares. Increases in the covariance term would therefore imply improvements in the allocation productive inputs (i.e. workers) across firms (within the industry).

However, this decomposition does not distinguish between reallocation between incumbent and reallocation due to churning (i.e. entry and exit of firms). By neglecting that entrants and exiters can have substantially different productivity than incumbents, the OP decomposition therefore understates the importance of creative destruction in the market. The literature has proposed several measures to overcome this limitation, which usually break down productivity growth in four components: the growth in productivity of the incumbents, the changes in market shares of the incumbents, the contribution of entrants, and that of exiters (Baily et al. (1992), Griliches and Regev (1995), Foster et al. (2001)). In our analysis, we rely on the dynamic decomposition proposed by Melitz and Polanec (2012). The authors propose a clear extension of the OP static decomposition which takes into account entry and exit. What is more, they show that previous dynamic decompositions suffer from biases by construction, and therefore fail to appropriately account for the contribution of entry and exit in aggregate productivity. Although the sign of such bias is theoretically ambiguos, the authors show that previous decompositions underestimate the role of survivors and overestimate that of entrants in the aggregate productivity of fast growing economies.

The second part of this paper extends our analysis of the process of creative destruction by investigating the determinants of firm-level productivity catch-up. Earlier literature on productivity convergence has traditionally focused on countries or regions as units of observations (Sala-i Martin (1996)), and their capability to bridge the gap with the highest productivity growth among all other units, or the global technological frontier. Our study takes a more micro-level approach instead, and evaluate the process of productivity convergence towards both national and international frontier. This is the strategy followed by Girma and Kneller (2005) to study the convergence process of the UK service sector, as well as by Alvarez and Crespi (2007) for the Chilean manufacturing sector and Iacovone and Crespi (2010) for Mexico. Contrary to Griffith et al. (2003) or Alvarez and Crespi (2007), however, we shall not define the catch up process only with respect to the national frontier, but with the international frontier as well (Griffith et al. (2004), Bartelsman et al. (2008a), Iacovone and Crespi (2010)). It seems rather implausible, especially for fast developing countries in the 2000s, to define the technological frontier as the national one. Although it may be true that many firms in these countries cannot compete with their best international peers, it is very likely that a number of them is exposed to the international market either through trade or foreign direct investment. For these firms, in light of the firm level differences in degree of internationalization, the process of convergence to the frontier may be substantially different across firms. What is more, in presence of differences in the evolution of national and global technological frontier, the within country convergence to the national frontier may be actually capturing biased by the absence of the convergence term towards international frontier, which may be especially problematic for firms integrated with the global economy. That is why we explore the extent to which exposure to the international market determine the speed of convergence. Furthermore, similarly to Iacovone and Crespi (2010), we also investigate how the catch up of firms with the best practice in their industry is affected by the degree of innovation, technological investment and investment in human capital of the firm. We focus our analysis on Latin American countries, thus building upon the contributions of Pages et al. (2009) and IADB (2010) among others, which previously explored several aspects of productivity evolution in the region.

5. 3. Descriptive Statistics

5. 3. 1. Data characteristics

This study focuses on the analysis of productivity growth and convergence in Colombia, Mexico and the US.[106] For Mexico, we rely on an unbalanced establishment level panel dataset which tracks manufacturing plants known as the Annual Industrial Survey (EIA) for the years 2003 to 2011. The survey is collected annually by the Mexican National Institute of Statistics (INEGI), it excludes firms with less than 15 employees, and aims at covering at least 85 percent of output in the whole manufacturing sector.[107] For Colombia the plant level information is obtained from the Manufacturing Survey (EAM) collected by the Departamento Administrativo Nacional de Estadistica (DANE), and it covers the universe of manufacturing firms with at least 10 employees or at least 136.4 million Colombian pesos in revenues from sales, for the years 2000 to 2011.[108] Plants are selected into the sample on the year of census (2003) for Mexico, or on a yearly basis

[106] A revised version of the paper will also include data for Chile, Uruguay.
[107] These statistics are for the year 2005. In year 2009, the survey covered 90 percent of manufacturing sales in Mexico.
[108] This is the threshold for the year 2012 and it changes yearly on the basis of the producer price index.

for Colombia, then followed over time. For Mexico, while this allows to construct a plant-level panel, it also implies that the sample allows for limited entry in non-census years for Mexico (usually when new firms are especially relevant in size). In Colombia, the DANE revised the sample on the basis of other sources of information in 2008. Exit is, on the other hand, consistently reported in both cases. The resulting sample (after cleaning) for Mexico contains 5782 plants in 2003 and 4499 in 2011; for Colombia, the sample covers 6925 plants in 2000 and 8988 in 2011.[109] Plants are distributed in 231 four-digit industries according to the classification Scian (2002 and 2007) for Mexico, in 142 four-digit Isic 3.1 sectors for Colombia, and in 473 six-digit Naics industries for the US.[110]

The surveys give access to information on all inputs of production and sources of revenues, by breaking them down according to their international vs. domestic origin or destination. The main outcome variable of interest is labor productivity or value added per worker, where value added is computed as revenues from sales minus the cost of intermediate inputs and electricity. Information on capital stock at book value and investment are also reported in the manufacturing surveys, which allows to construct a measure of investment in technology (or net investment in capital equipment which is not buildings). The Mexican one also includes data on expenditure in certain forms of external innovation (i.e. patents, consultancy services, advisory services, etc.). We do not have information on R&D expenditure for Mexico, but we do have it for Colombia by merging the EAM with the Innovation Survey,[111] and for the US merging the Business Research and Development and Innovation Survey.[112] All variables are deflated using the most disaggregated deflator at our disposal, then transformed into US Dollars.[113]

Table 5.1 reports basic statistics for our sample for Mexico and Colombia, pooling over all years. It highlights significant differences in the type of surveyed establishments. While the Mexican sample covers relatively large plants, with 220 employees and 30.5 million USD in revenues per year on average, plants in the Colombian dataset are significantly smaller on average (70 employees and 5 million USD). The within-country heterogeneity in productivity is also high, with low productivity firms (bottom decile) producing 5 thousand USD per employee in Mexico (3.6 thousand USD for Colombia) versus almost 400 thousand USD in high productivity firms at the top decile (163 thousand USD for Colombia). Differences in plants' labor productivity are unsurprisingly correlated to exposure to international trade and innovation. Only a fraction of establishments engages in exporting (36 percent of plants export on average each year in our Mexican sample, and 23 percent in the Colombian one), and for those that exports only 11 percent

[109] For more information on entry and exit and for the cleaning procedure, please refer to the appendix.
[110] Mexican data are reported at the six-digit Scian level, Colombian one at the four digit level. In order to be able to compare Colombian, Mexican and US data in the descriptive statistics, we constructed a conversion table between Scian/Naics 2002 and Isic3.1 classification. This is discussed more in details in the appendix.
[111] This survey covers the years 2003-2010 and reports firm level information. In consideration of the fact that just 8 percent of observations are multiplant firms, we do not believe that inputing firm level expenditure at the plant level is severely biasing our results.
[112] The innovation surveys in both Colombia and US collect information at the firm level, while our main accounting data refers to establishments as observational units. In light of the relative scarcity of multi-plant firms in Colombia (contrary to the US), we performed all our econometric analysis again on a sample of single-plant firms (tables are not reported). The inference does not change with respect to the complete sample.
[113] For further details on the construction of the capital variable and on deflation, please refer to the appendix.

of revenues are due to exports on average for Mexico and 6 percent for Colombia. 39 percent of plants import on average in a given year in Mexico and 19 percent in Colombia, but the expenditure on imported intermediate inputs is a much lower fraction of revenues from sales, as this import ratio is on average 7 percent in Mexico and 3 percent percent in Colombia. Furthermore, engagement in innovation is even more limited, with expenditure on consulting services and patents reaching 4 percent of revenues in Mexico, and essentially zero for Colombian plants on average.[114]

Table 5.1. Sample Description

	count	mean	sd	p5	p10	p25	p50	p75	p90	p99
Mexico										
Sales	47,868	31,626	183,192	193	404	1,297	4,982	18,604	60,040	333,675
Employment	47,868	221	389	10	17	39	98	242	512	1,936
Capital	47,868	11,648	71,296	30	68	229	1,027	4,943	20,398	163,975
Value Added	47,868	15,019	76,334	84	180	601	2,294	8,685	29,956	179,814
Value added/Employment	47,868	45.28	83.46	4.51	6.65	11.90	22.62	46.81	94.04	394.68
Export/Sales	47,408	0.11	0.23	0.00	0.00	0.00	0.00	0.07	0.43	0.99
Import/Sales	47,413	0.07	0.14	0.00	0.00	0.00	0.00	0.09	0.28	0.60
External Innovation/Sales	47,865	0.04	0.20	0.00	0.00	0.00	0.00	0.00	0.04	0.82
Investment/Sales	47,866	0.02	0.26	0.00	0.00	0.00	0.00	0.02	0.06	0.27
Equipment Investment/Sales	47,522	0.02	0.24	0.00	0.00	0.00	0.00	0.02	0.05	0.23
Colombia										
Sales	84,815	5,207	55,208	74	106	224	624	2,256	9,197	68,030
Employment	84,815	70	153	5	7	12	24	64	162	713
Capital	82,050	2,396	20,787	9	19	57	179	684	3,142	40,375
Value Added	84,815	2,523	31,005	35	52	114	328	1,150	4,110	33,567
Value Added/Employment	84,815	22.94	74.25	3.58	4.98	7.91	13.16	22.95	42.36	162.88
Export/Sales	84,389	0.06	0.16	0.00	0.00	0.00	0.00	0.00	0.19	0.89
Import/Sales	84,356	0.03	0.11	0.00	0.00	0.00	0.00	0.00	0.10	0.53
Internal Innovation/Sales	51,972	0.00	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.03
External Innovation/Sales	51,972	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.05
Investment/Sales	84,389	0.10	12.33	0.00	0.00	0.00	0.01	0.03	0.10	0.57
Equipment Investment/Sales	84,389	0.08	12.32	0.00	0.00	0.00	0.00	0.03	0.08	0.40

All statistics are constructed using deflated values in the clean sample. *Sales*, *Capital* and *ValueAdded(perEmployee)* are reported in thousand USD. The Mexican sample covers the years 2003-2011, the Colombian one the years 2000-2011.
Source: Authors' calculations.

In Tables 5.2 to 5.4 we propose similar statistics but for the sample of plants which engage in twoway trade (Table 5.2), external innovation (Table 5.3), and investment in machinery and at least one type of innovation (internal or external) (Table 5.4). Previous literature has already established that trade and innovation are strongly correlated with productivity, a fact we will exploit in our econometric analysis below. Our sample confirms this stylized fact that plants engaged in international trade (in particular here, plants which both import and export goods) are bigger than average in terms of sales, capital stock and employment on average, and they are more productive. Furthermore, they spend in external innovation more than the average plant in Mexico (expenditure reaches 7 percent of revenues on average), and this is driven by the intensity of investment at the top of the distribution (the intensity of investments among last decile is 6 times higher than the overall Mexico average, while a difference can be observed only at the top

[114] Note that the fall in the number of observations for the innovation variables is due to the fact that information on innovation is altogether absent for some years in the sample (2000 to 2002, and 2011).

percentile of the distribution in Colombia). Two-way traders are also investing more often than plants in the entire population in both countries of interest, although they do not invest more on average, at least in machinery. Colombian firms seem to be investing a greater portion of their revenues from sales than Mexican ones, both in the complete sample and in the sample of two-way traders.

Table 5.2. Sample Description by Activity: Twoway Trade

	count	mean	sd	p5	p10	p25	p50	p75	p90	p99
Mexico										
Sales	11,893	59,834	196,624	1,344	2,322	6,055	17,442	47,838	121,583	705,810
Employment	11,893	386	501	35	55	112	229	445	878	2,835
Capital	11,893	20,725	71,579	194	389	1,233	4,454	15,508	42,111	292,945
Value Added	11,893	28,132	75,829	627	1,097	2,865	8,530	24,397	63,224	314,827
Value added/Employment	11,893	63.36	96.78	9.03	12.00	19.60	35.76	69.85	131.85	452.70
Export/Sales	11,893	0.32	0.31	0.01	0.02	0.06	0.20	0.53	0.85	1.00
Import/Sales	11,893	0.19	0.16	0.01	0.02	0.05	0.15	0.29	0.43	0.65
External Innovation/Sales	11,893	0.07	0.24	0.00	0.00	0.00	0.00	0.00	0.24	0.97
Investment/Sales	11,893	0.02	0.06	0.00	0.00	0.00	0.01	0.03	0.06	0.24
Equipment Investment/Sales	11,829	0.02	0.05	0.00	0.00	0.00	0.01	0.02	0.05	0.21
Colombia										
Sales	9,201	16,851	51,161	445	738	1,778	5,253	16,035	40,453	160,653
Employment	9,201	212	295	18	26	53	114	255	504	1,331
Capital	9,151	8,626	30,371	67	145	407	1,507	6,369	19,480	119,217
Value Added	9,201	8,087	22,038	209	368	927	2,677	7,844	19,721	73,904
Value Added/Employment	9,201	36.7	65.33	6.6	8.55	13.31	21.5	39.26	72.3	238.92
Export/Sales	9,201	0.24	0.24	0.01	0.01	0.05	0.15	0.35	0.61	0.96
Import/Sales	9,201	0.19	0.23	0.00	0.01	0.04	0.13	0.28	0.46	0.85
Internal Innovation/Sales	5,221	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.04
External Innovation/Sales	5,221	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.06
Investment/Sales	9,201	0.05	0.33	0.00	0.00	0.01	0.02	0.05	0.10	0.42
Equipment Investment/Sales	9,201	0.04	0.24	0.00	0.00	0.00	0.01	0.04	0.08	0.31

All statistics are constructed using deflated values in the clean sample. *Sales*, *Capital* and *ValueAdded*(*perEmployee*) are reported in thousand USD. The Mexican sample covers the years 2003-2011, the Colombian one the years 2000-2011.

Source: Authors' calculations.

Table 5.3. Sample Description by Activity: External Innovation

	count	mean	sd	p5	p10	p25	p50	p75	p90	p99
Mexico										
Sales	6,131	69,175	272,270	1,891	3,210	7,925	23,011	59,024	138,142	659,067
Employment	6,131	436	565	32	51	101	256	521	1,018	3,094
Capital	6,131	24,257	105,265	155	316	1,230	5,357	20,224	50,756	246,422
Value Added	6,131	36,622	125,849	996	1,728	4,133	12,322	32,660	79,435	328,112
Value added/Employment	6,131	79.29	103.42	11.72	15.95	26.87	49.18	89.27	165.65	501.22
Export/Sales	6,124	0.18	0.27	0.00	0.00	0.00	0.03	0.26	0.64	0.99
Import/Sales	6,124	0.14	0.17	0.00	0.00	0.00	0.07	0.24	0.40	0.62
External Innovation/Sales	6,131	0.31	0.48	0.00	0.01	0.05	0.17	0.40	0.72	1.82
Investment/Sales	6,131	0.02	0.10	0.00	0.00	0.00	0.01	0.03	0.06	0.21
Equipment Investment/Sales	6,097	0.02	0.07	0.00	0.00	0.00	0.01	0.02	0.05	0.17
Colombia										
Sales	8,148	15,627	140,469	97	176	496	1,803	7,806	25,986	138,866
Employment	8,148	134	263	8	11	21	55	140	319	1,182
Capital	7,993	7,072	47,225	16	37	121	462	2,429	10,206	117,855
Value Added	8,148	8,111	85,241	55	95	279	973	3,673	11,612	70,738
Value Added/Employment	8,148	36.86	199.82	4.21	5.7	9.49	17.06	32.44	64.46	289.47
Export/Sales	8,052	0.09	0.18	0.00	0.00	0.00	0.00	0.07	0.33	0.89
Import/Sales	8,052									
Internal Innovation/Sales	8,052	0.02	0.47	0.00	0.00	0.00	0.00	0.00	0.01	0.14
External Innovation/Sales	8,052	0.03	0.84	0.00	0.00	0.00	0.00	0.01	0.03	0.26
Investment/Sales	8,052	0.07	0.66	0.00	0.00	0.00	0.02	0.05	0.12	0.66
Equipment Investment/Sales	8,052	0.06	0.64	0.00	0.00	0.00	0.01	0.04	0.09	0.50

All statistics are constructed using deflated values in the clean sample of plants displaying nonzero expenditure in external innovation. *Sales*, *Capital* and *ValueAdded*(*perEmployee*) are reported in thousand USD. The Mexican sample covers the years 2003-2011, the Colombian one the years 2000-2011.

Source: Authors' calculations.

Table 5.4. Sample Description by Activity: Innovation and Investment in Equipment

	count	mean	sd	p5	p10	p25	p50	p75	p90	p99
Mexico										
Sales	4,515	75,611	309,956	2,456	3,962	8,923	25,451	63,597	142,286	692,207
Employment	4,515	464	590	39	57	116	276	556	1,070	3,201
Capital	4,515	27,832	119,345	222	431	1,623	6,540	23,250	56,815	299,745
Value Added	4,515	40,049	143,122	1,284	1,992	4,729	13,642	34,471	81,596	337,299
Value added/Employment	4,515	77.84	97.80	12.30	16.46	27.32	49.64	88.94	163.14	482.34
Export/Sales	4,512	0.19	0.27	0.00	0.00	0.00	0.04	0.29	0.66	0.98
Import/Sales	4,512	0.14	0.17	0.00	0.00	0.00	0.08	0.24	0.41	0.64
External Innovation/Sales	4,515	0.30	0.50	0.00	0.01	0.05	0.18	0.39	0.69	1.96
Investment/Sales	4,515	0.03	0.11	0.00	0.00	0.01	0.02	0.04	0.07	0.24
Equipment Investment/Sales	4,515	0.03	0.07	0.00	0.00	0.00	0.01	0.03	0.06	0.20
Colombia										
Sales	6,603	18,374	153,836	195	323	786	2,622	10,139	31,050	148,845
Employment	6,603	153	282	11	15	29	68	168	359	1,235
Capital	6,511	8,289	51,952	41	70	190	672	3,234	12,346	130,998
Value Added	6,603	9,321	91,916	93	157	407	1,261	4,460	13,253	74,746
Value Added/Employment	6,603	36.6	163.34	4.8	6.57	10.55	18.32	33.98	65.36	274.89
Export/Sales	6,603	0.10	0.19	0.00	0.00	0.00	0.00	0.10	0.35	0.90
Import/Sales	6,510	0.06	0.17	0.00	0.00	0.00	0.00	0.05	0.22	0.61
Internal Innovation/Sales	6,603	0.01	0.21	0.00	0.00	0.00	0.00	0.00	0.01	0.10
External Innovation/Sales	6,603	0.03	0.89	0.00	0.00	0.00	0.00	0.01	0.03	0.24
Investment/Sales	6,603	0.09	0.73	0.00	0.00	0.01	0.02	0.06	0.14	0.74
Equipment Investment/Sales	6,603	0.07	0.71	0.00	0.00	0.01	0.02	0.05	0.10	0.59

All statistics are constructed using deflated values in the clean sample of plants displaying nonzero expenditure in external innovation and purchases of equipment. *Sales*, *Capital* and *ValueAdded*(*perEmployee*) are reported in thousand USD. The Mexican sample covers the years 2003-2011, the Colombian one the years 2000-2011.

Source: Authors' calculations.

Similar characteristics are displayed by plants which do some external innovation (through purchasing patents or consulting services), with even more pronounced differences with respect to the average plant in the entire population (Table 5.3). The same can be said if the plant both invests in new machinery and innovates, with the exception of labor productivity in Mexico: the distribution of value added per employee in the latter type of plants is slightly to the left than that of innovators.[115] This is not the case for Colombia, where the average plant investing in new equipment and in at least one of the two innovation activities is twice as productive than the average plant in the entire sample, and the entire distribution is shifted to the right.

5. 3. 2. Distance from the frontier

Our analysis relies on the possibility of identifying a technological frontier serving as a benchmark for the firm productivity. We compute the national frontier as the mean of the top quartile of the distribution of value added per employee in the four digit industry and year. The global frontier is similarly computed on the basis of the survey of U.S. manufacturing plants collected by the U.S. Census Bureau.[116] Figures 5.2 and 5.3 show the ratio between the global and local frontier at (two

[115] We define innovators those plants engaged in purchase of patents or consulting services.

[116] Choosing the mean of the top quartile is coherent with Bartelsman et al. (2008b). Alternatively, computing the frontier based on the top decile would have reduced the number of available sector-year pairs for which a value for the global (US) frontier could be issued, in light of the confidentiality constraints imposed by data distribution.

digit) sector level.[117] Unsurprisingly, the US frontier is above the Mexican and Colombian ones in all sectors, with the Colombian frontier lagging further behind than the Mexican one. On the other hand, the distance between the two frontiers does not seem to have changed in a relevant way in the considered time span, with the exception of the crisis years in Mexico in particular, where the most productive firms (as an average of those at or above the top quartile) lost ground[118] with respect to their US peers.[119] In Colombia, the distance between global and local frontier displays a distinct inverted-U shape in most sectors. More importantly, in both countries substantial cross-industry heterogeneity is also evident in the level of the distance, with sectors where the global frontier is a higher multiple of the national one than others (for Mexico: leather, medical equipment, wood; for Colombia: chemicals, communication equipment, medical equipment).[120]

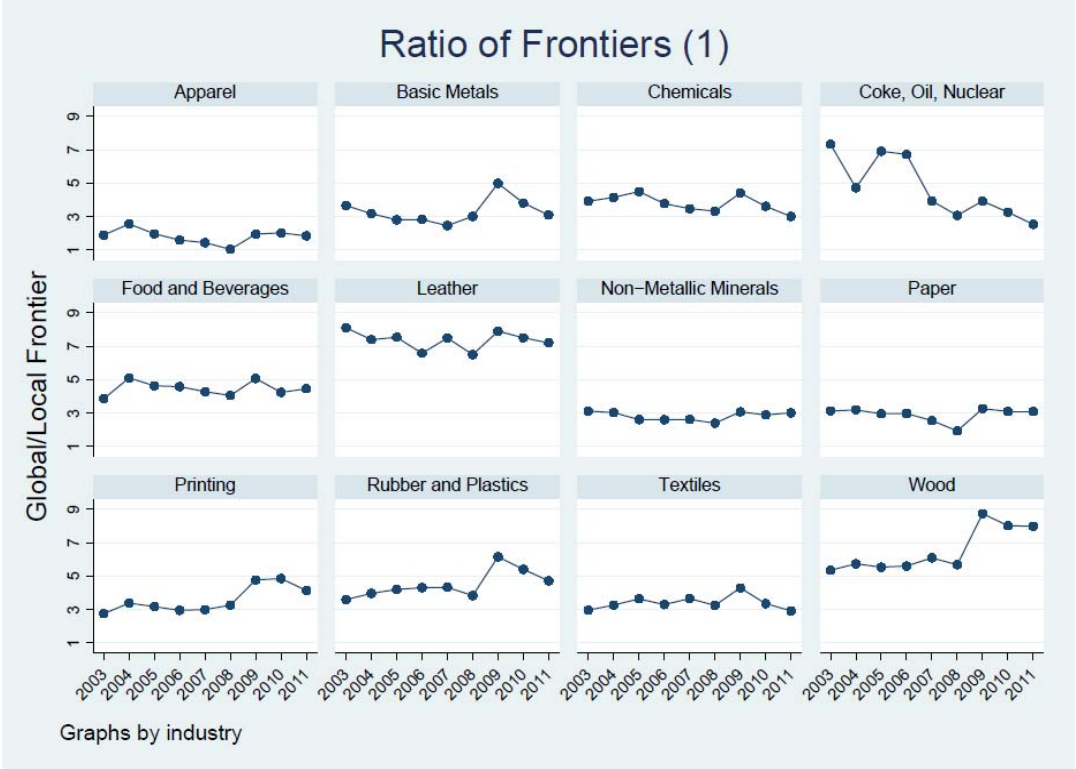
[117] Sectors are divided in two graphs to enhance readability. Part (1) includes sectors which roughly correspond to ISIC3.1 codes 15 to 28, part (2) the other manufacturing ones.

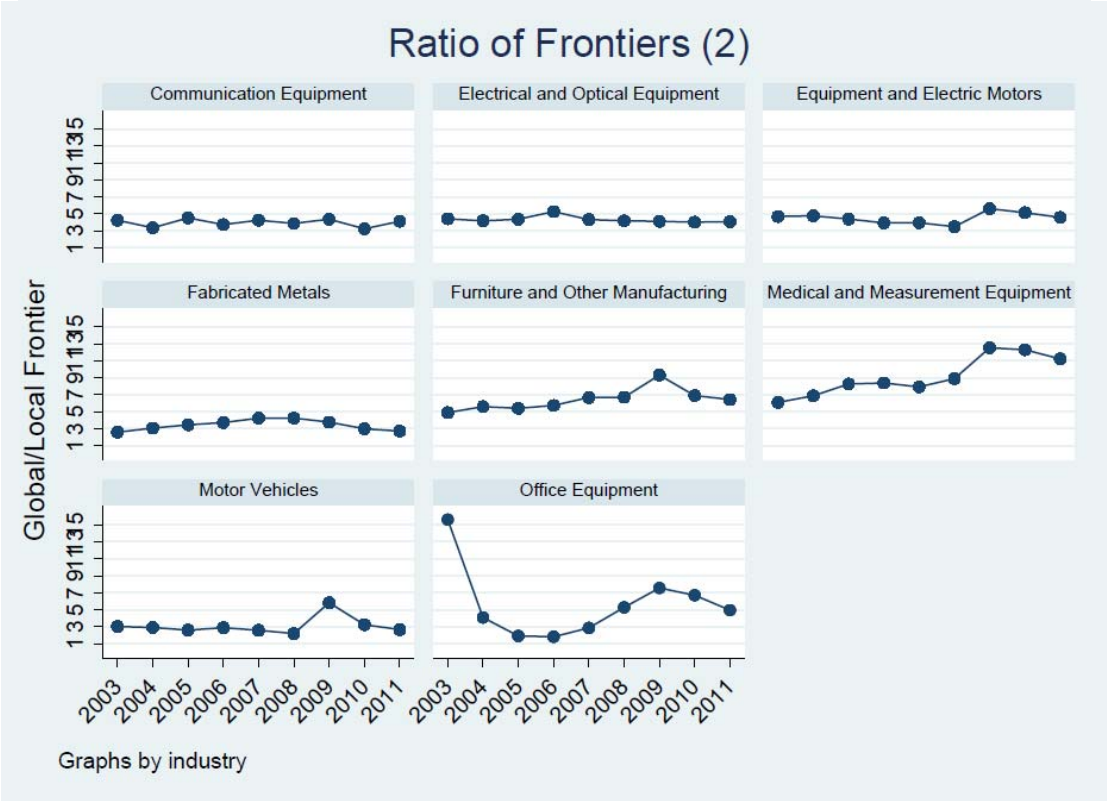
[118] While a general pattern, this does not apply to all sectors, as in the case of communication and electrical equipment for Mexico.

[119] In principle, this increase in the distance could be due to both an increase in the value of the global frontier, or a decrease in the domestic frontier. The value of the global frontier decreased on average across all sectors between 2007 and 2008, but it increased again starting from 2008. For Mexico and Colombia the decrease in domestic frontier takes place between 2008 and 2009, i.e. one year later.

[120] There are no graphs for the US here as the global and local frontiers coincide by definition.

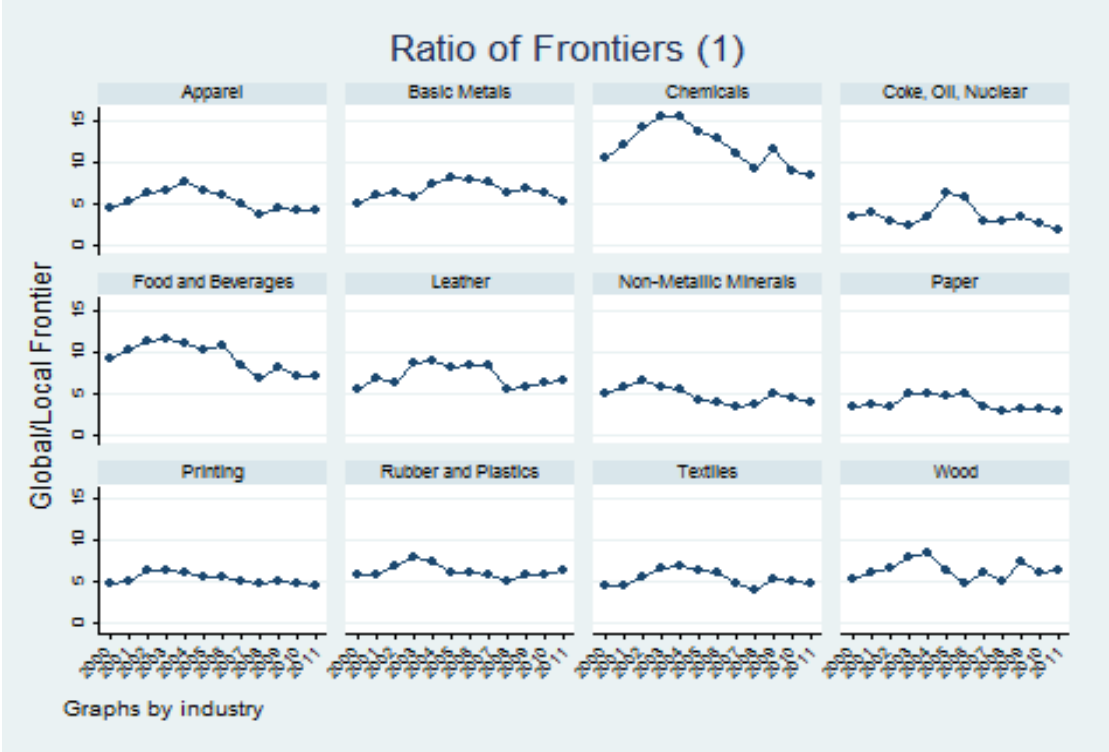
Figure 5.2. Mexico: Trend in the ratio of Global vs Domestic Frontier, by sector

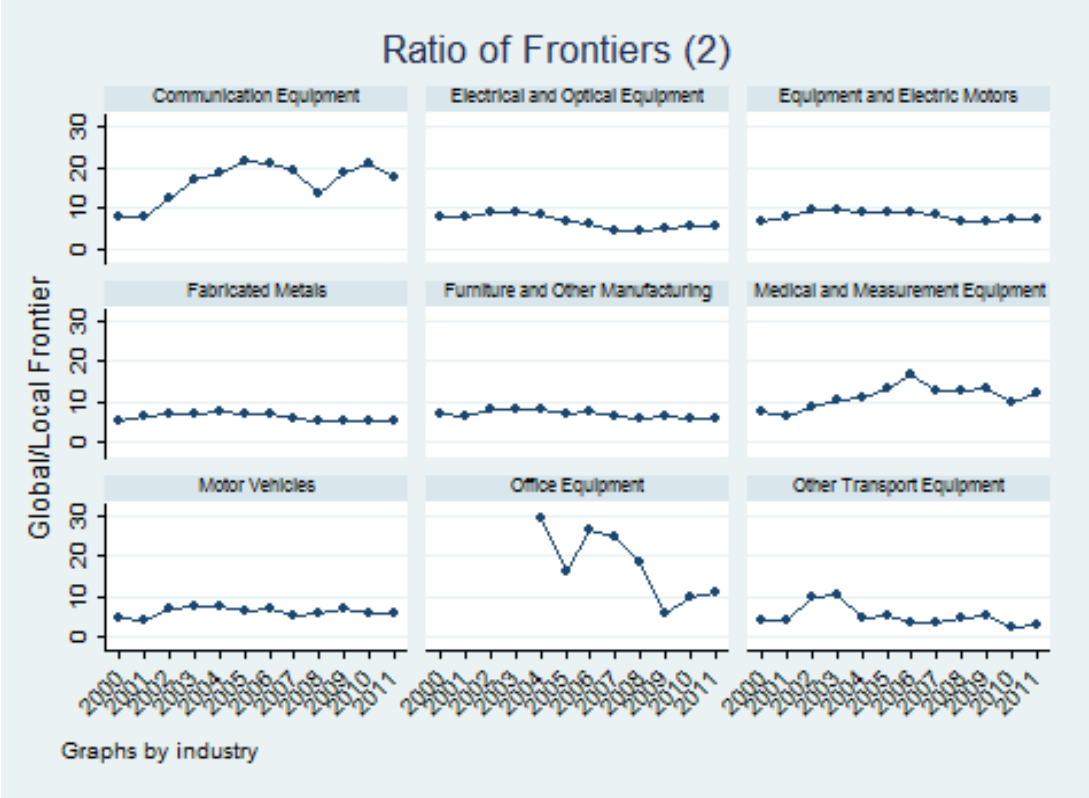




Source: Authors' calculations.

Figure 5.3. Colombia: Trend in the ratio of Global vs Domestic Frontier, by sector



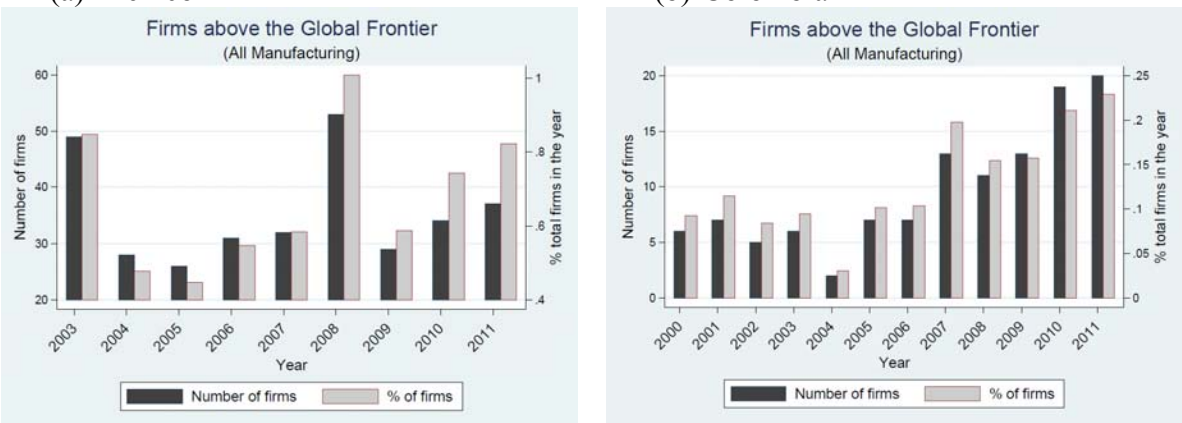


Source: Authors' calculations.

Despite the fact that both Mexican and Colombian frontier are away from the global one, in both countries we still have a small number of plants that are highly productive at the "global" level. Specifically, Figure 5.4 reports the number of plants which are more productive than the global frontier (black bars), in each year. The grey bars show instead the number of plants which are above the global frontier, as a percentage of the total number of plants in the same year. The latter figure never exceeds 1 percent, and it has clearly been affected by the global economic crisis of 2008-2009. The relatively high percentage in 2008 in Mexico reflects the decrease in value of the global frontier caused by the decrease in output in the US.[121] If the number (and percentage) of plants above the global frontier has reached the pre-crisis level in Colombia but not in Mexico, these numbers are still considerably lower in Colombia than in Mexico.

Figure 5.4. **Exceeding the Global Frontier (all years)**

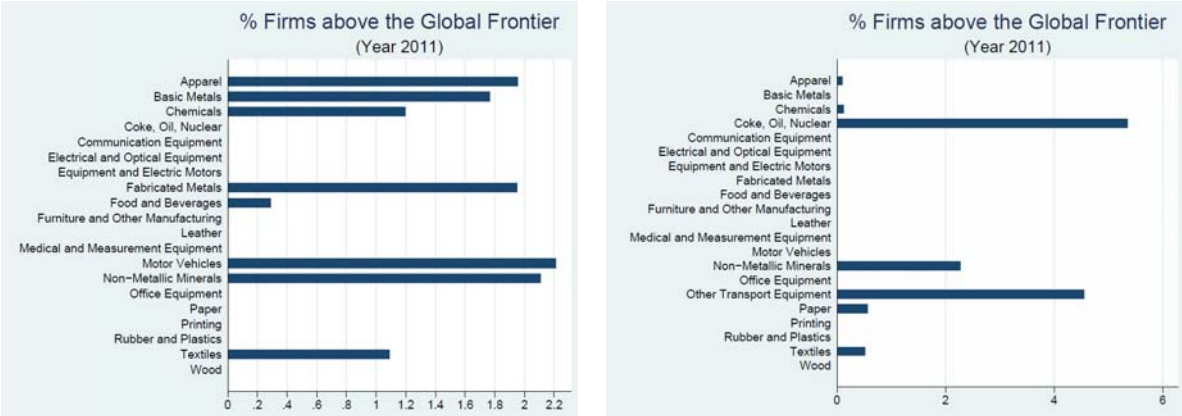
(a) Mexico (b) Colombia



Source: Authors' calculations.

Figure 5.5. **Exceeding the Global Frontier (by sector)**

1.2.1. Mexico **1.2.2.** Colombia



Source: Authors' calculations.

[121] This result does not necessarily contradict what shown in the previous figure, as it may still be that more firms exceed the international frontier despite a general decrease in the relative value of the local frontier with respect to the global one.

As before, aggregate numbers display substantial industry heterogeneity. Figure 5.5 shows that the percentage of plants which are more productive than the global frontier is substantially different across two digit industries in a given year.[122] Each bar represents the number of plants with higher productivity than the frontier as a percentage of the total number of plants in the same two-digit industry. It is clear that a number of sectors do not have any plant which performs better than the frontier, while others have up to 2 and 5 percent such plants respectively in Mexico and Colombia.

Another way of showing the relative standing of Mexican and Colombian firms with respect to the frontier is calculating the distance between the frontier and the median plant's productivity.[123] Figures 5.6 and 5.7 display this ratio for the five biggest and smallest sectors in the economy (in terms of their gross deflated value added), as well as aggregating over all industries (first panel in both part (a) and (b)). In all cases, the left vertical axis measures the distance with respect to the global frontier, the right axis the distance with respect to the domestic frontier. Although both distances often seem to move together, the magnitude of the distance is clearly different, with the distance with respect to the global frontier always exceeding the distance with the domestic one by a multiple of three to four times.

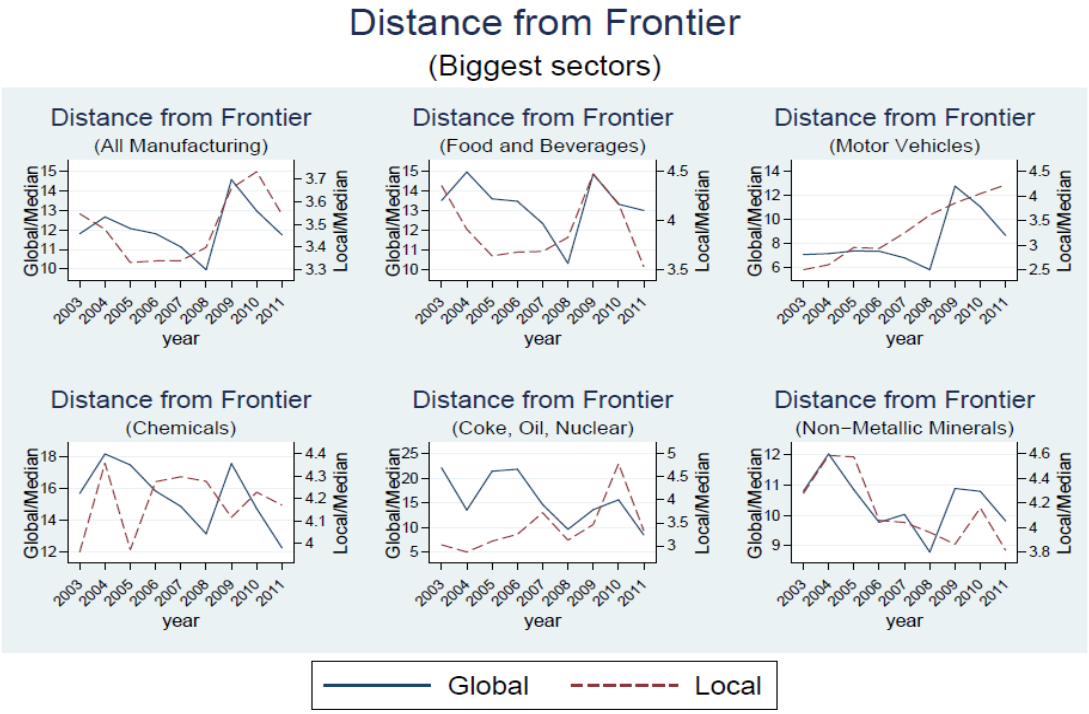
At the aggregate level, this picture suggests a small decrease in the distance from the global frontier for Mexico and a relatively more noticeable one for Colombia, especially after 2003. The patterns of convergence with respect to the domestic frontier instead are less clear. Overall, in the Mexico the convergence process seems to have been negatively affected by the Great Recession, as shown by the sudden increase in distance from frontier during the crisis years. Distances, however, clearly differ across industries in both countries, ranging for Mexico from 2 to 5 for the local frontier, and from 5 to 20 for the global one; in Colombia, the average distance of the median plant from the global frontier can be more sizeable, reaching 60 in chemicals or communication equipment. Similarly, patterns of convergence through time differ between sectors. In some sectors there is clear evidence of divergence relative to both the local and global frontier (e.g. motor vehicles in Mexico, communication equipment in Colombia), in others of convergence with respect to both (e.g. non-metallic minerals in Mexico, fabricated metal in Colombia), and in others still of divergence towards only one of the two frontiers (e.g. chemicals in Mexico, medical equipment in Colombia). Figure 5.8 plots the distance (with respect to the local frontier only) for US firms: at the aggregate, the distance from the frontier was lower in 2011 than in 1995, but the downward trend seem to have reversed ever since 2004. On the other hand, the distance has been increasing throughout the sample for four out of five of the biggest sectors in the economy, and mostly decreasing for as many among the smallest sectors.

[122] The last year of the sample was chosen arbitrarily, but the same can be shown for other years in the sample.

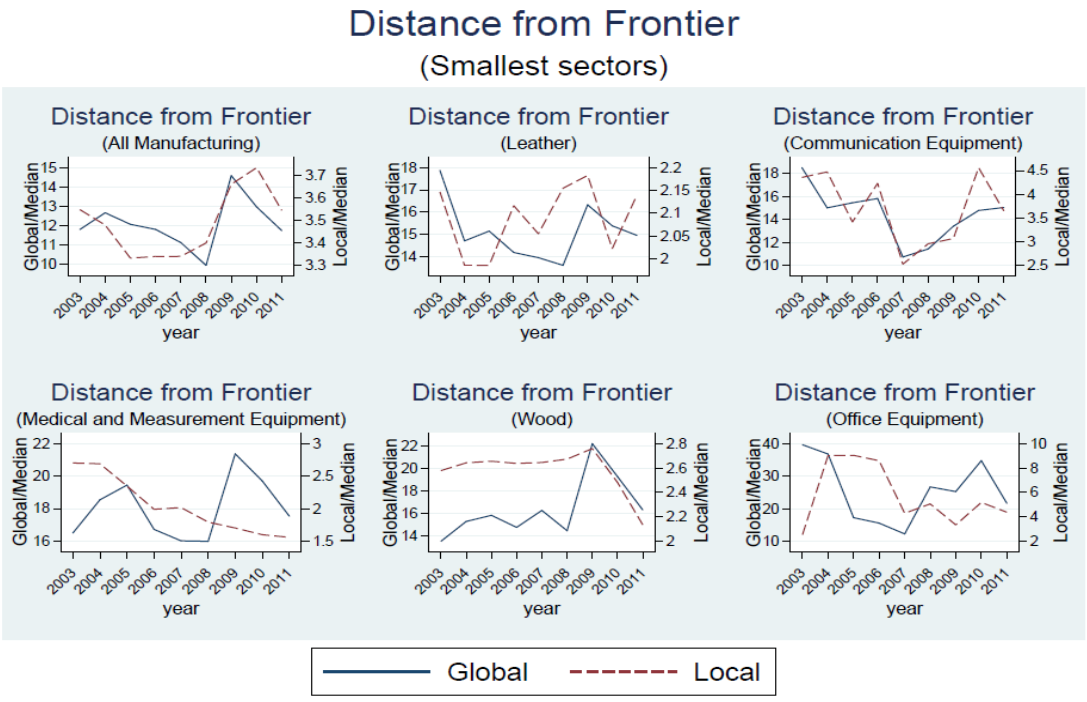
[123] Recall that both domestic and global frontiers are calculated per each four-digit industry and year. The two-digit graphs in this section are obtained as weighted averages of the ratio of frontier and median productivity in the four digit Mexican sector, where the weights are the employment shares of the four digit sector in the two digit sector in the same year. For the aggregate graph the weight is the employment share of each four digit sector in total manufacturing in each year.

Figure 5.6. Mexico: Distance between Frontier and Plant, by sector

(a) Top 5 sectors by aggregate value added



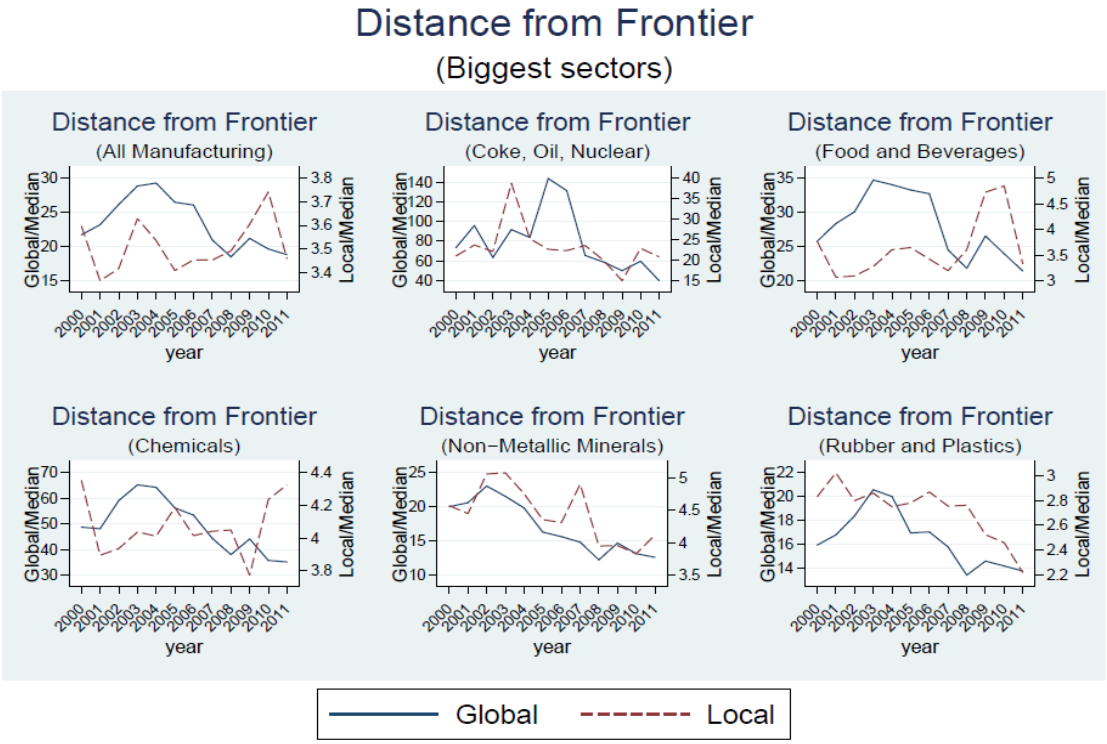
(b) Bottom 5 sectors by aggregate value added



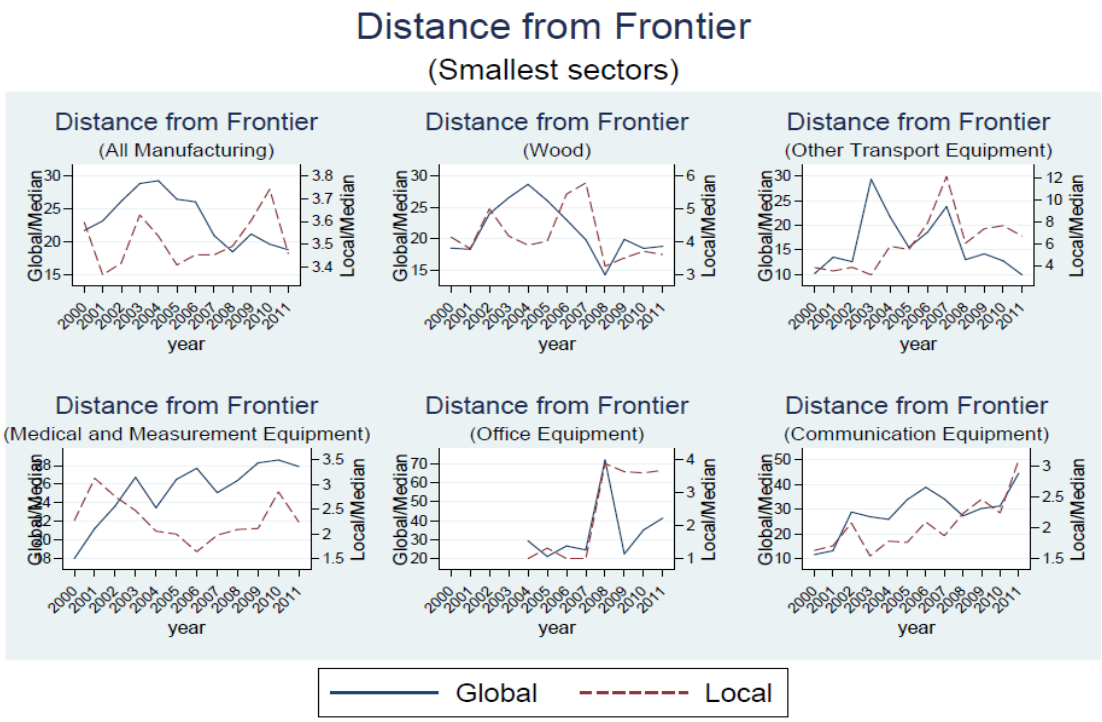
Source: Authors' calculations

Figure 5.7. Colombia: Distance between Frontier and Plant, by sector

(a) Top 5 sectors by aggregate value added



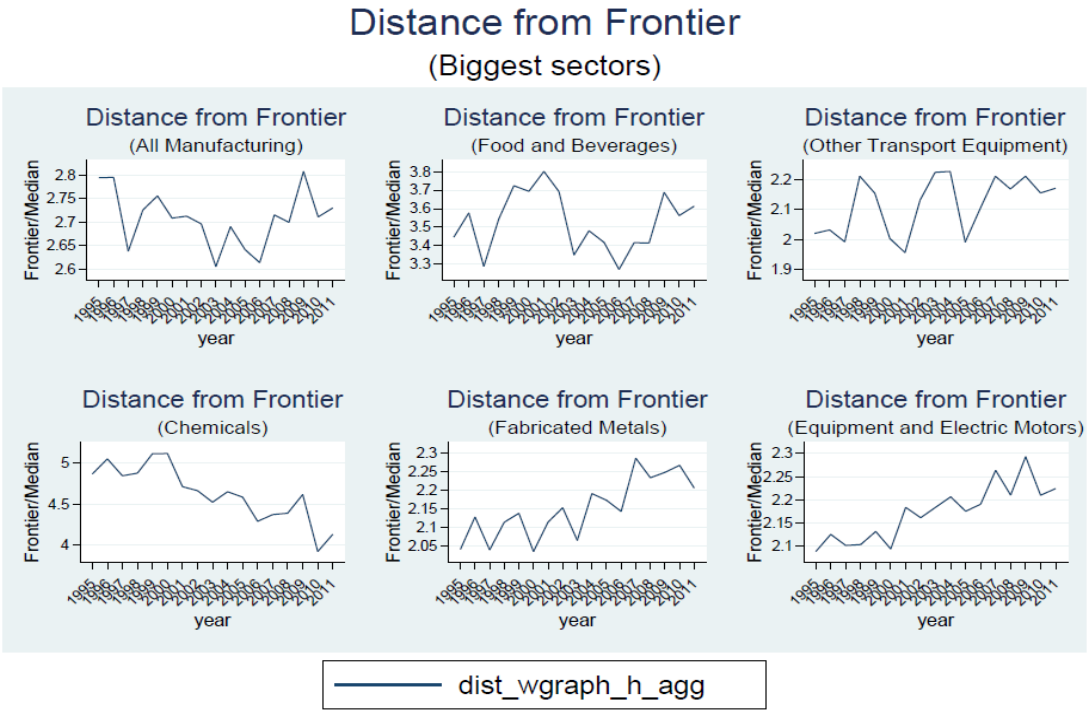
(b) Bottom 5 sectors by aggregate value added



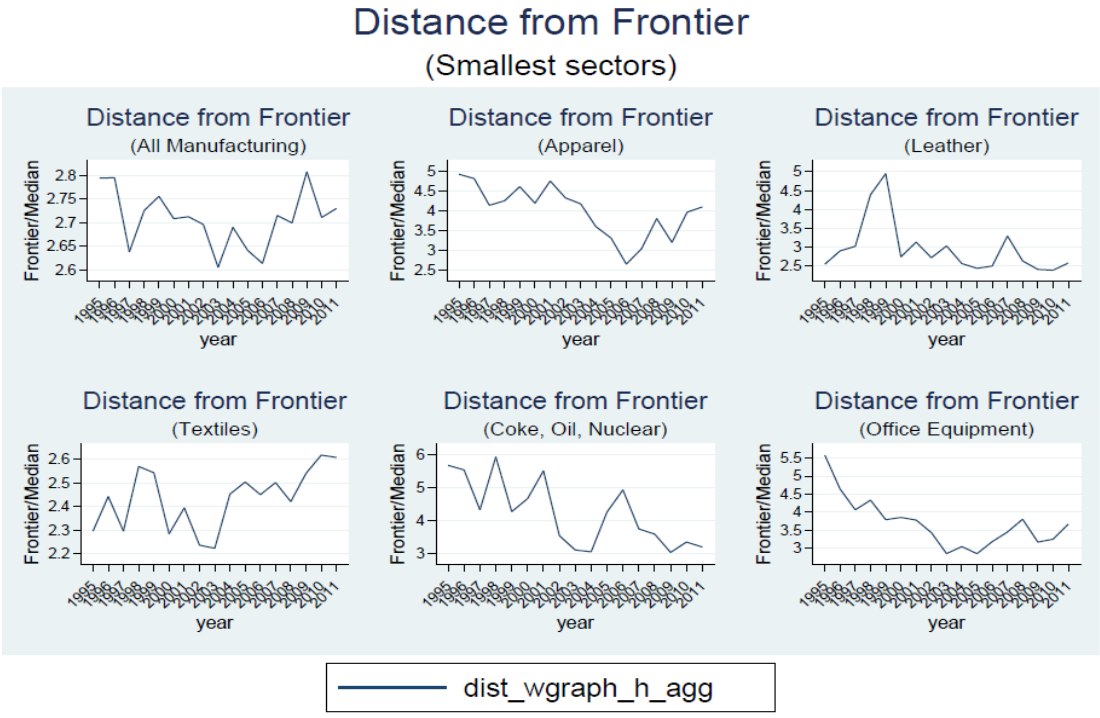
Source: Authors' calculations.

Figure 5.8. USA: Distance between Frontier and Plant, by sector

(a) Top 5 sectors by aggregate employment



(b) Bottom 5 sectors by aggregate employment



Source: Authors' calculations.

5. 3. 3. Productivity Decomposition

In this section we explore another aspect of industry heterogeneity, i.e. the extent by which allocation of market shares towards more productive firms can explain the pattern of aggregate productivity. To this purpose, we can redefine the aggregate labor productivity of industry j at time t, Ω_{jt}, as the weighted average of firm-level labor productivity where the weights are calculated as the share firm employment in total industry employment.[124] Aggregate industry productivity can then be decomposed into unweighted mean productivity, $\overline{\omega}_{jt} = \frac{1}{n_{jt}} \sum \omega_{ijt}$, and a term capturing the covariance between firm productivity and firm size $\sum (s_{ijt} - \overline{s}_{jt})(\omega_{ijt} - \overline{\omega}_{jt})$. With $s_{ijt} \geq 0$ representing the weight (i.e. importance) of firm i in industry j, and $\overline{s}_{jt} = \frac{1}{n_{jt}}$, one can write:

$$\Omega_{jt} = \overline{\omega}_{jt} + \sum (s_{ijt} - \overline{s}_{jt})(\omega_{ijt} - \overline{\omega}_{jt}) \qquad (1)$$

This productivity decomposition was first proposed by Olley and Pakes (1996)[125] and has the advantage of being easily interpretable. Aggregate productivity will grow because average productivity grows ("within firm component") or because market reallocation increases the size (i.e. weight) of more productive firms. In fact, the higher the covariance between productivity and size is, the higher is market efficiency, because a bigger share of the industry employment is attributed to the most productive firms. Given a fixed number of firms with heterogeneous productivity, shifting employment away from low productivity to high productivity firms increases both aggregate productivity and the covariance between firm efficiency and size.

Figure 5.9 plots the trend in aggregate productivity (value added per employee) for the Mexican, Colombian and US manufacturing sector (left vertical axis) as well as the relative size of the covariance term as a percentage of aggregate productivity (right hand vertical axis).[126] With the exception of the dip caused by the Great Recession, Mexican manufacturing sector experienced (on aggregate) a substantial growth in labor productivity in the period considered (from 55 thousand USD per employee in 2003 to 88 thousand USD in 2011, approximately). The same can be said for the US, which displays almost double the value added per employee than Mexico, and which suffered a smaller decrease in labor productivity during the crisis years. Colombian aggregate productivity also increased from 35 thousand to 50 thousand USD per employee

[124] An important part of the literature computes this decomposition using output instead of employment weights. It is mostly the case, however, that output weights are used when productivity is estimated as total factor productivity (TFP) (Bartelsman et al. (2009), Bartelsman et al. (2013b)). As we are focusing our analysis on labor productivity only, we prefer using employment weights. In our context the weights measure the extent to which the labor input is allocated across firms

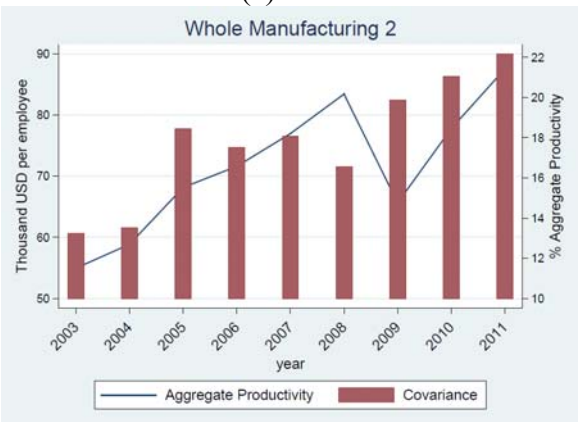
[125] Note that the subscript for the country is omitted to simplify the notation.

[126] Notice that this is the aggregate productivity in the overall manufacturing, i.e. the weighted average of the aggregate 2-digit sectoral productivity Ω_{jt} across sectors, where the weights are constructed as the share of sector employment in total manufacturing employment. Consistently, the covariance term is also measured as the weighted average of the 2-digit sector covariances.

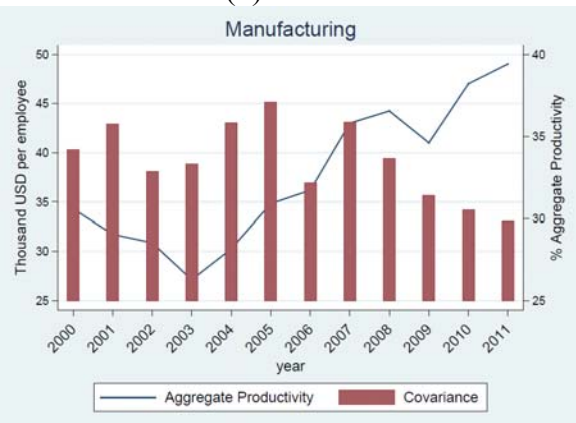
between 2000 and 2011. In Mexico, this was also associated to an increase in the covariance term between employment and productivity, thus signalling a general improvement in the allocation of employment shares across plants in the manufacturing sector. The same cannot be said in Colombia, where the last few years have seen a deterioration of the allocative efficiency of the markets. No clear pattern is identifiable for the US. It is important to notice, on the other hand, that the covariance term is generally relatively small in Mexico (at most 22 percent in the aggregate) and even smaller in the US (at most 8 percent of aggregate productivity), so that productivity growth in the country seems to be driven mainly by improvements in the within firm component. The covariance term in Colombia, on the contrary, always represented at least 30 percent of aggregate productivity throughout the sample.

Figure 5.9. **Firm-level Static Decomposition (Manufacturing)**

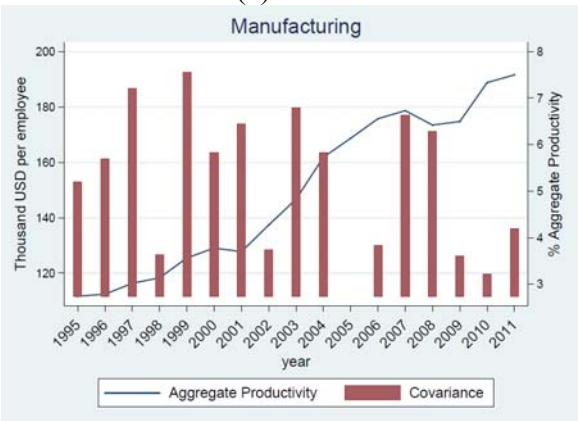
(a) Mexico



(b) Colombia



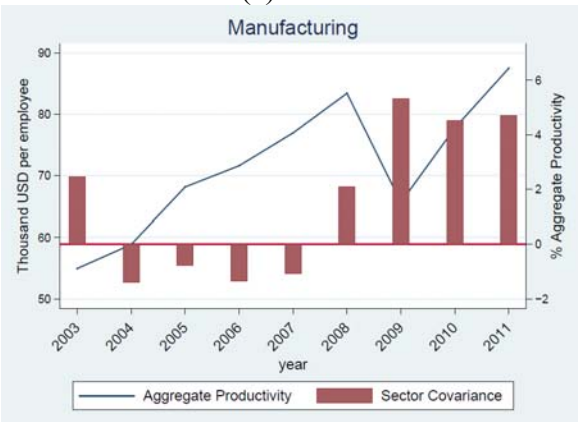
(c) USA



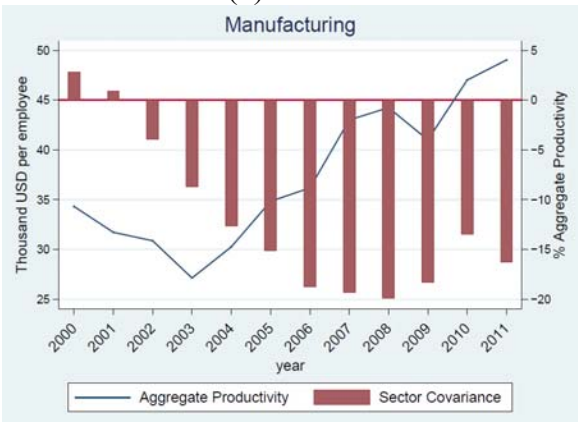
Source: Authors' calculations

Figure 5.10. Industry-level Static Decomposition (Manufacturing)

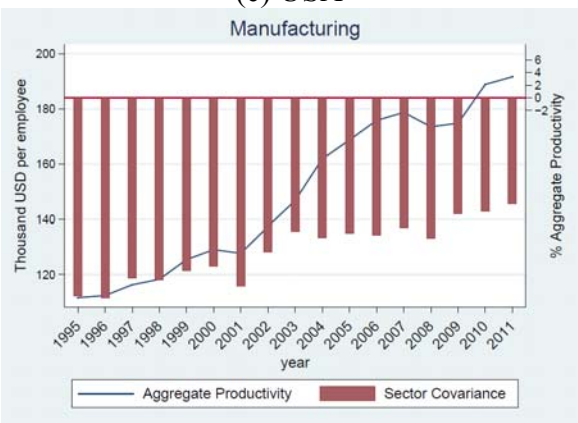
(a) Mexico



(b) Colombia



(c) USA



Source: Authors' calculations.

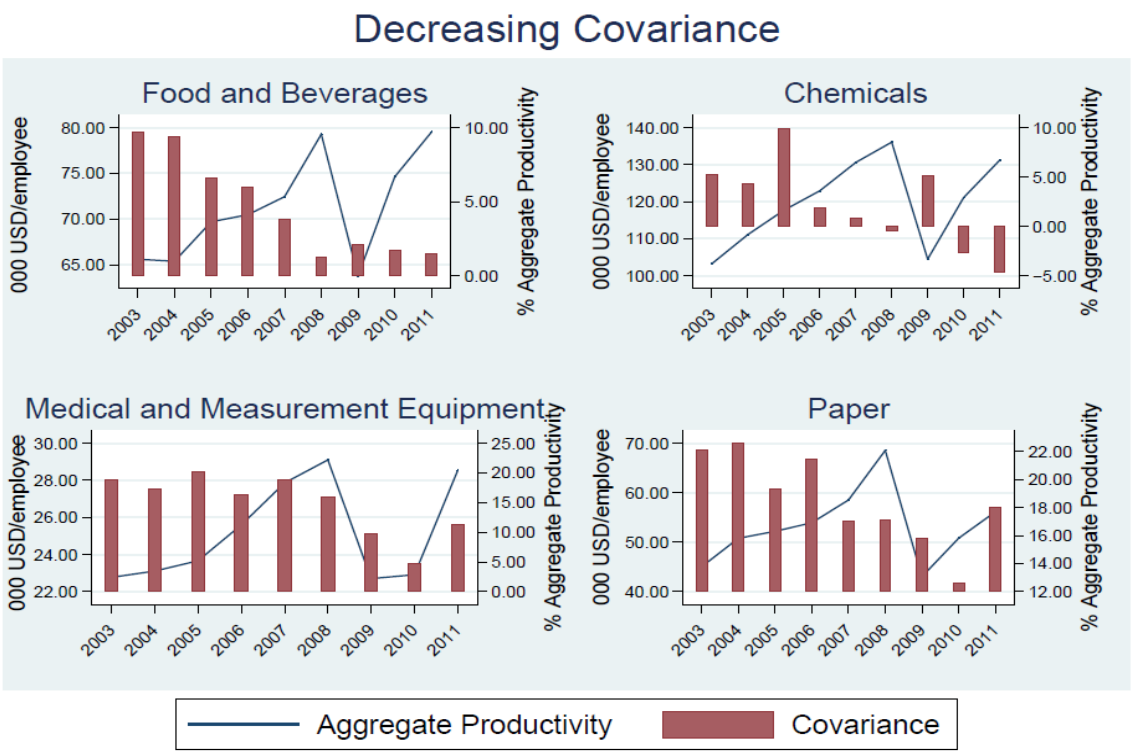
Very similar conclusions can be drawn from the analysis of the economy-wide decomposition which we report in figure 5.10 and which takes the industry level as a point of observation. In these graphs we explore whether aggregate productivity (the same as in the previous decomposition graphs) is mostly determined by the (unweighted) average productivity growth of sectors, or by an improvement in the allocation of employment across sectors.[127] We find that the contribution of cross-sector reallocation to aggregate productivity in Mexico is even lower than in the within-industry case which we reported in 5.9, reaching at most 5 percent of aggregate productivity in Mexico. For Colombia and the US, this covariance is negative in most years, suggesting that employment moved from more productive manufacturing sectors to less productive ones.[128]

[127] In formal terms, the covariance is here a function of the difference between the aggregate productivity at industry level Ω_{jt} and its average across industries $\overline{\Omega}_t$ on the one side, and the difference between the employment share of the industry in total manufacturing $s_{jt} = \frac{n_j t}{n_t}$ and the cross-industry average of such shares $\bar{s}_t = \frac{1}{J}(s_{jt})$. Hence covariance $= \sum_j (\Omega_{jt} - \overline{\Omega}_t)(s_{jt} - \bar{s}_t)$.

[128] Negative values for the covariance term imply that more productive firms are downsizing (or doing so faster than less productive firms). When this is associated with aggregate productivity growth, such growth is achieved by the

On the other hand, Figure 5.9 hides significant heterogeneity across sectors once again, as far as both aggregate industry productivity and the extent of within-sector misallocation are concerned. In Figure 5.11 to 5.13 we focus on the within-sector reallocation process, and report the graphs for a few sectors as a way of examples, while grouping them with respect to the trend in their covariance term. Aggregate industry productivity is upward sloping in almost all sectors, but it obviously differs in levels.[129] Despite an overall positive trend, covariances can still significantly decrease in selected sectors, or even turn negative (e.g. apparel and chemicals in Mexico, apparel or leather in Colombia, Food or Rubber in the US). With the exception of very few sectors (e.g. motor vehicles), the covariance term remains relatively small with respect to within-firm productivity in all Mexican sectors. In Colombia, almost all sectors experienced a decrease in the covariance term except for the production of coke and oil, and of transportation equipment (hence the omission of the graph with increasing covariance sectors). In the US, only one sector (other transportation equipment) shows a clear upward trend in the covariance term (figure not reported).

Figure 5.11. Firm-level Static Decomposition (Mexico, selected sectors)

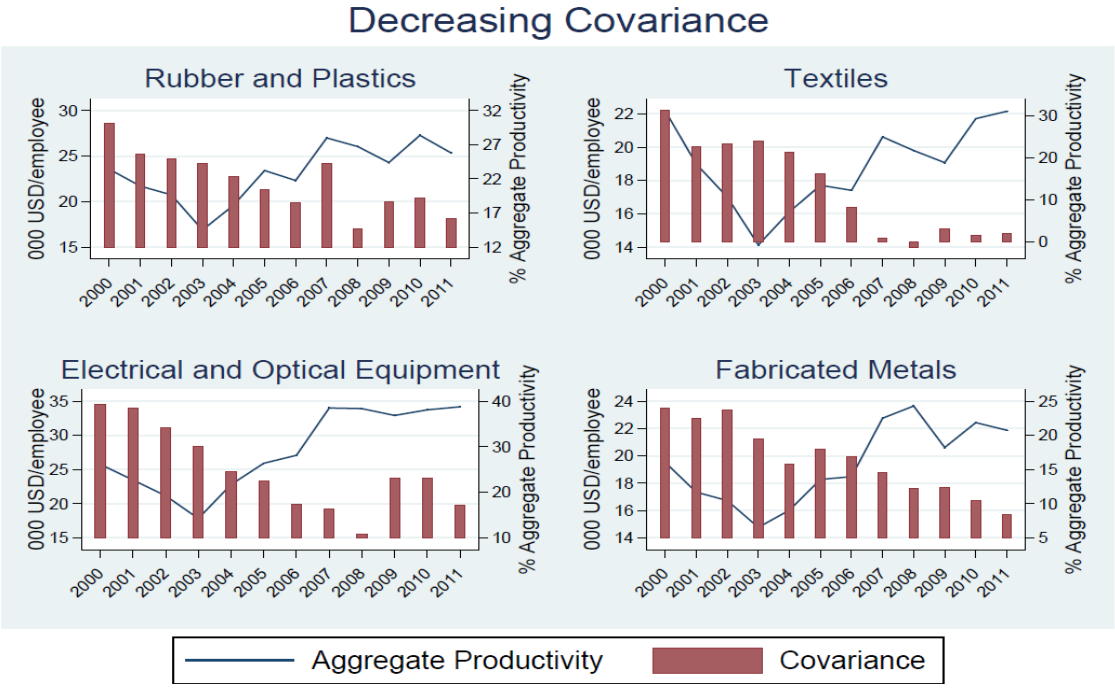


Source: Authors' calculations

job destruction process. For a thorough analysis of the meaning and likelihood of negative covariances when investigating labor productivity using employment weights, refer to Nishida et al. (2013).

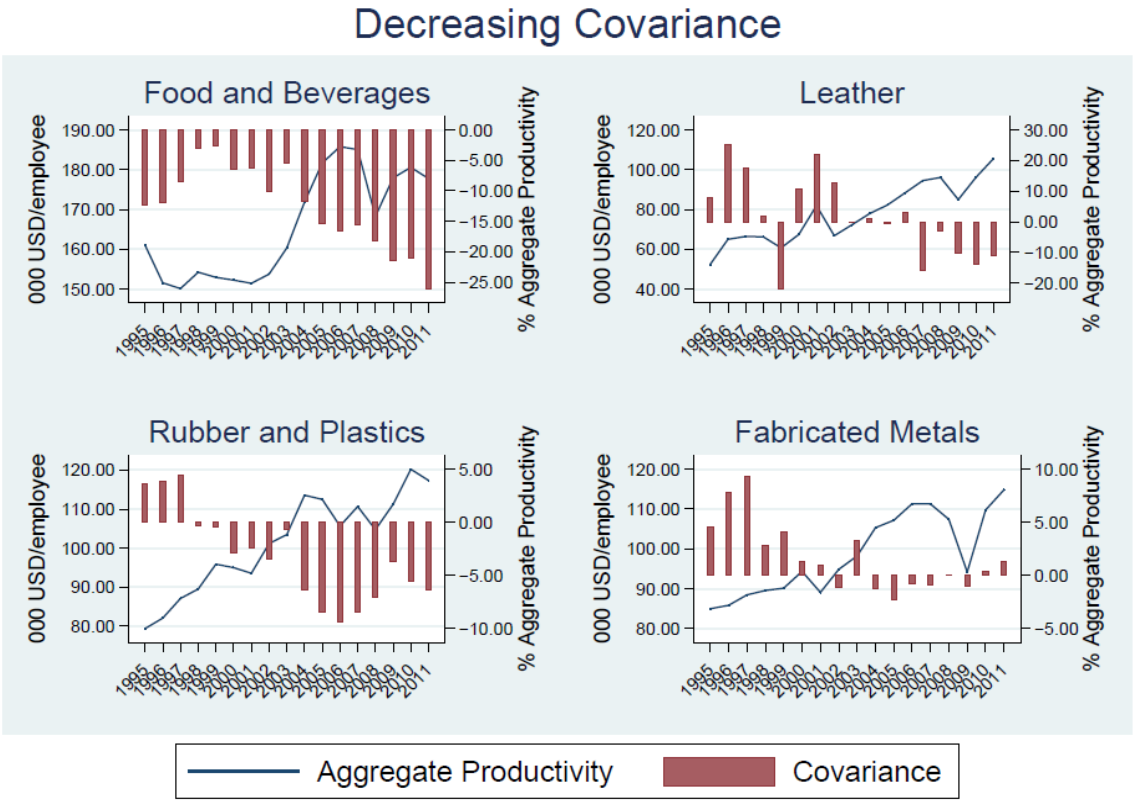
[129] The covariance terms is here at the 2-digit sector and is rescaled by Ω_{jt}.

Figure 5.12. Firm-level Static Decomposition (Colombia, selected sectors)



Source: Authors' calculations

Figure 5.13. Firm-level Static Decomposition (USA, selected sectors)



Source: Authors' calculations.

We look for confirmation of these descriptive evidence by adopting an alternative decomposition for productivity growth rather than for productivity levels as this allows us to take into account the role of entry and exit. Equation 1 keeps the number of firms constant and analyzes productivity in levels. When not controlling for entry and exit, however, it would be possible to observe changes in the covariance term which do not appropriately reflect changes in the allocative efficiency of the economy. Consider, for instance, the exit of a low productivity firm, whose employees are hired by a high productivity firm: aggregate productivity would increase, while the covariance term would decrease. In the dynamic form of decomposition, on the other hand, changes in aggregate productivity can be decomposed in a term capturing the performance of incumbent firms, that of firms entering and exiting the market, and of the consequent changes in market shares of each firm in the sector. Accordingly, aggregate productivity shifts can be broken down into four components: (i) changes in the average productivity of the incumbents which stay in the market in all years (or "survivors"); (ii) changes in market shares among these survivors; (iii) the contribution of entrants in the second period; and (iv) the contribution of exiting firms. As we mentioned earlier in the literature section, we follow Melitz and Polanec (2012) and extend the Olley and Pakes (1996)decomposition, so that:

$$\Delta\Omega_{jt} = \Delta\overline{\omega}_{pjt} + \Delta Cov_{pt} + (\sum_{i\in E} s_{ijt})(\Omega_{Ejt} - \Omega_{Pjt}) + (\sum_{i\in X} s_{ijt-1})(\Omega_{Pjt-1} - \Omega_{Xjt-1}) \qquad (2)$$

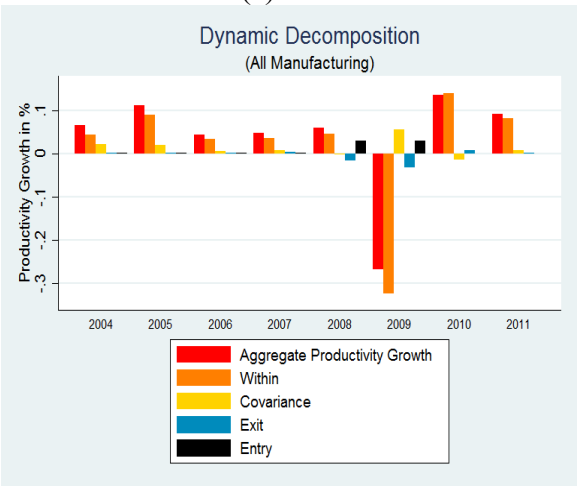
where subscript p refers to survivors, e to entrants in t and x to exiters in $t-1$. The first and second terms on the right hand side measure the contribution of survivors to aggregate (sectoral) productivity, which is decomposed according to Olley and Pakes (1996) into a change in average productivity of the survivors between t and $t-1$, and a term for the change in covariance between market share and productivity for the same category of firms and timeline. The contribution of entrants (respectively, exiters) is a function of the share of the firm's output in total entrants' (respectively, exiters') output in the industry, $\sum_{i \in E} s_{ijt}$ and $\sum_{i \in X} s_{ijt-1}$, and of the difference between aggregate productivity of the entrants (respectively, exiters) and that of survivors: $(\Omega_{Ejt} - \Omega_{Pjt})$ and $(\Omega_{Pjt-1} - \Omega_{Xjt-1})$.[130]

Figure 5.14 reports the dynamic decomposition of the overall manufacturing sector in Mexico, Colombia and the US, by year. Each component of the decomposition is made scale-independent and expressed in terms of aggregate productivity growth, following the appendix in Melitz and Polanec (2012). Once again we find that the within-firm productivity component (the change in productivity of the incumbents or survivors) is more important than all other components. For Mexico and the US, it is also positive in all years except the crisis years. For Colombia, on the other hand, the pattern is much less clear. The contribution of the survivors' covariance term is relatively small and can change in sign in both Latin American countries, but it's consistently positive (albeit small) in the US. The positive sign in the crisis year, especially in Mexico, hints at a pro-competitive effect of the crisis on incumbents. While we refrain from interpreting the results for entrants in light of the data limitation, we note that the contribution of exiters to aggregate productivity growth is usually small and volatile for both Mexico and Colombia, with the exception, once again, of the crisis years for Mexico, where their component is negative. This suggests that the crisis has negatively especially affected high productivity plants as well, so that the aggregate productivity of exiters is higher than the survivors' one. Exit in the US, on the other hand, is consistently productivity-enhancing throughout the sample period, while entrants decrease productivity growth as their productivity is lower than the of average incumbent.

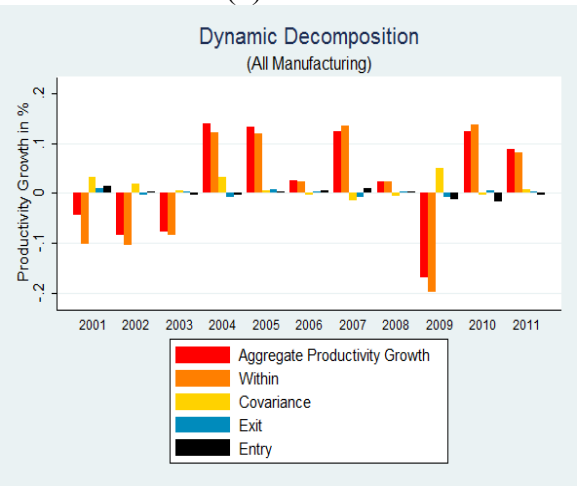
[130] In order to properly compute changes in productivity between $t-1$ and t the fact that a firm enters in $t-1$ or that a firm exits in t is irrelevant, as both cases will be captured by the terms referring to survivor firms.

Figure 5.14. Dynamic Decomposition (Manufacturing)

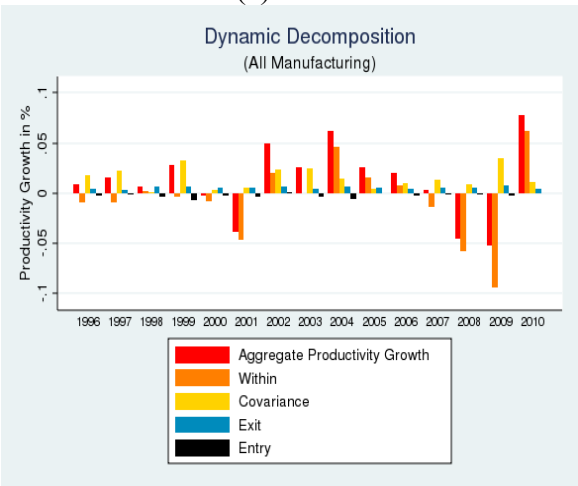
(a) Mexico



(b) Colombia



(c) USA



Source: Authors' calculations.

5. 4. Econometric Estimation

The importance of the within-firm component of aggregate productivity growth motivates the second part of our analysis, where we investigate the process of convergence of firm level productivity to the technological frontier, where the latter is defined both at national and global level, as described before. With this micro-level approach, we stress the heterogeneity of productivity growth between firms in the same industry. This is consistent with a model where firms have different capacity to absorb knowledge, as well as in their strategic decisions about integrating with global economy or investing in knowledge acquisition, and therefore differ in their speed of convergence towards the technological frontier. Let us therefore define the production function at the firm (plant) level in a standard way, as:

$$Y_{ijt} = A_{ijt} F(L_{ijt}, K_{ijt}) \qquad (3)$$

where F(.) is the plant's production function transforming labor and capital inputs (L and K) into output (Y), and A_{ijt} is an index capturing technical efficiency or, equivalently, the plant's stock of knowledge capital[131]. Following Griffith et al. (2003, 2004),we therefore consider a very general specification of knowledge spillover linking the stock of knowledge in (non-frontier) firm i in sector j at time t with the frontier. This reads:

$$A_{ijt} = \phi(A_{jt-1}; A_{jt}^{NF}; A_{jt}^{GF}; X_{ijt-1}) \qquad (4)$$

The plant's productivity this year (A_{ijt}) is a function of the same outcome last year (A_{jt-1}), the domestic technological frontier (A_{jt}^{NF}) and the global one (A_{jt}^{GF}), and a set of plant characteristics the previous year (X_{ijt-1}), the most important of which is innovation effort. The productivity gap between plant i and the frontier is the measure of potential technological transfer. Assuming a Cobb Douglas functional form and constant returns to scale for production and knowledge formation, log-linearizing and taking first differences, we can derive our estimation equation:

$$\Delta log(A_{ijt}) = \beta_1(\frac{A_{jt}^{NF} - A_{ijt-1}}{A_{jt}^{NF}}) + \beta_2(\frac{A_{jt-1}^{GF} - A_{ijt-1}}{A_{jt-1}^{GF}}) + \beta_3 \Delta log(\frac{K_{ijt}}{L_{ijt}}) +$$
$$+ \lambda_1 \Delta log(A_{jt-1}^{NF}) + \lambda_2 \Delta log(A_{jt-1}^{GF}) + \theta_i + \chi_j + \gamma_t + \varepsilon_{ijt} \qquad (5)$$

where the outcome variable is proxied by value added per worker in the plant $A_{ijt} = \frac{Y_{ijt}}{L_{ijt}}$, $log(\frac{K_{ijt}}{L_{ijt}})$ is the logarithm of the ratio of capital and labor endowments of the plant, and $\frac{A_{jt}^{NF} - A_{ijt-1}}{A_{jt}^{NF}}$ is the distance between the plant's labor productivity and the sector efficiency frontier. The change in the (domestic or global) frontier $\Delta log(A_{jt-1}^{NF})$ is a technological shifter. χ_j stays for a series of industry dummies capturing time-invariant industry-specific determinants of changes in value added per worker, γ_t for year dummies capturing macroeconomic fluctuations, while θ_i reflects unobserved plant-specific, time invariant characteristics. The main coefficients of interest are therefore β_1 and β_2, which estimate the response of convergence to the plant's distance from the technological frontier, i.e. the speed of plant catch up to the productivity frontier. We then consider what factors at the plant level may influence the catch up process. The previous equation can be expanded as:

$$\Delta log(A_{ijt}) = \beta_1(\frac{A_{jt}^{NF} - A_{ijt-1}}{A_{jt}^{NF}}) + \beta_2(\frac{A_{jt-1}^{NF} - A_{ijt-1}}{A_{jt-1}^{NF}})(log(Z_{ijt-1})) +$$
$$+ \beta_3(\frac{A_{jt-1}^{GF} - A_{ijt-1}}{A_{jt-1}^{GF}}) + \beta_4(\frac{A_{jt-1}^{GF} - A_{ijt-1}}{A_{jt-1}^{GF}})(log(Z_{ijt-1})) + \beta_5 log(Z_{ijt-1}) + [...] + \varepsilon_{ijt} \qquad (6)$$

[131] In the notation of the previous section, $\omega_{ijt} = A_{ijt}$, i.e. in this study we shall consider only labor productivity and not total factor productivity.

Following previous studies (Griffith et al. (2003), Iacovone and Crespi (2010)), we assess whether catch up changes in magnitude and sign (through β_3 and β_4) when firms invest in innovation, engage in international trade, invest in human capital or in new capital equipment, activities which are captured by Z_{ijt-1}. Technological upgrade (either in the form of innovation or investment in capital equipment) can indeed increase the speed of convergence to the frontier (Griffith et al. (2004)). It also seems likely that firms which are exposed to international competition and have access to international technology are more likely to converge faster to the frontier than firms which are not. Finally, firms which employ more skilled workforce are also likely to manage the process of technological upgrade more successfully. All regressors in our specifications are indeed lagged once in respect of the functional assumptions stated in 3. This also helps in reducing the possibility of endogeneity (reverse causality) between labor productivity and the main regressors of interest.

We estimate equation 6 both using OLS and fixed effect. The latter specification has the advantage of providing estimates of the main coefficients of interest which are net of plant-specific time invariant unobservable characterstics. Furthermore, reporting both OLS and FE specifications is especially important in our context, where the existence of a lagged dependent variable on the right hand side can result in inconsistent estimates for both OLS and FE estimators. Indeed, the distance term (which enters alone and in interaction with other plant-level covariates) is a (reverse) function of the plant's productivity in the previous year. For OLS, this form of endogeneity biases the coefficient downwards, according to Bond (2002). The fixed effect estimator, on the contrary, is upward biased, as the technology gap and the error term are positively correlated. In the lack of an appropriate instrumental variable specification taking care of the lagged dependent variable endogeneity, we report both OLS and FE estimates, highlighting that the "true" coefficient should lie between the OLS (lower bound) and the FE (upper bound) estimates.

Equation 5 and 6 are estimated separately for each country which is covered in this study, as we cannot stack information from the various countries in one single dataset.[132]

5. 5. Estimation Results

Table 5.5 to 5.7 report the results of estimating equation 5 with both OLS and FE, respectively, for Mexico, Colombia and the US.[133] For the first two specifications (columns 1 to 4) in Mexico and Colombia, we show that including only one distance term (distance from the local or global frontier respectively) would lead to biased estimates for the convergence parameter. In fact, plants would appear to converge both towards the domestic and the global frontier.[134] When introducing both distances, on the other hand (columns 5 and onwards) the coefficient on the firm distance from the global frontier becomes either insignificant or negative, thus suggesting lack of convergence with respect to the global frontier. On the contrary, the coefficient of the domestic

[132] This is due to confidentiality reasons and rules governing access to data for each one of the countries analyzed.
[133] The reported number of observations and firms is approximated to comply with restrictions in data distribution at the US Census.
[134] A comparison of the speed of convergence between global and local frontiers is invalidated by the fact that the "true" coefficient lies between the OLS and FE ones, and we cannot assess whether endogeneity biases the coefficient on the distance from the local frontier differently than that on the distance from the global frontier.

distance is always positive and significant, even in more complex specifications where we include our most important controls (lagged firm size and capital-labor ratio): Mexican and Colombian plants appear to convergence towards the domestic most productive firms, but not towards the absolute (international) best practices. Catch up with the (local and only) frontier is found for US firms as well.[135]

[135] In order to enhance the comparability between Mexican and Colombian results on the one side, and US results on the other, we ran our estimation with a single frontier for Mexico and Colombia as well. Results are reported in Appendix 2, and commented further below.

Table 5.5. Mexico Estimation Results: Baseline

	OLS1	FE1	OLS2	FE2	OLS3	FE3	OLS4	FE4	OLS5	FE5	OLS6	FE6
Distance (Local)	0.078***	0.585***			0.102***	0.583***	0.125***	0.695***	0.115***	0.667***	0.125***	0.664***
	(0.008)	(0.043)			(0.008)	(0.039)	(0.008)	(0.037)	(0.008)	(0.036)	(0.008)	(0.036)
Distance (Global)			0.098**	0.833***	-0.058***	0.006	-0.101***	-0.217	-0.098***	-0.219*	-0.105***	-0.218*
			(0.038)	(0.258)	(0.017)	(0.188)	(0.011)	(0.138)	(0.012)	(0.131)	(0.011)	(0.130)
Delta Log Frontier (Local)							0.535***	0.556***	0.534***	0.552***	0.535***	0.552***
							(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Delta Log Frontier (Global)							-0.013	-0.009	-0.017	-0.012	-0.014	-0.013
							(0.021)	(0.022)	(0.021)	(0.022)	(0.021)	(0.022)
Delta Log (K/L)									0.166***	0.171***	0.164***	0.169***
									(0.013)	(0.013)	(0.013)	(0.013)
Log Size (Medium)											0.053***	0.036***
											(0.005)	(0.014)
Log Size (Large)											0.075***	0.050***
											(0.006)	(0.019)
Observations	40,545	40,545	40,545	40,545	40,545	40,545	40,545	40,545	40,216	40,216	40,216	40,216
R-squared	0.154	0.235	0.150	0.200	0.154	0.235	0.196	0.282	0.210	0.296	0.214	0.296
Number of id		6,197		6,197		6,197		6,197		6,157		6,157

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the change in the logarithm of value added per employee. $Distance(Local)$ is the lagged difference between the plant's productivity and the (domestic) frontier over the value of the frontier, as expressed in equation 5. $DeltaLogFrontier(Local)$ is the change in the value of the local frontier (in logs) between t and $t-1$. All other terms are lagged once. K/L is the capital-labor ratio in the plant, while $LogSize(Medium, Large)$ is a dummy having value 1 if the firm has between 50 and 200 employees (respectively, more than 200 employees) in year $t-1$. All specifications include time dummies, 2 digit industry dummies and the cross product of the two. Our Mexican sample covers the years 2003 to 2011.

Source: Authors' calculations.

Table 5.6. Colombia Estimation Results: Baseline

	OLS1	FE1	OLS2	FE2	OLS3	FE3	OLS4	FE4	OLS5	FE5	OLS6	FE6
Distance (Local)	0.208***	0.685***			0.208***	0.689***	0.219***	0.731***	0.189***	0.620***	0.199***	0.628***
	(0.009)	(0.035)			(0.016)	(0.059)	(0.016)	(0.059)	(0.014)	(0.036)	(0.014)	(0.036)
Distance (Global)			0.817***	2.446***	-0.004	-0.021	-0.051	-0.197	0.011	0.358	0.003	0.348
			(0.082)	(0.519)	(0.091)	(0.497)	(0.088)	(0.483)	(0.074)	(0.262)	(0.075)	(0.263)
Delta Log Frontier (Local)							0.145***	0.215***	0.128***	0.181***	0.128***	0.181***
							(0.014)	(0.019)	(0.014)	(0.015)	(0.014)	(0.015)
Delta Log Frontier (Global)							-0.068***	-0.059**	-0.064***	-0.038**	-0.065***	-0.038**
							(0.017)	(0.023)	(0.017)	(0.019)	(0.017)	(0.019)
Delta Log (K/L)									0.286***	0.259***	0.282***	0.259***
									(0.008)	(0.008)	(0.008)	(0.008)
Log Size (Medium)											0.028***	-0.023**
											(0.004)	(0.011)
Log Size (Large)											0.064***	-0.035*
											(0.006)	(0.021)
Log Age											0.003	-0.012
											(0.003)	(0.018)
Observations	68,533	68,533	68,533	68,533	68,533	68,533	68,533	68,533	66,119	66,119	65,996	65,996
R-squared	0.105	0.192	0.093	0.143	0.105	0.192	0.107	0.197	0.155	0.241	0.157	0.242
Number of id		11,924		11,924		11,924		11,924		11,681		11,667

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the change in the logarithm of value added per employee. $Distance(Local)$ is the lagged difference between the plant's productivity and the (domestic) frontier over the value of the frontier, as expressed in equation 5. $DeltaLogFrontier(Local)$ is the change in the value of the local frontier (in logs) between t and $t-1$. All other terms are lagged once. K/L is the capital-labor ratio in the plant, while $LogSize(Medium, Large)$ is a dummy having value 1 if the firm has between 50 and 200 employees (respectively, more than 200 employees) in year $t-1$. $LogAge$ is the logarithm of the plant's age increased by one (so that entrants would not be dropped from the sample). All specifications include time dummies, 2 digit industry dummies and the cross product of the two. Data availability in Colombia also permits to control for age and regional dummies. Our Colombian sample covers the years 2000 to 2011.

Source: Authors' calculations.

Table 5.7. U.S.A. Estimation Results: Baseline

	OLS1	FE1	OLS2	FE2	OLS3	FE3	OLS4	FE4
Distance (Local)	0.275***	0.744***	0.278***	0.751***	0.250***	0.711***	0.251***	0.712***
	(0.003)	(0.007)	(0.003)	(0.007)	(0.003)	(0.006)	(0.003)	(0.006)
Delta Log Frontier (Local)			0.222***	0.266***	0.199***	0.254***	0.198***	0.254***
			(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)
Delta Log (K/L)					0.273***	0.256***	0.269***	0.257***
					(0.004)	(0.004)	(0.004)	(0.005)
Log Size (Medium)							0.027***	0.005
							(0.002)	(0.005)
Log Size (Large)							0.032***	-0.011
							(0.002)	(0.007)
Log Age							0.009***	0.000
							(0.001)	(0.005)
Observations	$\approx 650,000$	$\approx 650,000$	$\approx 650,000$	$\approx 650,000$	$\approx 490,000$	$\approx 490,000$	$\approx 490,000$	$\approx 490,000$
R-squared	0.064	0.159	0.067	0.162	0.114	0.202	0.115	0.202
Number of id		$\approx 140,000$		$\approx 140,000$		$\approx 110,000$		$\approx 110,000$

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the change in the logarithm of value added per employee. $Distance(Local)$ is the lagged difference between the plant's productivity and the (domestic) frontier over the value of the frontier, as expressed in equation 5. $DeltaLogFrontier(Local)$ is the change in the value of the local frontier (in logs) between t and $t-1$. No global frontier is available for the U.S. (by definition). All other terms are lagged once. K/L is the capital-labor ratio in the plant, while $LogSize(Medium, Large)$ is a dummy having value 1 if the firm has between 50 and 200 employees (respectively, more than 200 employees) in year $t-1$. $LogAge$ is the logarithm of the plant's age increased by one (so that entrants would not be dropped from the sample). All specifications include time dummies, 2 digit industry dummies and the cross product of the two. Data availability in the U.S.A. also permits to control for age and regional (State-level) dummies. Our US sample covers the years 1995 to 2011. The number of observations is not precisely reported to respect disclosure constraints.

Source: Authors' calculations.

Columns 7 to 13 in Tables 5.5 and 5.6, as well as columns 3 to 8 in Table 5.7 are estimated including the change in industry (local or global) frontier between t and $t-1$, as in equation 5 and 6. The estimates of these technological shifters should be interpreted as the spillovers from the frontier itself and the plant's productivity: the general level of productivity in the domestic or international market can only influence the productivity of the firm if there are technological spillovers. From Tables 5.5 to 5.7 it is evident that spillovers from the domestic frontier are positive and strong, contrary to spillovers from the global frontier; for Colombia, a faster change in the global frontier has a negative impact on productivity growth at the plant level. In another specification, we also introduce an interaction term between the distance from the frontier and the spillover term and the results confirm the absence of any significant effect as far as spillovers from the global frontier are concerned, but not from the domestic frontier: when further away from the domestic frontier, the spillover effect on productivity growth is significantly lower.[136] This results is consistent with the concept of absorptive capabilities and the idea that firms that are further away from the tecnology frontier may be unable to benefit from spillovers.[137] We conclude the analysis of Tables 5.5 to 5.7 by highlighting that more capital intensive plants seem to enjoy higher productivity growth in all countries, while there is a positive premium due to size (relative to small firms) in Mexico only.

A key objective of our analysis is to identify whether certain firm characteristics alter the speed of convergence. In particular, we will focus on the degree to which firms invest in knowledge and technological upgrade, and the extent to which these are integrated with the global economy. We do so by including an interaction term between the plant's distance from the frontier and these covariates of interest, as in equation 6.

Tables 5.8 to 5.10 highlight that innovation effort and investment in new equipment influence plants' productivity convergence. In fact, plants' productivity convergence in Mexico is increased by greater investments in machinery (specification 1 and 3) and in expenses to purchase external knowledge (specification 3). On the other hand, convergence towards global frontier is not influenced by investment in innovation. For Colombia, the speed of convergence to the domestic frontier is positively affected by innovation only (specifications 2 to 5), and not by purchases of capital equipment (specifications 1, 4 and 5). Internal innovation efforts are more effective in increasing the speed of productivity convergence toward the domestic frontier than purchase of external innovation (specifications 4 and 5). As far as the US are concerned, we find a positive (but not very robust) role of investment in stimulating productivity catch up; innovation, on the other hand, even reduces the speed of convergence when far away from the frontiere. When at the frontier, though (zero distance), internal innovation positively contributes to productivity growth.

[136] For reasons of space these results have not been included but are available upon request.
[137] This result is also consistent with the work of Griffith et al. (2003)

Table 5.8. Mexico Estimation Results: Innovation and Technology Interactions

	OLS1	FE1	OLS2	FE2	OLS3	FE3
Distance (Local)	0.181***	0.845***	0.171***	0.873***	0.237***	1.029***
	(0.017)	(0.048)	(0.023)	(0.059)	(0.030)	(0.072)
Distance (Global)	-0.166***	-0.483***	-0.174***	-0.293	-0.292***	-0.542**
	(0.022)	(0.145)	(0.053)	(0.193)	(0.069)	(0.214)
Delta Log Frontier (Local)	0.538***	0.562***	0.535***	0.551***	0.537***	0.560***
	(0.024)	(0.024)	(0.023)	(0.023)	(0.024)	(0.024)
Delta Log Frontier (Global)	-0.011	-0.014	-0.014	-0.009	-0.011	-0.010
	(0.022)	(0.022)	(0.021)	(0.021)	(0.022)	(0.022)
Delta Log (K/L)	0.168***	0.182***	0.164***	0.168***	0.168***	0.182***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)
Log (Investment/Sales)	0.011***	0.024*			0.012***	0.020*
	(0.003)	(0.013)			(0.003)	(0.012)
Distance (Local)*Log(Investment/Sales)	0.011***	0.028***			0.011***	0.026***
	(0.003)	(0.006)			(0.003)	(0.006)
Distance (Global)*Log (Investment/Sales)	-0.012***	-0.035**			-0.014***	-0.030*
	(0.004)	(0.018)			(0.004)	(0.016)
Log (Ext Inno/Sales)			0.006*	0.012	0.010**	0.015*
			(0.004)	(0.008)	(0.004)	(0.008)
Distance (Local)*Log (Ext Inno/Sales)			0.006**	0.028***	0.007***	0.027***
			(0.002)	(0.006)	(0.003)	(0.006)
Distance (Global)*Log (Ext Inno/Sales)			-0.008	-0.012	-0.013**	-0.014
			(0.005)	(0.012)	(0.006)	(0.012)
Log Size (Medium)	0.054***	0.037***	0.056***	0.042***	0.057***	0.043***
	(0.005)	(0.014)	(0.005)	(0.014)	(0.005)	(0.014)
Log Size (Large)	0.077***	0.037**	0.080***	0.063***	0.080***	0.050***
	(0.006)	(0.019)	(0.006)	(0.019)	(0.006)	(0.019)
Observations	36,847	36,847	40,214	40,214	36,846	36,846
R-squared	0.218	0.303	0.214	0.300	0.218	0.307
Number of id		6,138		6,157		6,138

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the change in the logarithm of value added per employee. $Distance(Local)$ is the lagged difference between the plant's productivity and the (domestic) frontier over the value of the frontier, as expressed in equation 5. $DeltaLogFrontier(Local)$ is the change in the value of the local frontier (in logs) between t and $t-1$. All other terms are lagged once. K/L is the capital-labor ratio in the plant, while $LogSize(Medium, Large)$ is a dummy having value 1 if the firm has between 50 and 200 employees (respectively, more than 200 employees) in year $t-1$. $ExtInno$ stays for expenditure in external innovation (patents) over revenues from sales, $Investment$ for net investment in machinery over sales. All specifications include time dummies, 2 digit industry dummies and the cross product of the two.

Source: Authors' calculations.

Table 5.9. Colombia Estimation Results: Innovation and Technology Interactions

	OLS1	FE1	OLS2	FE2	OLS3	FE3	OLS4	FE4	OLS5	FE5
Distance (Local)	0.204***	0.706***	0.440***	0.985***	0.481***	1.102***	0.509***	1.137***	0.490***	1.178***
	(0.032)	(0.052)	(0.054)	(0.088)	(0.055)	(0.100)	(0.058)	(0.106)	(0.065)	(0.116)
Distance (Global)	0.037	0.101	-0.019	1.098**	-0.034	0.480	-0.038	0.858	-0.052	0.710
	(0.127)	(0.419)	(0.225)	(0.497)	(0.234)	(0.489)	(0.257)	(0.604)	(0.287)	(0.716)
Delta Log Frontier (Local)	0.128***	0.182***	0.114***	0.168***	0.115***	0.171***	0.115***	0.168***	0.115***	0.168***
	(0.014)	(0.015)	(0.016)	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)
Delta Log Frontier (Global)	-0.063***	-0.039**	-0.062***	-0.039*	-0.062***	-0.042*	-0.062***	-0.040*	-0.062***	-0.039*
	(0.017)	(0.019)	(0.020)	(0.022)	(0.020)	(0.022)	(0.020)	(0.022)	(0.020)	(0.022)
Delta Log (K/L)	0.283***	0.263***	0.278***	0.247***	0.277***	0.248***	0.277***	0.247***	0.278***	0.251***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Log (Investment/Sales)	0.002	0.044							0.008	0.028
	(0.020)	(0.040)							(0.023)	(0.033)
Distance (Local)*Log(Investment/Sales)	0.001	0.014*							-0.004	0.010
	(0.006)	(0.007)							(0.007)	(0.009)
Distance (Global)*Log (Investment/Sales)	0.007	-0.042							0.002	-0.025
	(0.024)	(0.046)							(0.028)	(0.039)
Log (Ext Inno/Sales)			0.002	-0.022			0.007	-0.046	0.004	-0.051*
			(0.019)	(0.038)			(0.023)	(0.031)	(0.023)	(0.031)
Distance (Local)*Log (Ext Inno/Sales)			0.033***	0.048***			0.017**	0.026***	0.017**	0.025***
			(0.006)	(0.009)			(0.008)	(0.010)	(0.008)	(0.010)
Distance (Global)*Log (Ext Inno/Sales)			-0.007	0.032			-0.007	0.059	-0.004	0.064*
			(0.024)	(0.045)			(0.028)	(0.037)	(0.028)	(0.037)
Log (Int Inno/Sales)					-0.003	0.042	-0.009	0.058	-0.005	0.065
					(0.021)	(0.044)	(0.024)	(0.040)	(0.025)	(0.044)
Distance (Local)*Log (Int Inno/Sales)					0.037***	0.062***	0.024***	0.043***	0.025***	0.044***
					(0.006)	(0.011)	(0.008)	(0.011)	(0.008)	(0.012)
Distance (Global)*Log (Int Inno/Sales)					-0.009	-0.041	-0.003	-0.059	-0.008	-0.068
					(0.025)	(0.051)	(0.029)	(0.047)	(0.030)	(0.052)
Log Size (Medium)	0.027***	-0.026**	0.049***	-0.000	0.044***	0.001	0.047***	0.004	0.043***	0.000
	(0.004)	(0.011)	(0.005)	(0.013)	(0.005)	(0.013)	(0.005)	(0.013)	(0.005)	(0.013)
Log Size (Large)	0.060***	-0.045**	0.083***	0.002	0.074***	0.013	0.079***	0.016	0.069***	0.008
	(0.006)	(0.021)	(0.008)	(0.025)	(0.009)	(0.025)	(0.009)	(0.025)	(0.009)	(0.025)
Log Age	0.005*	-0.003	0.006*	-0.025	0.005*	-0.023	0.005*	-0.021	0.006**	-0.013
	(0.003)	(0.018)	(0.003)	(0.026)	(0.003)	(0.026)	(0.003)	(0.026)	(0.003)	(0.026)
Observations	65,684	65,684	46,131	46,131	46,131	46,131	46,131	46,131	46,131	46,131
R-squared	0.158	0.244	0.164	0.281	0.164	0.281	0.165	0.283	0.165	0.284
Number of id		11,637		9,510		9,510		9,510		9,510

All notes to the previous table apply here. *IntInno* stays for expenditure in R&D over revenues from sales.

Source: Authors' calculations.

Table 5.10. U.S.A. Estimation Results: Innovation and Technology Interactions

	OLS1	FE1	OLS2	FE2	OLS3	FE3	OLS4	FE4	OLS5	FE5
Distance (Local)	0.274***	0.761***	0.189***	0.590***	0.169***	0.566***	0.182***	0.580***	0.191***	0.628***
	(0.007)	(0.011)	(0.009)	(0.016)	(0.007)	(0.012)	(0.009)	(0.016)	(0.014)	(0.019)
Delta Log Frontier (Local)	0.198***	0.254***	0.239***	0.300***	0.239***	0.301***	0.239***	0.301***	0.238***	0.301***
	(0.008)	(0.009)	(0.013)	(0.015)	(0.013)	(0.015)	(0.013)	(0.015)	(0.013)	(0.015)
Delta Log (K/L)	0.270***	0.258***	0.277***	0.273***	0.277***	0.272***	0.277***	0.272***	0.278***	0.274***
	(0.004)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Log (Investment/Sales)	0.002**	-0.001							0.005***	0.001
	(0.001)	(0.001)							(0.001)	(0.001)
Distance (Local)*Log(Investment/Sales)	0.005***	0.010***							0.002	0.010***
	(0.001)	(0.002)							(0.002)	(0.002)
Log (Ext Inno/Sales)			0.001***	0.001			-0.001	-0.000	-0.001	-0.000
			(0.000)	(0.001)			(0.000)	(0.001)	(0.000)	(0.001)
Distance (Local)*Log (Ext Inno/Sales)			-0.001*	-0.001			0.002*	0.002	0.002*	0.002
			(0.001)	(0.001)			(0.001)	(0.001)	(0.001)	(0.001)
Log (Int Inno/Sales)					0.003***	0.002***	0.003***	0.002***	0.003***	0.002***
					(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Distance (Local)*Log (Int Inno/Sales)					-0.005***	-0.005***	-0.006***	-0.006***	-0.006***	-0.006***
					(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Size (Medium)	0.026***	0.004	0.023***	0.003	0.022***	0.002	0.022***	0.002	0.019***	0.001
	(0.002)	(0.005)	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)
Log Size (Large)	0.030***	-0.013*	0.026***	-0.007	0.025***	-0.007	0.025***	-0.007	0.020***	-0.009
	(0.002)	(0.007)	(0.004)	(0.013)	(0.004)	(0.013)	(0.004)	(0.013)	(0.004)	(0.013)
Log Age	0.010***	0.002	0.004**	0.000	0.004**	-0.000	0.004**	-0.000	0.004***	0.001
	(0.001)	(0.005)	(0.002)	(0.009)	(0.002)	(0.009)	(0.002)	(0.009)	(0.002)	(0.009)
Observations	$\approx 490,000$	$\approx 490,000$	$\approx 200,000$	$\approx 200,000$	$\approx 200,000$	$\approx 200,000$	$\approx 200,000$	$\approx 200,000$	$\approx 200,000$	$\approx 200,000$
R-squared	0.116	0.202	0.095	0.170	0.095	0.170	0.095	0.170	0.096	0.171
Number of id		$\approx 110,000$		$\approx 50,000$		$\approx 50,000$		$\approx 50,000$		$\approx 50,000$

All notes to the previous table apply here. $IntInno$ stays for expenditure in R&D over revenues from sales.

Source: Authors' calculations

In Table 5.11 we report only the estimates for the interaction terms, across multiple specifications, when only one interaction variable is introduced in each specification.[138] In both Mexico and Colombia, paying workers more (on average) while holding all other plant's feature constant (and in particular capital intensity and distance from the frontier) significantly decrease the speed of catch-up toward the local frontier. In Colombia, the same applies for convergence to the global frontier. The differences in cost of skilled vs. unskilled employees impact productivity growth positively in the US and negatively in Colombia.[139] These signs are confirmed when only including interactions with the local frontier (see Appendix 2, table A5.22). In a context where supply of skills is especially limited such as in Colombia this ratio is capturing this scarcity and the fact that firms have to pay a high premium to hire skilled workers which increases their costs. In the US instead, where the skill supply constraints is much less binding, this ratio is likely to capture the decision of the firm to invest in a more skilled workforce.[140] Trade, on the other hand, does not influence the speed of convergence towards the global frontier in either Colombia nor Mexico. On the opposite, it decreases the speed of convergence to the local frontier in Colombia, while it increases it in the US (even if the two estimated models are different).[141] This difference in the results could be determined by the different pattern of trade between US on the one side, and Colombia and Mexico on the other.[142] The nexus trade-productivity has been at the center of a large literature and our results are consistent with more recent work suggesting that where a firm exports and how it is engaged in international trade it matters for its effect on productivity (De Loecker (2007), Bai et al. (2013), Bastos and Silva (2010)). These results are robust to alternative measures of integration and separating imports from exports.

[138] For example, the first two columns (the interaction terms for external innovation) report the same results as in specification 2 of the previous tables.
[139] This metrics is computed as the ratio of costs of all skilled employees in the plant over the costs of all unskilled employees.
[140] Ideally we would like to control for local availability of skilled workers to confirm our interpretation but these data are not available.
[141] Our measure for trade is the ratio of revenues generated by international trade over total revenues from sales, where trade is either import or export.
[142] Differences may of course derive also from the differences in the estimated models. However, while looking at Table A5.22 in Appendix 2, where we only include interactions with the local frontier for Mexico and Colombia as well, we find different significance and sign with respect to the US.

Table 5.11. Estimation Results: One Interaction per Specification

	Log(Ext Inno/Sales)		Log(Int Inno/Sales)		Log(Investment/Sales)		Log(Trade/Sales)		Log(Avg Wage)		Log(Avg Wage Sk/Unsk)	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Mexico												
X	0.006*	0.012			0.011***	0.024*	0.002	0.020*	0.008	-0.152**		
	(0.004)	(0.008)			(0.003)	(0.013)	(0.003)	(0.011)	(0.024)	(0.074)		
Distance (Local)*X	0.006**	0.028***			0.011***	0.028***	-0.001	0.002	-0.082***	-0.253***		
	(0.002)	(0.006)			(0.003)	(0.006)	(0.002)	(0.006)	(0.016)	(0.035)		
Distance (Global)*X	-0.008	-0.012			-0.012***	-0.035**	0.003	-0.015	0.077**	0.346***		
	(0.005)	(0.012)			(0.004)	(0.018)	(0.005)	(0.014)	(0.036)	(0.087)		
Observations	40,214	40,214			36,847	36,847	39,763	39,763	35,687	35,687		
ID		6,157				6,138		6,137		5,725		
Colombia												
X	0.002	-0.022	-0.003	0.042	0.002	0.044	-0.010	-0.009	0.341***	0.375**	0.004	0.004
	(0.019)	(0.038)	(0.021)	(0.044)	(0.020)	(0.040)	(0.014)	(0.024)	(0.116)	(0.188)	(0.008)	(0.012)
Distance (Local)*X	0.033***	0.048***	0.037***	0.062***	0.001	0.014*	-0.011***	-0.012**	-0.093***	-0.183***	-0.006***	-0.014***
	(0.006)	(0.009)	(0.006)	(0.011)	(0.006)	(0.007)	(0.004)	(0.005)	(0.021)	(0.037)	(0.002)	(0.003)
Distance (Global)*X	-0.007	0.032	-0.009	-0.041	0.007	-0.042	0.019	0.022	-0.306**	-0.401*	0.000	0.002
	(0.024)	(0.045)	(0.025)	(0.051)	(0.024)	(0.046)	(0.016)	(0.028)	(0.132)	(0.216)	(0.009)	(0.014)
Observations	46,131	46,131	46,131	46,131	65,684	65,684	65,684	65,684	65,986	65,986	65,996	65,996
ID		9,510		9,510		11,637		11,637		11,667		11,667
U.S.A.												
X	0.001***	0.001	0.003***	0.002***	0.002**	-0.001	0.000	-0.002**	0.045***	-0.014*	0.001*	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.007)	(0.001)	(0.001)
Distance (Local)*X	-0.001*	-0.001	-0.005***	-0.005***	0.005***	0.010***	0.000	0.005***	-0.076***	-0.263***	0.005***	0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.006)	(0.010)	(0.002)	(0.002)
Observations	200,000	200,000	200,000	200,000	$\approx 490,000$	$\approx 490,000$	$\approx 270,000$	$\approx 270,000$	$\approx 490,000$	$\approx 490,000$	$\approx 490,000$	$\approx 490,000$
ID		$\approx 50,000$		$\approx 50,000$		$\approx 110,000$		$\approx 60,000$		$\approx 110,000$		$\approx 110,000$

All variable definitions stay as in previous tables. $Trade$ is the sum of expenditure for imports and revenues from exports, over revenues from sales, in $t-1$. $AvgWage$ stays for average wage in the plant in $t-1$, $AvgWageSk/Unsk$ for the ratio of the cost of employment of all skilled workers in the plant over that of unskilled workers, in $t-1$. Each column corresponds to a different specification in which the lagged value of the variable at the top of the column ($= X$) is interacted with the firm's distance from global and local frontier. The following regressors are also included in each specification: the distance from global and local frontier, the one-year change in the global and local frontier, the change in capital-labor ratio, the size dummies, industry, time, and industry-time dummies. For Colombia and U.S., regional (State) dummies and a control for the firm's age are also included. For the U.S., no global frontier is available (by definition).

Source: Authors' calculations

Finally, in Tables 5.12 and 5.13, we include trade and innovation interaction terms in the same specification (specifications 1), and all interactions together (specifications 2 and 3). In this horse-race between trade and innovation we find that trade does not seem to affect the speed of productivity convergence with neither global nor domestic frontier in either Mexico nor Colombia, but it does so in the US once again. Further, greater expenditure in innovation (relative to sales) increases the speed of catch up toward the domestic frontier in both countries, whether measured as purchase of external knowledge (Mexico) or R&D (Colombia).[143] These results confirm that plant productivity convergence to the domestic frontier is slowed down by higher average wages in all three countries of analysis, and by the higher wage gap between skilled and unskilled workers in Colombia while not in the US.

Finally, as a robustness check, to control for the possibility that our results are driven by reversion to the mean,[144] we re-estimate equations 5 and 6 using four-year changes (refer to Appendix 1 for the relevant tables). The sign on the main coefficients of interest remains the same, with the exception of the speed of convergence toward the global frontier, which turns insignificant for Mexico as well.[145] Once again the only firm-level characteristic which still has a positive impact on plant-level productivity convergence is innovation effort (external innovation for Mexico, internal innovation for Colombia). The negative impact of higher wages is robust to this specification, too. Results for the US, on the other hand, are somewhat less consistent with respect the specifications looking at year-on-year changes: investment seems to be the only significant determinant of catch up in this scenario.

[143] In view of the strong correlation between R&D and external innovation, it is possible that the coefficient on external innovation in Mexico is capturing the effect of internal innovation as well, which is absent in the Mexican specifications. As R&D expenditure information is unavailable in the Mexican data, we cannot improve on these results.

[144] After receiving a productivity shock, a plant may move back to its long term productivity pattern (mean reversion). Exploiting year-on-year changes may increase the probability that our coefficients attribute the effect of mean reversion to convergence.

[145] Notice that the estimates for some covariates were omitted from the Colombian table (but not from the estimation) for layout purposes.

Table 5.12. Estimation Results: Multiple Interactions per Specification - I

	Mexico 1		Mexico 2		Colombia 1		Colombia 2		Colombia 3	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Log (Trade/Sales)	-0.001	0.018	-0.003	0.009	-0.003	-0.023	0.010	-0.017	0.001	-0.019
	(0.003)	(0.011)	(0.004)	(0.009)	(0.015)	(0.024)	(0.017)	(0.022)	(0.017)	(0.023)
Distance (Local)*Trade	-0.003	-0.001	-0.000	0.002	-0.007**	-0.012**	-0.002	-0.008	-0.005	-0.009
	(0.002)	(0.005)	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.005)	(0.004)	(0.006)
Distance (Global)*Trade	0.007	-0.010	0.007	-0.002	0.008	0.035	-0.009	0.027	0.003	0.030
	(0.005)	(0.014)	(0.006)	(0.012)	(0.018)	(0.029)	(0.020)	(0.026)	(0.020)	(0.028)
Log (Investment/Sales)	0.014***	0.013	0.010	0.004	0.010	0.028	0.008	0.030	0.009	0.034
	(0.004)	(0.010)	(0.007)	(0.013)	(0.022)	(0.033)	(0.027)	(0.030)	(0.022)	(0.031)
Distance (Local)*Investment	0.012***	0.022***	0.011***	0.021***	-0.003	0.011	0.001	0.013	-0.002	0.014*
	(0.003)	(0.005)	(0.004)	(0.007)	(0.007)	(0.009)	(0.006)	(0.009)	(0.006)	(0.008)
Distance (Global)*Investment	-0.017***	-0.021	-0.011	-0.008	-0.001	-0.025	-0.001	-0.029	-0.001	-0.034
	(0.005)	(0.015)	(0.010)	(0.018)	(0.027)	(0.040)	(0.032)	(0.037)	(0.026)	(0.036)
Log (Ext Inno/Sales)	0.010**	0.013*	0.015***	0.009	0.004	-0.048	0.013	-0.044	-0.002	-0.055*
	(0.004)	(0.008)	(0.005)	(0.009)	(0.023)	(0.031)	(0.022)	(0.030)	(0.023)	(0.030)
Distance (Local)*Ext Inno	0.006**	0.023***	0.008***	0.026***	0.016**	0.026***	0.011	0.016*	0.014*	0.024***
	(0.002)	(0.006)	(0.003)	(0.006)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Distance (Global)*Ext Inno	-0.013**	-0.012	-0.021***	-0.008	-0.004	0.060	-0.013	0.059*	0.004	0.068*
	(0.006)	(0.011)	(0.007)	(0.013)	(0.028)	(0.037)	(0.027)	(0.035)	(0.029)	(0.036)
Log (Int Inno/Sales)					-0.005	0.059	-0.006	0.046	-0.007	0.052
					(0.025)	(0.042)	(0.022)	(0.036)	(0.025)	(0.041)
Distance (Local)*Int Inno					0.024***	0.043***	0.018**	0.031***	0.023***	0.039***
					(0.008)	(0.011)	(0.007)	(0.010)	(0.008)	(0.011)
Distance (Global)*Int Inno					-0.008	-0.060	-0.005	-0.043	-0.005	-0.052
					(0.030)	(0.049)	(0.027)	(0.042)	(0.030)	(0.048)
Log (Avg Wage)			0.025	-0.180***			0.305**	0.471**		
			(0.027)	(0.064)			(0.135)	(0.239)		
Distance (Local)*Avg W			-0.072***	-0.234***			-0.082***	-0.144***		
			(0.017)	(0.035)			(0.027)	(0.050)		
Distance (Global)*Avg W			0.044	0.360***			-0.267*	-0.511*		
			(0.039)	(0.079)			(0.156)	(0.277)		
Log (Avg Wage Sk/Unks)									0.005	0.011
									(0.008)	(0.010)
Distance (Local)*Avg Wage(Sk/Unks)									-0.005**	-0.013***
									(0.002)	(0.003)
Distance (Global)*Avg Wage(Sk/Unks)									-0.002	-0.005
									(0.009)	(0.012)
Observations	36,415	36,415	32,308	32,308	46,131	46,131	46,122	46,122	46,131	46,131
Number of id		6,116		5,671		9,510		9,510		9,510

All variable definitions stay as in previous tables. The following regressors were also included in each specification: the distance from global and local frontier, the one-year change in the global and local frontier, the change in capital-labor ratio, the size dummies, industry, time, and industry-time dummies. For Colombia, regional dummies and a control for the firm's age were also included.

Source: Authors' calculations

Table 5.13. Estimation Results: Multiple Interactions per Specification - II

	USA1		USA2		USA3	
	OLS	FE	OLS	FE	OLS	FE
Log (Trade/Sales)	-0.003***	-0.003**	-0.004***	-0.006***	-0.003***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Distance (Local)*Trade	0.007***	0.011***	0.009***	0.017***	0.007***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log (Investment/Sales)	0.005***	0.001	0.004***	0.001	0.005***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Distance (Local)*Investment	0.002	0.010***	0.002	0.011***	0.001	0.010***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Log (Ext Inno/Sales)	0.000	0.001	0.001	0.001	0.000	0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Distance (Local)*Ext Inno	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log (Int Inno/Sales)	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Distance (Local)*Int Inno	-0.007***	-0.008***	-0.007***	-0.008***	-0.007***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log (Avg Wage)			0.026***	-0.009		
			(0.006)	(0.011)		
Distance (Local)*Avg W			-0.049***	-0.210***		
			(0.009)	(0.015)		
Log (Avg Wage Sk/Unks)					0.000	0.002
					(0.001)	(0.002)
Distance (Local)*Avg Wage(Sk/Unks)					0.007***	0.004
					(0.002)	(0.003)
Observations	$\approx 180,000$	$\approx 180,000$	$\approx 180,000$	$\approx 180,000$	$\approx 180,000$	$\approx 180,000$
Number of id		$\approx 40,000$		$\approx 40,000$		$\approx 40,000$

All variable definitions stay as in previous tables. The following regressors were also included in each specification: the distance from global and local frontier, the one-year change in the global and local frontier, the change in capital-labor ratio, the size dummies, industry, time, and industry-time dummies. State dummies and a control for the firm's age were also included.

Source: Authors' calculations

As a further robustness check, we estimate baseline and simple interaction specifications with System GMM correcting for autocorrelation and heteroskedasticity in the errors, and for small sample biases (Windmeijer correction).[146] The results of these specifications are contained in Table A5.20 in Appendix 1. All models except for $4b$ use the same number of lags as instruments for the endogeneous variables, where the growth in the frontier and the level variable for the interaction variable (e.g. trade) are considered predetermined, while the distances and the cross products between distances and the interaction variable are considered endogeneous. Specification $4b$ is included to improve on the failure of specification $4a$ to pass the Hansen test of joint validity of the instruments. The existence of catch up to the local frontier is confirmed. Investment in capital goods positively affects it even when expenditure in external innovation is also taken into consideration. Innovation, on the other hand, is no longer significantly impacting convergence to the local frontier when included together with investment, contrary to what we found when not taking into account the existence of endogeneity in the regressors. Trade and wages do not seem to be affecting convergence at all.

To conclude, we also re-estimate equation 6 where Z_{jt} is measured at industry level (rather than plant level). In particular, we are interested in assessing whether higher levels of allocative efficiency at the industry level does affect the plant's speed of convergence toward the technology frontier. We find no evidence in this direction (ref. Tables 5.14 to 5.16): the coefficient on the covariance interaction term is never significant for both OLS and FE in any of the countries. On the other hand, higher levels of productivity dispersion in the industry (as captured by the coefficient of variation) significantly reduce the speed of catching up toward the local frontier in all countries, while they do so towards the global frontier in Colombia only (and not in Mexico). When at the frontier, higher productivity dispersion, on the other hand, implies higher productivity growth for Colombia and Mexico, but not (unambiguously) for the US.

[146] In the current draft, only results for Mexico are available.

Table 5.14. Mexico Estimation Results: Covariance Interaction

	OLS1	FE1	OLS2	FE2
Distance (Local)	0.133***	0.641***	0.146***	0.771***
	(0.011)	(0.030)	(0.016)	(0.044)
Distance (Global)	-0.132***	-0.144*	-0.097***	0.080
	(0.023)	(0.075)	(0.032)	(0.105)
Delta Log Frontier (Local)	0.539***	0.560***	0.548***	0.581***
	(0.023)	(0.023)	(0.024)	(0.024)
Delta Log Frontier (Global)	-0.014	-0.012	-0.010	0.008
	(0.021)	(0.021)	(0.021)	(0.021)
Delta Log (K/L)	0.164***	0.168***	0.164***	0.168***
	(0.013)	(0.012)	(0.013)	(0.013)
Covariance	-0.000	-0.002**		
	(0.000)	(0.001)		
Distance (Local)*Covariance	-0.000	0.003**		
	(0.000)	(0.001)		
Distance (Global)*Covariance	-0.000	-0.002***		
	(0.000)	(0.001)		
Coeff Variation			0.034***	0.212***
			(0.008)	(0.034)
Distance (Local)*Coeff Variation			-0.032**	-0.184***
			(0.013)	(0.042)
Distance (Global)*Coeff Variation			0.024**	0.039
			(0.011)	(0.024)
Log Size (Medium)	0.052***	0.037***	0.053***	0.036***
	(0.005)	(0.014)	(0.005)	(0.014)
Log Size (Large)	0.074***	0.050***	0.077***	0.049***
	(0.006)	(0.019)	(0.006)	(0.019)
Observations	40,216	40,216	40,214	40,214
Number of id		6,157		6,156

All notes to the previous table apply here. Errors are clustered at the establishment level. *Covariance* is the covariance of producivity and size in percentage terms of aggregate productivity in the sector-year; $CoeffVar$ stays for the coefficient of variation.

Source: Authors' calculations

Table 5.15. Colombia Estimation Results: Covariance Interaction

	OLS1	FE1	OLS2	FE2
Distance (Local)	0.221***	0.633***	0.254***	0.733***
	(0.019)	(0.045)	(0.035)	(0.065)
Distance (Global)	-0.058	0.315	0.453***	1.340***
	(0.088)	(0.280)	(0.169)	(0.333)
Delta Log Frontier (Local)	0.127***	0.175***	0.119***	0.163***
	(0.014)	(0.015)	(0.014)	(0.015)
Delta Log Frontier (Global)	-0.067***	-0.039**	-0.058***	-0.026
	(0.017)	(0.019)	(0.017)	(0.018)
Delta Log (K/L)	0.282***	0.259***	0.281***	0.258***
	(0.007)	(0.008)	(0.008)	(0.008)
Covariance	-0.001	-0.002		
	(0.002)	(0.005)		
Distance (Local)*Covariance	-0.001*	-0.000		
	(0.001)	(0.001)		
Distance (Global)*Covariance	0.002	0.003		
	(0.002)	(0.006)		
Coeff Variation			0.228***	0.496**
			(0.085)	(0.202)
Distance (Local)*Coeff Variation			-0.080***	-0.167***
			(0.029)	(0.059)
Distance (Global)*Coeff Variation			-0.212**	-0.439*
			(0.107)	(0.246)
Log Size (Medium)	0.027***	-0.023**	0.030***	-0.024**
	(0.004)	(0.011)	(0.004)	(0.011)
Log Size (Large)	0.059***	-0.036*	0.067***	-0.034*
	(0.006)	(0.021)	(0.006)	(0.020)
Log Age	0.003	-0.013	0.002	-0.010
	(0.003)	(0.018)	(0.003)	(0.018)
Observations	65,996	65,996	65,990	65,990
Number of id		11,667		11,667

All notes to the previous table apply here. Errors are clustered at the establishment level. *Covariance* is the covariance of producivity and size in percentage terms of aggregate productivity in the sector-year; $CoeffVar$ stays for the coefficient of variation.

Source: Authors' calculations

Table 5.16. U.S.A. Estimation Results: Covariance Interaction

	OLS1	FE1	OLS2	FE2
Distance (Local)	0.251***	0.712***	0.326***	0.922***
	(0.003)	(0.006)	(0.008)	(0.017)
Delta Log Frontier (Local)	0.196***	0.246***	0.194***	0.243***
	(0.008)	(0.009)	(0.008)	(0.009)
Delta Log (K/L)	0.269***	0.257***	0.268***	0.255***
	(0.004)	(0.005)	(0.004)	(0.005)
Covariance	0.000**	0.001***		
	(0.000)	(0.000)		
Distance (Local)*Covariance	-0.000	-0.000		
	(0.000)	(0.000)		
Coeff Variation			-0.011	0.097***
			(0.008)	(0.018)
Distance (Local)*Coeff Variation			-0.083***	-0.241***
			(0.010)	(0.021)
Log Size (Medium)	0.027***	0.005	0.027***	0.003
	(0.002)	(0.005)	(0.002)	(0.005)
Log Size (Large)	0.032***	-0.011	0.033***	-0.014**
	(0.002)	(0.007)	(0.002)	(0.007)
Log Age	0.009***	0.001	0.009***	0.002
	(0.001)	(0.005)	(0.001)	(0.005)
Observations	490,000	490,000	490,000	490,000
Number of id		110,000		110,000

All notes to the previous table apply here. Errors are clustered at the establishment level. *Covariance* is the covariance of producivity and size in percentage terms of aggregate productivity in the sector-year; $CoeffVar$ stays for the coefficient of variation.

Source: Authors' calculations

5. 6. Conclusions

Understanding the driver of productivity growth is a first order question in Latin America as growth in the last decade as been mostly driven by favorable external conditions which may not continue forever. Historically productivity growth in Latin America has been sluggish and the region has not been able to keep the pace of productivity growth in its northern neighbor, the United States.

For the first time we have performed a comparative analysis of productivity convergence at the firm-level for various Latin American countries and the US. Our analysis has focused on the decade of the 2000s and has been organized around two main questions.

First, we evaluated the extent to which aggregate productivity growth (in the manufacturing sector) is driven by growth in the productivity at the firm-level or by reallocation of employment shares across firms. Our results are very clear and show that if we want to understand productivity growth during the 2000s we need to focus on firm-level productivity growth as this contributed the most to overall productivity growth. Reallocation between firms,

within sectors, is a weak force of productivity growth. Even further, reallocation between sectors is an even weaker source of growth.

Second, building on the previous result, we zoomed in on the determinants of productivity catch-up at the firm level to evaluate the extent to which firms convergence with the "technology frontier", and even more to analyze the "drivers" of productivity catch up. Uniquely, for the various Latin American countries in this study, we are able to assess not only convergence towards the "domestic frontier", measured as the average productivity of most productive firms in the sector (at 4 digits ISIC), but also convergence towards the "global frontier", measured the average productivity of most productive US firms in the sector (at 4 digits ISIC). Our results suggest that while firms do convergence towards the domestic frontier and there are spillovers arising from the growth of the domestic frontier, unfortunately no convergence happens with respect to the global frontier. Finally, from a policy perspective an especially crucial result is that what seems to be increasing the speed of convergence with the domestic frontier is investment to expand the innovation and technological capabilities of firms, no effect comes from integration with trade for Latin American countries while on the opposite trade appears beneficial for US companies to accelerate their convergence with the domestic frontier.

From our analysis the picture that emerges for Mexico and Colombia is that of a situation where very few firms exist that are at the "global frontier" and catch up is limited to converging towards the local frontier. In a context where the local frontier is not converging with the global frontier this is an especially worrying situation for the Latin America manufacturing firms.

In conclusion, given the importance of innovation and technological capabilities for productivity catch up at the firm level, our results point towards an agenda of research and policy to understand how to develop technological capabilities to speed up the convergence with the frontier both in Mexico and Colombia. At the same time, these results raise the question of why reallocation appears to be so limited in explaining overall productivity growth.

5. 7. Appendix

5. 7. 1. Appendix 1: Further Estimation Results

Table A5.17. Mexico: 4-Year Changes

	OLS1	FE1	OLS2	FE2	OLS3	FE3	OLS4	FE4
Distance (Local)	0.408***	1.524***	0.374***	1.454***	0.570***	1.894***	1.460***	3.094***
	(0.027)	(0.100)	(0.036)	(0.113)	(0.089)	(0.181)	(0.252)	(0.492)
Distance (Global)	-0.404***	-0.535	-0.337***	-0.339	-0.496**	0.052	-0.999	-0.917
	(0.068)	(0.414)	(0.074)	(0.472)	(0.246)	(0.545)	(0.947)	(2.674)
Delta Log Frontier (Local)	0.560***	0.532***	0.553***	0.526***	0.564***	0.510***	0.534***	0.486***
	(0.028)	(0.033)	(0.028)	(0.033)	(0.029)	(0.032)	(0.029)	(0.032)
Delta Log Frontier (Global)	-0.082*	-0.180***	-0.090**	-0.163***	-0.059	-0.156***	-0.079*	-0.114**
	(0.043)	(0.050)	(0.044)	(0.050)	(0.045)	(0.048)	(0.046)	(0.046)
Delta Log (K/L)	0.135***	0.134***	0.136***	0.145***	0.130***	0.140***	0.140***	0.133***
	(0.014)	(0.018)	(0.015)	(0.018)	(0.015)	(0.020)	(0.015)	(0.020)
Log (Trade/Sales)			-0.001	-0.016				
			(0.012)	(0.024)				
Distance (Local)*Log (Trade/Sales)			-0.010	-0.008				
			(0.007)	(0.015)				
Distance (Global)*Log (Trade/Sales)			0.021	0.040				
			(0.017)	(0.029)				
Log (Invest/Sales)					-0.007	-0.077***		
					(0.013)	(0.029)		
Distance (Local)*Log(Invest/Sales)					0.001	-0.005		
					(0.008)	(0.013)		
Distance (Global)*Log (Invest/Sales)					0.018	0.107***		
					(0.019)	(0.041)		
Log (Ext Inno/Sales)					0.019	0.035		
					(0.014)	(0.030)		
Distance (Local)*Log (Ext Inno/Sales)					0.020**	0.060***		
					(0.008)	(0.018)		
Distance (Global)*Log (Ext Inno/Sales)					-0.023	-0.026		
					(0.021)	(0.039)		
Log (Avg Wage)							0.053	-0.045
							(0.131)	(0.408)
Distance (Local)*Log (Avg Wage)							-0.215***	-0.368***
							(0.049)	(0.098)
Distance (Global)*Log (Avg Wage)							0.131	0.217
							(0.173)	(0.501)
Log Size (Medium)	0.080***	0.061**	0.071***	0.064**	0.090***	0.071**	0.079***	0.054*
	(0.015)	(0.030)	(0.015)	(0.031)	(0.016)	(0.032)	(0.016)	(0.031)
Log Size (Large)	0.143***	0.085*	0.122***	0.087*	0.158***	0.109**	0.139***	0.076*
	(0.017)	(0.044)	(0.018)	(0.045)	(0.018)	(0.047)	(0.018)	(0.044)
Observations	23,259	23,259	22,874	22,874	21,301	21,301	21,017	21,017
R-squared	0.207	0.397	0.211	0.396	0.208	0.408	0.215	0.406
Number of id		5,528		5,495		5,492		5,123

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the 4 year change in the logarithm of value added per employee. $Distance(Local)$ is the difference between the plant's productivity and the (domestic) frontier over the value of the frontier, all lagged 4 years. $DeltaLogFrontier(Local)$ is the 4-year change in the value of the local frontier (in logs) between t and $t-4$. All other terms are lagged four years. All other notes notes to the previous tables apply here.

Source: Authors' calculations

Table A5.18. Colombia: 4-Year Changes

	OLS1	FE1	OLS2	FE2	OLS3	FE3	OLS4	FE4	OLS5	FE5
Distance (Local)	0.476***	1.335***	0.439***	1.325***	1.182***	1.937***	3.194***	4.398***	0.390***	1.165***
	(0.036)	(0.063)	(0.050)	(0.075)	(0.171)	(0.214)	(0.503)	(0.654)	(0.038)	(0.060)
Distance (Global)	-0.120	0.457	-0.093	0.203	0.138	2.129*	5.069	9.294**	-0.068	0.594
	(0.188)	(0.415)	(0.263)	(0.503)	(0.732)	(1.098)	(3.121)	(3.990)	(0.185)	(0.376)
Log (Trade/Sales)			-0.002	0.037						
			(0.030)	(0.035)						
Distance (Local)*Log (Trade/Sales)			-0.011	-0.008						
			(0.008)	(0.009)						
Distance (Global)*Log (Trade/Sales)			0.014	-0.027						
			(0.036)	(0.041)						
Log (Investment/Sales)					-0.058	-0.034				
					(0.044)	(0.058)				
Distance (Local)*Log(Investment/Sales)					-0.000	0.003				
					(0.017)	(0.021)				
Distance (Global)*Log (Investment/Sales)					0.076	0.054				
					(0.055)	(0.071)				
Log (Ext Inno/Sales)					0.035	-0.118***				
					(0.055)	(0.045)				
Distance (Local)*Log (Ext Inno/Sales)					0.038**	0.021				
					(0.016)	(0.016)				
Distance (Global)*Log (Ext Inno/Sales)					-0.032	0.152***				
					(0.065)	(0.053)				
Log (Int Inno/Sales)					-0.020	0.060				
					(0.064)	(0.071)				
Distance (Local)*Log (Int Inno/Sales)					0.064***	0.085***				
					(0.018)	(0.021)				
Distance (Global)*Log (Int Inno/Sales)					-0.003	-0.069				
					(0.075)	(0.083)				
Log (Avg Wage)							0.631**	0.794**		
							(0.254)	(0.333)		
Distance (Local)*Log (Avg Wage)							-0.286***	-0.328***		
							(0.048)	(0.064)		
Distance (Global)*Log (Avg Wage)							-0.458	-0.823**		
							(0.291)	(0.380)		
Avg Wage(Sk/Unsk)									0.013	-0.009
									(0.019)	(0.023)
Distance (Local)*Avg Wage(Sk/Unks)									-0.015***	-0.031***
									(0.004)	(0.005)
Distance (Global)*Avg Wage(Sk/Unks)									-0.003	0.027
									(0.022)	(0.027)
Observations	38,055	38,055	37,850	37,850	22,392	22,392	38,052	38,052	38,055	38,055
Number of id		6,975		6,947		6,103		6,974		6,975

All notes to the previous table in the Appendix apply here as well. The coefficients for the changes in local and global frontiers, the size dummies, the capital-labor ratio and the plants' age are omitted for layout purposes.

Source: Authors' calculations

Table A5.19. U.S.A: 4-Year Changes

	OLS1	FE1	OLS2	FE2	OLS3	FE3	OLS4	FE4	OLS5	FE5
Distance (Local)	0.616***	1.493***	0.596***	1.538***	0.598***	1.602***	1.509***	3.191***	0.623***	1.499***
	(0.007)	(0.013)	(0.012)	(0.020)	(0.030)	(0.041)	(0.054)	(0.088)	(0.008)	(0.014)
Delta Log Frontier (Local)	0.339***	0.465***	0.340***	0.469***	0.374***	0.527***	0.342***	0.465***	0.338***	0.466***
	(0.012)	(0.016)	(0.015)	(0.020)	(0.018)	(0.024)	(0.012)	(0.016)	(0.012)	(0.016)
Delta Log (K/L)	0.147***	0.149***	0.145***	0.151***	0.149***	0.159***	0.150***	0.139***	0.147***	0.149***
	(0.004)	(0.006)	(0.006)	(0.009)	(0.007)	(0.009)	(0.004)	(0.006)	(0.004)	(0.006)
Log (Trade/Sales)			0.000	-0.008***						
			(0.001)	(0.002)						
Distance (Local)*Log (Trade/Sales)			-0.003	0.022***						
			(0.002)	(0.003)						
Log (Investment/Sales)					0.000	0.000				
					(0.002)	(0.002)				
Distance (Local)*Log(Investment/Sales)					0.021***	0.028***				
					(0.004)	(0.005)				
Log (Ext Inno/Sales)					-0.003**	0.000				
					(0.001)	(0.001)				
Distance (Local)*Log (Ext Inno/Sales)					0.002	0.002				
					(0.002)	(0.002)				
Log (Int Inno/Sales)					0.012***	-0.000				
					(0.001)	(0.001)				
Distance (Local)*Log (Int Inno/Sales)					-0.015***	0.002				
					(0.002)	(0.003)				
Log (Avg Wage)							0.168***	0.065***		
							(0.009)	(0.015)		
Distance (Local)*Log (Avg Wage)							-0.234***	-0.453***		
							(0.014)	(0.022)		
Avg Wage(Sk/Unsk)									0.003*	-0.000
									(0.002)	(0.003)
Distance (Local)*Avg Wage(Sk/Unks)									0.008**	0.007
									(0.003)	(0.005)
Log Size (Medium)	0.019***	-0.055***	-0.020**	-0.075***	-0.025**	-0.072***	0.023***	-0.067***	0.019***	-0.055***
	(0.005)	(0.012)	(0.008)	(0.021)	(0.010)	(0.025)	(0.005)	(0.012)	(0.005)	(0.012)
Log Size (Large)	0.016***	-0.098***	-0.034***	-0.122***	-0.051***	-0.122***	0.018***	-0.125***	0.016***	-0.098***
	(0.006)	(0.017)	(0.009)	(0.027)	(0.010)	(0.028)	(0.006)	(0.017)	(0.006)	(0.017)
Log Age	-0.017***	-0.022*	-0.026***	-0.037**	-0.030***	-0.034	-0.019***	-0.014	-0.018***	-0.022*
	(0.003)	(0.012)	(0.004)	(0.017)	(0.004)	(0.021)	(0.003)	(0.012)	(0.003)	(0.012)

All notes to the previous table in the Appendix apply here as well. Number of observations and firms are omitted out of disclosure concerns.

Source: Authors' calculations

Table A5.20. Mexico: GMM

	1	2	3	4a	4b	5	6	7
Distance (Local)	0.436***	0.401***	0.368***	0.739***	0.819***	0.790***	0.981***	0.264
	(0.088)	(0.080)	(0.098)	(0.167)	(0.209)	(0.226)	(0.274)	(0.504)
Distance (Global)	-0.232*	-0.224***	-0.231	-0.867**	-0.946**	-1.674**	-2.065**	1.580
	(0.131)	(0.065)	(0.240)	(0.342)	(0.454)	(0.743)	(0.815)	(1.344)
Log (Trade/Sales)			0.020					
			(0.032)					
Distance (Local)*Log (Trade/Sales)			0.028					
			(0.018)					
Distance (Global)*Log (Trade/Sales)			-0.031					
			(0.047)					
Log (Investment/Sales)				0.061*	0.064		0.113**	
				(0.035)	(0.048)		(0.048)	
Distance (Local)*Log(Investment/Sales)				0.088***	0.088**		0.083***	
				(0.029)	(0.038)		(0.026)	
Distance (Global)*Log (Investment/Sales)				-0.118**	-0.125*		-0.181***	
				(0.053)	(0.074)		(0.068)	
Log (Ext Inno/Sales)						0.103*	0.056	
						(0.053)	(0.037)	
Distance (Local)*Log (Ext Inno/Sales)						0.044**	0.022	
						(0.021)	(0.018)	
Distance (Global)*Log (Ext Inno/Sales)						-0.145**	-0.079	
						(0.073)	(0.052)	
Log (Avg Wage)								0.309
								(0.230)
Distance (Local)*Log (Avg Wage)								0.032
								(0.110)
Distance (Global)*Log (Avg Wage)								-0.437
								(0.313)
Hansen p-value	0.475	0.416	0.355	0.026	0.188	0.365	0.181	0.667
AB p-value	0.640	0.605	0.606	0.387	0.351	0.566	0.360	0.156
Number of IVs	177	182	200	200	193	200	226	200
Observations	40,545	40,216	39,763	36,847	36,847	40,214	36,846	35,687
Number of id	6,197	6,157	6,137	6,138	6,138	6,157	6,138	5,725

*** p<0.01, ** p<0.05, * p<0.1. All variables have the same definition as in previous tables. *Hansen* is the p-value of the test of joint validity of the instruments in presence of heteroskedastic errors; *AB* is the p-value of the Arellano Bond test for the absence of autocorrelation in the errors of order higher than one. All models except for 4*b* use the same number of lags as instruments for the endogeneous variables, where the growth in the frontier and the level variable for the interaction variable (e.g. trade) are considered predetermined, while the distances and the cross products between distances and the interaction variable are considered endogeneous. Specification 4*b* is included to improve on the failure of specification 4*a* to pass the Hansen test. The following regressors are included in the estimation but omitted in the table: change in capital-labor ratio, size dummies, change in frontiers. All specifications include time dummies, 2 digit industry dummies and the cross product of the two. Standard errors are robust and corrected to account for small sample biases.

Source: Authors' calculations

5. 7. 2. Appendix 2: Estimation Results with Local Frontier only

Table A5.21. Estimation Results: Baseline, with Local Frontier only

	Mexico				Colombia			
	OLS1	FE1	OLS2	FE2	OLS1	FE1	OLS2	FE2
Distance (Local)	0.083***	0.618***	0.080***	0.587***	0.210***	0.697***	0.199***	0.682***
	(0.009)	(0.045)	(0.009)	(0.045)	(0.009)	(0.036)	(0.008)	(0.022)
Delta Log Frontier (Local)	0.529***	0.542***	0.529***	0.538***	0.134***	0.201***	0.119***	0.187***
	(0.023)	(0.022)	(0.023)	(0.022)	(0.014)	(0.015)	(0.014)	(0.014)
Delta Log (K/L)			0.164***	0.168***			0.282***	0.260***
			(0.013)	(0.013)			(0.008)	(0.008)
Log Size (Medium)			0.052***	0.037***			0.028***	-0.021**
			(0.005)	(0.014)			(0.004)	(0.011)
Log Size (Large)			0.074***	0.051***			0.064***	-0.035*
			(0.006)	(0.019)			(0.006)	(0.021)
Log Age							0.003	-0.012
							(0.003)	(0.018)
Observations	40,545	40,545	40,216	40,216	68,533	68,533	65,996	65,996
R-squared	0.194	0.281	0.213	0.295	0.107	0.197	0.156	0.242
Number of id		6,197		6,157		11,924		11,667

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the change in the logarithm of value added per employee. $Distance(Local)$ is the lagged difference between the plant's productivity and the (domestic) frontier over the value of the frontier, as expressed in equation 5. $DeltaLogFrontier(Local)$ is the change in the value of the local frontier (in logs) between t and $t-1$. All other terms are lagged once. K/L is the capital-labor ratio in the plant, while $LogSize(Medium, Large)$ is a dummy having value 1 if the firm has between 50 and 200 employees (respectively, more than 200 employees) in year $t-1$. $LogAge$ is the logarithm of the plant's age increased by one (so that entrants would not be dropped from the sample). All specifications include time dummies, 2 digit industry dummies and the cross product of the two. Data availability permits to control for age and regional dummies in Colombia but not Mexico. Our Colombian sample covers the years 2000 to 2011, our Mexican sample the years 2003 to 2010.

Source: Authors' calculations

Table A5.22. Estimation Results: One Interaction per Specification, with Local Frontier only

	Log(Ext Inno/Sales)		Log(Int Inno/Sales)		Log(Investment/Sales)		Log(Trade/Sales)		Log(Avg Wage)		Log(Avg Wage Sk/Unsk)	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Mexico												
X	0.000	0.004			0.003*	-0.001	0.004***	0.010***	0.060***	0.084***		
	(0.001)	(0.002)			(0.002)	(0.003)	(0.001)	(0.003)	(0.009)	(0.030)		
Distance (Local)*X	0.005***	0.026***			0.005	0.018***	-0.000	-0.002	-0.057***	-0.144***		
	(0.002)	(0.004)			(0.003)	(0.005)	(0.002)	(0.005)	(0.011)	(0.042)		
Observations	40,214	40,214			36,847	36,847	39,763	39,763	35,687	35,687		
ID		6,157				6,138		6,137		5,725		
Colombia												
X	-0.004	0.005	-0.010***	0.009*	0.007***	0.010**	0.006***	0.010***	0.079***	0.028	0.004***	0.006***
	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.001)	(0.002)	(0.009)	(0.018)	(0.001)	(0.001)
Distance (Local)*X	0.031***	0.051***	0.035***	0.054***	0.002	0.006	-0.007***	-0.008**	-0.139***	-0.230***	-0.006***	-0.013***
	(0.003)	(0.006)	(0.004)	(0.009)	(0.005)	(0.007)	(0.002)	(0.004)	(0.010)	(0.020)	(0.001)	(0.002)
Observations	46,131	46,131	46,131	46,131	65,684	65,684	65,684	65,684	65,986	65,986	65,996	65,996
ID		9,510		9,510		11,637		11,637		11,667		11,667

All variable definitions stay as in previous tables. $Trade$ is the sum of expenditure for imports and revenues from exports, over revenues from sales, in $t-1$. $AvgWage$ stays for average wage in the plant in $t-1$, $AvgWageSk/Unsk$ for the ratio of the cost of employment of all skilled workers in the plant over that of unskilled workers, in $t-1$. Each column corresponds to a different specification in which the lagged value of the variable at the top of the column ($= X$) is interacted with the firm's distance from the local frontier. The following regressors are also included in each specification: the distance from the local frontier, the one-year change in the local frontier, the change in capital-labor ratio, the size dummies, industry, time, and industry-time dummies. For Colombia, regional dummies and a control for the firm's age are also included.

Source: Authors' calculations

Table A5.23. Estimation Results: Multiple Interactions per Specification, with Local Frontier only

	Mexico				Colombia					
	OLS1	FE1	OLS2	FE2	OLS1'	FE1	OLS2	FE2	OLS3	FE3
Log (Trade/Sales)	0.004***	0.011***	0.001	0.009***	0.004***	0.007***	0.003*	0.006***	0.003**	0.006***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Distance (Local)*Trade	-0.000	-0.005	0.003*	0.000	-0.005**	-0.008*	-0.004	-0.006	-0.005*	-0.006
	(0.002)	(0.005)	(0.002)	(0.006)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Log (Investment/Sales)	0.003*	-0.001	0.001	-0.003	0.009***	0.008**	0.007**	0.007*	0.008***	0.007**
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
Distance (Local)*Investment	0.005*	0.017***	0.009***	0.022***	-0.003	0.006	0.000	0.007	-0.002	0.007
	(0.003)	(0.005)	(0.002)	(0.005)	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)	(0.006)
Log (Ext Inno/Sales)	0.000	0.004*	0.000	0.004	0.001	0.003	0.003	0.005	0.001	0.002
	(0.001)	(0.002)	(0.001)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Distance (Local)*Ext Inno	0.004**	0.021***	0.002	0.025***	0.016***	0.034***	0.008*	0.024***	0.014***	0.034***
	(0.002)	(0.004)	(0.002)	(0.005)	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)	(0.006)
Log (Int Inno/Sales)					-0.011***	0.008*	-0.009***	0.010**	-0.011***	0.008*
					(0.003)	(0.005)	(0.003)	(0.004)	(0.003)	(0.005)
Distance (Local)*Int Inno					0.023***	0.033***	0.017***	0.025***	0.022***	0.031***
					(0.005)	(0.009)	(0.005)	(0.008)	(0.006)	(0.009)
Log (Avg Wage)			0.054***	0.064**			0.080***	0.028		
			(0.009)	(0.027)			(0.011)	(0.025)		
Distance (Local)*Avg W			-0.056***	-0.116***			-0.126***	-0.201***		
			(0.011)	(0.037)			(0.016)	(0.033)		
Log (Avg Wage Sk/Unks)									0.003***	0.007***
									(0.001)	(0.001)
Distance (Local)*Avg Wage(Sk/Unks)									-0.005***	-0.013***
									(0.001)	(0.002)
Observations	36,415	36,415	32,308	32,308	46,131	46,131	46,122	46,122	46,131	46,131
Number of id		6,116		5,671		9,510		9,510		9,510

All variable definitions stay as in previous tables. The following regressors were also included in each specification: the distance from local frontier, the one-year change in the local frontier, the change in capital-labor ratio, the size dummies, industry, time, and industry-time dummies. For Colombia, regional dummies and a control for the firm's age were also included.

Source: Authors' calculations

5. 7. 3. Appendix 3: Data Construction

We have access to two plant-level panel datasets, one for Colombia (*Encuesta Anual Manufacturera - EAM*) and one for Mexico (*Encuesta Industrial Anual - EIA*), thanks to the respective national institutes of statistics (DANE and INEGI). These datasets contain accounting information on plants in the manufacturing sector for the years 2000-2011 for Colombia, and 2003-2011 for Mexico. We also match the plant-level information of the EAM with the annual survey on innovation activities of Colombian manufacturing firms (*Encuesta de Desarrollo e Innovación Tecnológica en la Industria Manufacturera - EDIT*) for the years 2003-2010. Finally, we have access to the US Annual Manufacturing Survey at the US Census, for the years 1995-2011. In this appendix we supplement the information on eligibility and coverage of the manufacturing surveys we provided in paragraph 2.1.

Data Cleaning

In order to proceed with our analysis, we needed our main variable of interest to be non-missing in all plants. That is why we dropped all observations without information for value added per employee, as well as industry classification (which is needed to issue descriptive statistics and to merge the values of the global frontier). We made sure that our data are reliable by eliminating observations in which employment was reported to be negative. We treated the presence of extreme values in the resulting sample by truncating the distribution of value added and growth in value added at the 1 and 99 percent.

What is more, we made sure that the sample used to issue tables of descriptive statistics and productivity decompositions was the same as the one of the baseline regressions in Tables 5.5 and 5.6. Since these regressions take value added per employee in logarithm, we also excluded observations with negative or zero value added. In a further effort to limit the extent of misreporting, we also dropped observations with positive value added but zero employment; as a consequence, we excluded the possibility of sole proprietorship, which we deemed more unlikely in manufacturing.

A final constraint in the Colombian and Mexican data was imposed after merging the values for the global frontier. Evidently, there were four-digit sectors for which a value of the global frontier was available, but which were not existing in the countries of operation (in a given year or throughout the sample): the values of the global frontier in these sectors were discarded without loss of information for Colombian or Mexican data. Viceversa, there were also cases (3 percent of the cleaned sample) in which the four-digit industry code was available in the main datasets of interest, but not in the global frontier data. It mostly happened in sectors-year pairs for which a value of the frontier could not be issued, in compliance to the US Census Bureau data protection rules.

Industry Classification and Conversion

We relied on industry information contained in the EAM for Colombia, in the EIA for Mexico, and in the AMS for the US. Each of these surveys follows a different industry classification: the EAM classifies plants according to a four-digit ISIC3 classification specifically adapted to the

Colombian context; the EIA uses a six-digit classification inspired by the US NAICS2002 and 2007 classification (SCIAN 2002, 2007); we elaborate US data based on the six-digit NAICS2002 classification. Using three different industry classifications would have hindered the cross-country comparison of descriptive statistics and productivity decompositions. What is more, we needed the US-based information to calculate Mexican and Colombian plant-level distances from the global frontier, where the value of the frontier was computed from a statistical moment of the firm productivity distribution at the industry level. As the Naics2002-Isic3 (or 3.1) conversion implies numerous many-to-many correspondences, we created a new industry classification for manufacturing, which could include all national classifications, on the basis of existing Naics2002-Naics2007, Naics-Scian, Isic3(Colombia)-Isic3.1(International), and Naics2002-Isic3.1(International) conversion tables.

We obtain a single classification inspired (but not coinciding) to the international Isic3.1 classification, which contains 104 four-digit classes and which we call NewInd hereafter. One Isic3.1 four-digit class (out of 122) and 7 six-digit Naics2002 classes (out of 473) have no correspondence in the new classification. All statistics in the paper requiring an industry declination (including the computation of the global frontier) are issued according to NewInd.

In constructing NewInd, we first converted the national classifications into either Naics2002 or Isic3.1. This proved to be a relatively straight-forward task, due to the existence of one-to-one conversions for almost all industries in each country. A one-to-many correspondence between a four-digit Isic3.1 and a six-digit Naics2002 code also resulted in the use of the Isic3.1 code (this happened for 281 out of 473 Naics manufacturing classes). In taking into consideration the many-to-many correspondences between Naics2002 and Isic3.1, on the other hand, we followed these priciples:

1. When one of the multiple Isic3.1 codes corresponding to a single Naics2002 code was not classified as manufacturing in the Isic3.1 classification, we dropped this Isic3.1 code altogether. This happened for 8 six-digit Naics codes.
2. When the Naics2002 classification is specific enough, we searched for the corresponding products in the Isic3.1. A description table for the Isic3.1 code can be found here: http://unstats.un.org/unsd/statcom/doc02/isic.pdf.
3. When in doubt about the attribution of a certain six-digit Naics code to an Isic code, we also took into consideration the meaning of the five- and four-digit Naics code.
4. When the "predominant meaning" of a Naics code was clear once aggregating two or more of the proposed four-digit Isic codes in the Naics-Isic conversion table, we merged the different Isic codes. We limited the number of cases in which this happened, as it reduced the number of final available industry codes in NewInd. In most cases, the merged Isic codes refer to the same two- or three-digit Isic class.
5. We dropped 7 Naics six-digit codes, whose meaning could not be linked to any single Isic or combination of Isic codes.

Deflation

All financial information in the different manufacturing surveys is reported in nominal terms. We therefore deflate these values with an appropriate deflator in base 2005. We then convert them to

thousand US dollars using the appropriate (yearly) exchange rate from the World Bank. As the values of the global frontier were computed in thousand USD, we converted them into the national currencies before merging them and calculating the plant-frontier distance.

So as to deflate *domestic sales* and *export sales*, we use six-digit producer index prices for Mexico,[147] and a manufacturing-level producer price index for Colombia. [148] As far as domesticly sourced *material inputs* are concerned, we use the appropriate four-digit PPI (based on the CMAE classification) for Mexico, and a manufacturing-wide deflator for Colombia. *Imported materials* in both Colombia and Mexico are deflated using the manufacturing-wide US price of exports of non-agricutural supplies and intermediate goods (available on the US Census webpage) once adjusted by the USD/country currency exchange rate. Expenditure for *electricity* was deflated using the producer price index for the electricity sector in both countries. Finally, we used the consumer price index to deflate both labor costs and expenditure for innovation.

The deflation of most *capital investment* is based for both countries on three-digit price indexes for investment from the US Bureau of Labor Statistics (http://www.bls.gove/mfp/mprtech.pdf), which we adjust by the exchange rate between USD and the country currency. The BLS provides prices deflators for different types of investment: all capital goods, equipment, structures, land, intellectual property products, inventories. We exploit the first three prices for, respectively, all investments, invesmtment in machinery, and investment in buildings. As far as *ICT capital investment* is concerned, we use the price of gross output for the "information-communications-technology-producting industries" elaborated by the Bureau of Economic Analysis[149] and adjusted by the exchange rate. We deflated *investment in transportation equipment* by the country-specific producer price index for the transportation sector.

Variable Construction

Our main outcome variable relies on the existence of *value added* at the plant level. As this is not directly reported in the dataset, we constructed it as the sum between (deflated) revenues from sales, minus the (deflated) cost of raw (either domestic or imported) materials and the (deflated) cost of electricity. If any component of this sum is missing, the result is also missing.

The EAM and EIA report the plant's *capital stock* at book value. However, this is not the actual use value of the capital for the plant, but rather the result of the depreciated value at which such capital was purchased. A better measure of the value of capital would be its replacement value, but we do not have access to it. This is why we assume that the book value in the first year of the sample (i.e. in 1995 for the US, 2000 for Colombia, and 2003 for Mexico) corresponds to the capital replacement value. We then construct the value of capital for the following years using the Perpetuary Inventory Method (PIM) according to the following equality:

$$K_{ijt} = K_{ijt-1}(1-\delta_{jt-1}) + I_{ijt-1}$$

[147] These are published on the INEGI website.
[148] At the moment of writing, a more disaggregated PPI time series is available from 2006 onwards only.
[149] This is a synthetic sector covering hardware and software producing industries including computer and electronic production, software publishing, telecommunication, data processing, internet publishing, web portals, computer system design and related services.

for $t \in [1997,201]$ for the US, $t \in [2001,201]$ for Colombia and $t \in [2004,201]$ for Mexico. I_{ijt-1} stays for investment, or the purchase of new capital goods (which is reported in the datasets), and K_{ijt} is the result of the calculation of capital stocks in the year. δ_{jt} is the depreciation rate of capital. Both EAM and EIA contain information on depreciation rates by type of capital. So as to limit the impact of possible misreporting, in the PIM we use the median of the two-digit sector depreciation rate from the data, where values above 100 percent and below 0 percent of capital stock were winsorized. Once we obtained a time series for the capital stock of each type of capital (buildings, equipment, ICT, transportation), we aggregated them into two variables, one for total capital and another for total capital except buildings and structures.

A final note is allocated to the creation of the innovation variables. We have information on expenditure for research and development (new and improved processes or products, which we call internal innovation) only for Colombia and the US. In Mexico, the external innovation variable covers the expenditure for the exploitation of the rights connected to a copyright, patent, brand or know-how. In Colombia, the external innovation variable is obtained as the sum of: expenditure for the purchase of R&D which was carried out by others, expenditure for patents and copyright, fees for technical assistance and consulting on technological know-how.

Entry and Exit

We define a plant appearing for the first time in the unclean sample an entrant. However, as we mentioned in paragraph 2.1, the Mexican EIA does not take into account entry in a systematic way: updates to the sample are carried out in presence of sizeable plants entering the market, or in case the number and coverage of plants in a sector drop below the mandatory minimum of the year. We therefore observe very limited entry in years other than the first year of the sample (2003). Accounting for entry in the Colombian survey is also problematic, as the methodology to update the sample changed in 2008. Until 2007, the EAM was updated on the basis of mini-surveys which were conducted by the DANE's regional offices; starting from 2008, the central DANE cross referenced its sample with other sources of information (Superintendence of Companies, Chambers of Commerce, Free Export Zones, the exporter's database). A plant is identified as exiter in the last year of operation in the dataset before cleaning.

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6. Institutions and Return to Firms' Innovation with a focus in Latin America

Ha Nguyen[*] and Patricio A. Jaramillo

6. 1. Introduction

Firms' innovation and technology adoption are widely considered as the key driver to economic growth. Google and Apple are prime examples in the developed world, where their innovation and new products not only contribute to the economy, but also fundamentally change the way we work, entertain and communicate. Many developing countries, via different means such as foreign direct investment, also try to encourage firms to adopt new technologies and management practices.

Yet many firms do not innovate or adopt new technology. In seeking explanations for that, the conventional focuses have been on the obstacles to firms. For example, firms might not have the ability to innovate: they might not have the know-how or access to new technologies[150]. Even if they do, they might not have access to finance for the research or the adoption. Girma et al (2008) shows that private and collectively owned firms without foreign capital participation and those with poor access to domestic bank loans innovate less than other firms do.

In this paper, we do not follow the conventional path to examine the obstacles to firms' innovation, but rather, turn our focus to firms' incentives to innovate. This angle, although more neglected, should deserve more attention in our view. We argue that in many developing countries, firms might not have the incentive to innovate because the reward to innovation is small. For instance, in an environment where property rights are not well protected, a firm's new product can be easily copied[151]. This will significantly reduce the return to innovation. Lin et al (2010) use the 2003 World Bank Enterprise Survey of over 2400 firms in 18 Chinese cities to show that firms' perception about property rights protection is positively and significantly related to corporate R&D activity. Another example is that in a monopolized sector, the incumbent might not need to innovate: their products, good or bad, are the only ones available in the market.

To make our point, we will proceed in two steps. In the first step, we estimate the return to firms' innovation across many developing countries. We measure the quantitative return in terms of sales, and sales per worker. We find that the return is low, which implies that the incentive to innovate is small. In the second step, we compare the return to innovation across countries with different

[*] The paper is a part of the World Bank Latin America Economic Policy Sector (LCSPE)'s project on Latin America's convergence. We thank the support from LCSPE. We thank Luis Serven, Ufuk Akcigit, Jorge Araujo, Francesco Caselli, Maya Eden, Matteo Iacoviello, Bill Maloney, Ekaterina Vostroknutova, Pluvia Zuniga for very helpful comments and feedback. We thank Maria Ivanova Reyes for her able research assistance. This paper reflects the authors' views and not necessarily those of the World Bank, its Executive Directors or the countries it represents. All errors are our own. Contact address: Ha Nguyen, Developing Research Group, The World Bank, 1818 H. St, N.W., Washington D.C. 20433. Email: hanguyen@worldbank.org.

[150] Burstein and Monge-Naranjo (2009) shows that developing countries' output can grow significantly when they eliminate all barriers to foreign know-how.
[151] In this line, see Branstetter et al (2006).

institutional quality. We find that in countries with lower institutional quality (in particular, rule of law, regulatory quality and property right protection), the return to firms' innovation is lower.

Estimating the return to firms' product innovation is not entirely new. Previous studies have tried to measure the sale and employment return to product innovation, but mostly are limited in a single country. Earlier studies focus on the manufacturing sector in developed countries, such as Van Reene (1997) for the UK, Greenan and Guellec (2001) for France, Hall et al. (2008) for Italy, Guadalupe et al (2012) for Spain. Recent studies start to quantify the return in developing countries, Benavente and Lauterbach (2008) for Chile, Aboal et al. (2011) for Uruguay, and Crespi and Tacsir (2012) for four Latin American countries.

The main contribution of this paper is at the second step, where we are the first to show the return to innovation positively correlates with countries institutional quality. In other words, in countries with lower levels of institution, the return to product innovation is lower. This is an interesting result because this implies that an important element for the lack of innovation in developing countries is the incentive to innovate. Related to our findings, Goni and Maloney (2014) find that at the country level, the rates of return from R&D expenditures follow an inverted U: they rise with distance to the frontier and then fall thereafter, potentially turning negative for the poorest countries.

The comparison across countries is made possible thanks to the World Bank's Enterprise Surveys (ES). The Enterprise Survey is a firm-level survey of a stratified representative sample of firms. It covers a large set of countries. This survey has been conducted since 2002 and typically answered by business owners and top managers. The surveys cover a broad range of business environment topics including access to finance, corruption, infrastructure, crime, competition, and performance measures[152]. ES is stratified using random sampling where the strata are firm size, business sector, and geographic region within a country. Firm size levels are 5-19 (small), 20-99 (medium), and 100+ employees (large-sized firms).

In our paper, we focus on product innovation. A firm is understood to innovate if it introduced a new product or service or upgraded an existing product or service. In our data, only firms in Latin America (LAC) and Eastern Europe and Central Asia (ECA) regions are surveyed about their product innovation. We estimate the percentage change in sales per worker *within* a firm if it has introduced or upgraded the products or services in the 3 years prior to the survey. The idea is that if a firm innovates, its sales and sales per worker should increase. Ideally one should look at firms' profit as the best measure of the return. Unfortunately that is not possible in our study because data on reported profit are much more infrequent than data on sales, and because we are concerned about firms' profit underreporting problem.

Overall, we found that after a firm innovates, its sale per worker increases by 18 percent, although the significance is only at the 10 percent level. Focusing on Latin America, we found that the returns to innovation in terms of sales and sales per worker for Latin American firms are not statistically different to zero. This implies that within a country, the return to innovation in Latin America is very small. Obviously, without the appropriate instrument to capture the exogenous

[152] Methodological details can be found at the link below
http://www.enterprisesurveys.org/~/media/FPDKM/EnterpriseSurveys/Documents/Methodology

component of product innovation, the results suffer from biases. We will go back to discuss the sources of biases and how we deal with them in more details in the Section 3. We will argue that if the biases are not systematically correlated with countries' institutions, the cross country comparison of the institutions' impacts -our ultimate interest- is valid.

We found that the return to innovation is higher in countries with better institutions. Overall, if a country is ranked 1 percentile higher in the world's rule of law and regulatory quality rankings, the sale return to innovation is about 1.7-1.9 percent higher and the sale per worker return is about 0.85-0.95 percent higher. This implies that in countries with better rule of law and regulatory quality, the incentives to innovate for firms is greater. We also zoom in an important component to the return to innovation: property right protection and patent right protection. We found that in countries with good property right protection, the return to innovation is higher. We found that countries with good property and patent right protection, the return to innovation is also higher, with about the same magnitude. If we restrict to Latin America only, the relationship between the return to innovation and a country's institution is even larger. However, due to the small sample problem, we should take the results with caution. We will go back to these points in greater details.

6. 2. Data and Variables

The data is the World Bank Enterprise Survey- a rich firm-level survey database that provides information about firms' characteristics such as ownership, size, sector, region in which it is located, annual sales, capacity utilization, employment, competition etc. In order to analyze the change within a firm, we specifically select firms that appear in at least 2 surveys (i.e. panel data). In our sample, 6,191 firms appear in two surveys and 256 firms appear in three. There are 44 countries with 6,447 unique firms. The detailed list of countries and firms are in Table A6.8 in the Appendix. Note that the innovation module in the survey only exists in LAC and ECA. At the end, only LAC and ECA countries remain. The data span from 2002 to 2010.

The innovation module in Latin America is quite different to that in Eastern Europe and Central Asia. In Latin America (LAC) we use the following question to get data for innovation:

During the last three years, did the establishment introduce onto the market any new or significantly improved products? (Yes/No/Don't Know)

We define a firm innovates when it answers Yes to this question.

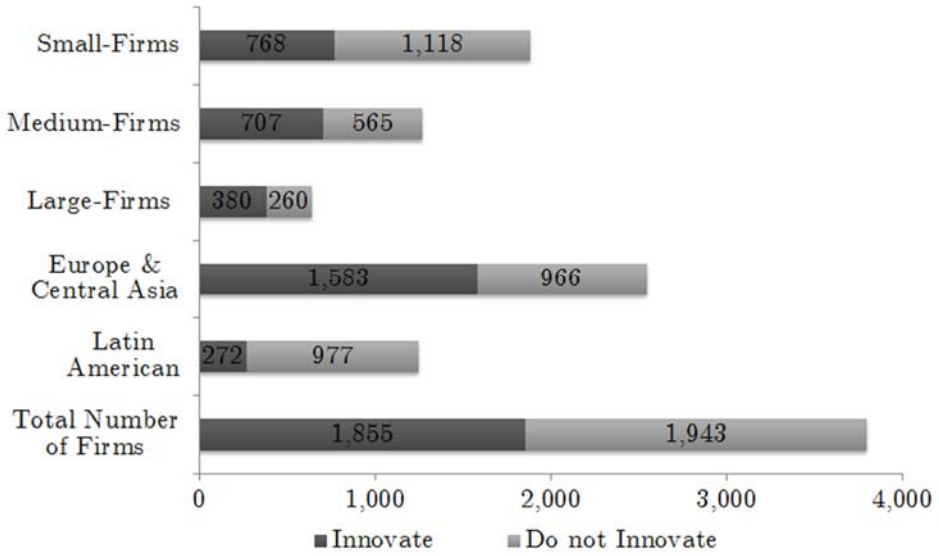
In Eastern Europe and Central Asia (ECA), we use the following two questions in the survey to get data for innovation:
Q1: In the last three years, has this establishment introduced new products or services (Yes/No/ Don't answer)
Q2: In the last three years, has this establishment upgraded an existing product line or service (Yes/No/Don't answer).

We define that a firm innovates when it answer Yes to either of the questions. By doing so, we can harmonize the innovation variable between LAC and ECA and hence can increase the sample size.

The downside of this is that in ECA, we will mix the return of an upgraded product and that of a completely new product[153].

Out of 3,798 observations that answer, 1,855 firms answer Yes to either of the innovation questions. Figure 6.1 summarizes the profile of innovating firms by size and by regions. Large firms are more likely to innovate than small firms. Europe and Central Asia firms are more likely to innovate than Latin American firms.

Figure 6.1. Firms' Innovation in Emerging Markets Economies
(Number of firms)



Source: Own elaboration based on The World Bank's Enterprise Surveys.

We use the following two proxies for firms' performance: real sales, and real sales per worker. They are admittedly not ideal measures. The ideal measure should be firms' profit. We do not use firms' profit because the data on profit are much spottier,[154] and because firms' profit might be under-reported in many developing countries.

Sales can go up or down with a new product. A new product may cannibalize the business and the profits made from producing the old products when the new products replace and drive out the old products from the market. On the other hand, the new product on the market can also compliment the old product. In any case, a successful introduction of a new or upgraded product should increase sales. Between the two measures of sales, in our view, sales per worker is a more precise measure of return to innovation than total sales. A sharper increase in sales per worker implies higher return.

Note that a firm can answer *Yes* to these questions even the firm just slightly modifies its product, or adopts the new product from overseas. It could also simply copy it from another domestic firm.

[153] See Akcigit and Kerr (2010) for a discussion about the innovation implications of completely new products and improve products.
[154] In the data set, a third of firms do not report labor costs, and 60 percent of firms do not report costs on intermediate input and raw material. The vast majority of firms do not report costs on fuel, electricity and water.

As long as the product is new or improved to that firm, the firm can answer *Yes* to the questions. In that sense, the understanding of "Innovation" is broader than one usually would think, but the implication to the return to innovation is unchanged: in an environment where a firm can freely copy a product and claim it as a new innovating product, the return to its "innovation" is not likely high. The return is not high for those that originally come up with the product and nor for those that copy it.

Choosing control variables are not straight-forward, we need to find factors that potentially affect firm sales. Besides the change of manager, we found two variables in the questionnaire: whether a firm becomes an exporter between the two waves of survey, and whether the number of a firm's competitor's increases or decreases. We expect that becoming an exporter will boost firms' sales and employment, and an increase of competitors will reduce sales and employment. We also include firm size, industry, and country*time fixed effects. The detailed rational and data sources of these variables are discussed in the next section.

We use Rule of Law and Regulatory quality to proxy for institutional quality. Rule of law reflects perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Regulatory quality reflects perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. The data are from the Worldwide Governance Indicators (WGI). It is a research dataset summarizing the views on the quality of governance provided by a large number of enterprises, citizen and expert survey respondents in industrial and developing countries (Kaufmann, Kraay and Mastruzzi, 2010). We use the property right index by the Heritage Foundation[155] to proxy for the property right protection. Property rights assess the extent to which private economic activity is facilitated by an effective legal system and rule-based governance structure in which property and contract rights are reliably respected and enforced. For the patent right protection, we use the patent right index from Park (2008).

6. 3. Model

6. 3. 1. Model setup

The baseline weighted regression is the following:

$$\Delta y_{ijt} = \alpha + \delta D_{ijt}^{innov} + \beta X_{ijt} + \mu_{jt}(f_j \cdot f_t) + \mu_s(f_s) + \varepsilon_{it}$$

where $\Delta y_{ijt} = \ln(y_{ijt}) - \ln(y_{ijt-1})$ is the dependent variable, and y_{ijt} are sales, employment and sales per worker of firm *i* in country *j* at time *t* respectively. D_{ijt}^{innov} equals 1 if firm *i* in country *j* innovates between time *t* and time *t-1*. The interactive dummy $f_j \cdot f_t$ captures the macroeconomic conditions for country *j* at time *t.* The dummy f_s captures the sector fixed effects. X_{jit} are different firm-level control variables.

The extended regression (to interact with various institution variables) is the following:

[155] http://www.heritage.org/index/property-rights

$$\Delta y_{ijt} = \alpha + \delta D_{ijt}^{innov} + \mu\left(D_{ijt}^{innov} \cdot Ins_j\right) + \beta X_{ijt} + \mu_{jt}\left(f_j \cdot f_t\right) + \mu_s(f_s) + \varepsilon_{it}$$

where Ins_j is the institutional variable for country j. Note that institutional variables here are time-invariant. Since the surveys are typically very close together, the institutional quality rarely changes. $D_{ijt}^{innov} \cdot Ins_j$ is the interaction between a country's institutional variables and a firm's innovation. We ultimately are interested in μ.

Note that since the data are collected by the stratified random sampling method, all the regressions are weighted accordingly to restore representativeness. In addition, we cluster the standard errors at the country level to capture potential correlations between the error terms, and allow for heteroscedasticity (i.e. having robust standard errors).

Dependent variables:

- *Log of real sales* (i.e. sales divided by the price level)
- Log of real sales per full-time employee

Explanatory variables:

- *Innovation:* whether a firm introduced products or services or upgraded its product or services in the last 3 years. This is problematic for our regression if the two rounds of survey are less than 3 years apart. For this reason, we only keep countries that have surveys more than 3 years apart.
- *Changing manager:* if a firm changed its manager between the two waves of the survey. This is to capture potential other restructuring activities besides innovation. There is no direct way to know if a firm changes its manager. We indirectly guess by using the manager's experience (as the firms are asked about the manager's experience). We identify if a firm changed it managers by comparing the change in the experience of the managers and the years between the two surveys. If the change in experience years is different to the change in years, we conclude that the firm changes its manager. For example, at the first round of the survey in 2005, the firm's manager had 10 year experience; at the second round of survey in 2009, the firm's manager has 20 year experience. Since $\Delta year_{EXPERIENCE}$ is great than $\Delta year_{SURVEY}$, we conclude that the firm must have changed its manager between the two rounds of the survey. We acknowledge that there is a possibility that the manager might not remember exactly his or her years of experience. As a robustness check we allow for that possibility by loosening the restriction: only when $year_{EXPERIENCE}$ is greater than $year_{SURVEY}+1$ or smaller than $year_{SURVEY}-1$ we can conclude the firm changes its manager. The variable is quite robust: if we follow the original criteria, we find that 3,495 out of 6,447 (54.2 percent) firms change their managers; if we follow the less restrictive criteria, we find that 2,616 (40.5 percent) firms change their managers. In the regression we use the original criteria.
- *Becoming an exporter:* this dummy variable equals 1 if a firm becomes an exporter between the two waves of the survey, it equals 0 otherwise.
- *Increasing number of competitors:* this dummy variable equals 1 if the number of a firm's competitor's increases between the two waves of the survey, it equals 0 otherwise.
- *Firm size:* small (0-20 full-time employees), medium (21-100 employees) and large (more than 100 employees).

- *Rule of law:* percentile rank of the country. We calculate the ranking from the entire population of countries provided by the Governance Indicators. The rank is 100 for the highest ranked countries, and 1 for the lowest ranked. The detailed ranking of countries for Rule of Law and other institutional variables are shown at Table A6.9 in the Appendix.
- *Regulatory quality:* percentile rank of the country. We calculate the ranking from the entire population of countries provided by the Governance Indicators). The rank is 100 for the highest ranked countries, and 1 for the lowest ranked.
- *Property right:* percentile rank of the country. We calculate the ranking from the entire population of countries provided by the Heritage Foundation. The rank is 100 for the highest ranked countries, and 1 for the lowest ranked.
- *Patent protection:* percentile rank of the country (by our own calculation from the entire population of countries). The rank is 100 for the highest ranked countries, and 1 for the lowest ranked. The data is a proxy for how well a patent is protected in a country. The data are from Park (2008). It is the sum of five separate scores for: coverage (inventions that are patentable); membership in international treaties; duration of protection; enforcement mechanism; and restrictions (Park, 2008).
- *Sector fixed effects:* 2-digit ISIC revision 3. This is to capture industry specific characteristics that may affect the return to innovation. For example, one might argue that a new product in electronics is likely to have better sales than a new line of shoes.
- *Country*time fixed effect:* to capture a country's macroeconomic effect.

6. 3. 2. Discussion about potential estimation biases

It is difficult to isolate and capture exogenous sources of innovation. There are several issues when it comes to measuring the impact of innovation. First is a concern that inherently good firms in general will do better than bad firms in sales, and at the same time more likely to innovate. In other words, the correlation between innovation and firms' performance might be driven by unobserved characteristics of the firms. We address that issue with the use of panel data: we only consider the change of sales within the same firm, not across firms. By looking for the change within a firm, we effectively control for firms' time-invariant characteristics.

The second issue is the issue of omitted variable. We will not be able to capture any unobserved change in firms' characteristics between the two waves of the survey. For example, a firm might go through a restructuring and at the same time introduce a new product. The observed change in sales and employment could then be the results of both innovation and the restructuring. In our regression, we try our best to capture unobserved changes by controlling for the change of the top manager. Specifically, we include a dummy which equals 1 if the firm changes the manager between the two waves of the survey. Many changes in a firm's structure, management style or marketing strategies come from a new manager (see Bloom and Van Reenen, 2010).

Another concern is the issue of reverse causality between the change in sales and innovation. Specifically, one could argue that perhaps changes in sales also affect innovation. For example, when a firm witnesses declines in sales and market share, it might want to introduce a new product or service to halt the declines. In this case, the correlation between innovation and the change in sales would tend to be negative (i.e. a negative change in sales leads to a positive change in innovation). The OLS results then would underestimate the true impacts of innovation on sale and

employment. The reverse causality is more severe if the innovation process is quick, for example, when the sale declines, the decision to innovate and the introduction of a new product all take place in the same period. The reverse causality is less severe if the innovation process takes time. If there is a "time-to-build" period between when the innovation decision is made and a new product is introduced, the introduction of a new or improved product is likely too late for, and hence uncorrelated with the sale declines.

None of the variables available in the survey can serve as a good instrument variable for innovation. An ideal instrument should capture firms' perception about *intellectual* right protection. Unfortunately the variable is not available. The best two candidates for the instrument that we can find are (1) firms' concern about competition practice of the informal sector and (2) the amount of R&D a firm invested in the previous wave of survey. They are still flawed because they still violate the exclusion restriction. Regarding (1), although a large part of the concern about informal sector has to do with intellectual property right infringement, the concern can also be about the labor or tax practices, which can affect the firm's non-innovation investment activities. Regarding (2), it is not a good instrument if the decision to do R&D also correlates with other non-innovation activities of the firm.

Having discussed all the drawbacks of the estimation, it is important to note that we are not interested in the precision of the return per se. We are instead interested in the comparison of the return across countries. To the extent that the biases are not systematically correlated with countries' institutional characteristics, the comparison across countries is valid.

6. 4. Regression Results

6. 4. 1. The return to innovation

Table 6.1. Returns of Innovation: All countries

Variables	Δln(sales)		Δln(sales/labor)	
Innovation	0.242	0.147	0.198*	0.183*
	(0.146)	(0.149)	(0.109)	(0.0967)
New Top Manager		-1.308***		-1.475***
		(0.328)		(0.366)
Exporter		0.0550		0.0274
		(0.101)		(0.166)
More Competitors		-0.902***		-0.697***
		(0.169)		(0.0990)
Small Size		-1.483***		-0.541**
		(0.324)		(0.215)
Medium Size		-1.136***		-0.555***
		(0.170)		(0.160)
Constant	1.355	4.142***	-0.0582	1.959***
	(1.202)	(1.365)	(0.109)	(0.568)
Year*Country FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
No of Obs	1,879	1,874	1,870	1,870
R-Squared	0.456	0.493	0.450	0.462

*** p<0.01, ** p<0.05, * p<0.1
Clustered robust standard errors by country in parentheses
Source: Authors' calculations

Table 6.1 presents the overall results when we pool all countries in ECA and LAC together, for a total of 1879 unique firms. Overall, only sales per worker are marginally significant at 10 percent level: an innovating firm sees its sales per worker increase by 18.3 percent. Since there are biases, it is safer to consider this as an association, not causation. The dummy variables "More Competitors" and "Firm Size" are significant and have expected signs. Firms that have more competitors between the two surveys see weaker growth in sales than those that have fewer competitors. In addition, small and medium firms see significantly weaker growth in sales than large firms do. This is counter-intuitive if one would think firms should converge to an optimal size. Our conjecture is that in developing countries, many obstacles (such as connection to politicians) prevent small firms' growth as fast as larger ones. The dummy "New Top Manager" is significant and negative. This could reflect adjustment costs to the restructuring associated with the new managers.[156] Focusing on Latin America, table 6.2 shows that the returns to innovation in terms of sales and sales per worker for Latin American firms are not statistically different to zero.

[156] Alternatively, reverse causality might be at play: firms with declining performance hire new managers.

This implies that within a country, the return to innovation in Latin America is very small. We also interact "Innovation" with the "LAC" dummy, but the interacting coefficient is not significant, implying that the return to innovation in LAC is not significantly different to that in ECA (results not shown).

Table 6.2. Returns of Innovation: Latin American Countries

Variables	Δln(sales)		Δln(sales/labor)	
Innovation	-0.379	-0.597	-0.541	-0.435
	(0.254)	(0.325)	(0.319)	(0.362)
New Top Manager		-1.466***		-1.677***
		(0.197)		(0.224)
Exporter		0.180***		0.0433*
		(0.0353)		(0.0161)
More Competitors		-1.054***		-0.795***
		(0.00106)		(0.000562)
Small Size		-2.157***		-0.919***
		(0.0842)		(0.0386)
Medium Size		-1.266***		-0.713***
		(0.00970)		(0.00747)
Constant	0.394	5.252***	0.681	2.922***
	(0.254)	(1.130)	(0.319)	(0.425)
Year*Country FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
No of Obs	547	546	546	543
R-Squared	0.147	0.224	0.224	0.163

*** p< 0.01, ** p< 0.05, * p< 0.1
Clustered robust standard errors by country in parentheses
Source: Authors' calculations

Table 6.3. Returns of Innovation for Monopolists

Variables	Δln(sales)		Δln(sales/labor)	
Innovation	0.111	-0.00814	-0.0483	-0.0451
	(0.288)	(0.323)	(0.252)	(0.283)
Monopolist*Innovation	-2.819*	-2.463	-2.472**	-2.376**
	(1.434)	(1.561)	(1.043)	(1.076)
Monopolist	1.614	1.258	1.005	0.848
	(1.357)	(1.526)	(0.892)	(0.969)
New Top Manager		-1.497***		-1.710***
		(0.337)		(0.383)
Exporter		0.0163		-0.125
		(0.129)		(0.112)
More Competitors		-1.029***		-0.826***
		(0.0971)		(0.0555)
Small Size		-1.569***		-0.656**
		(0.445)		(0.250)
Medium Size		-1.151***		-0.584***
		(0.0891)		(0.0707)
Constant	-0.0967	-1.497	0.188	2.604***
	(0.288)	(1.255)	(0.252)	(0.432)
Year*Country FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
No of Obs	970	969	965	965
R-Squared	0.261	0.317	0.248	0.270

*** p<0.01, ** p<0.05, * p<0.1
Clustered robust standard errors by country in parentheses
Source: Authors' calculations

An important exercise is to examine the return to innovation for monopolist. It is usually argued that monopolist have little incentives to innovate: their product, good or bad, is the only one available in the market and they have already captured the market anyway. For example, if a bad flight service is the only option available for travelers, an improved flight service will not generate much return to an airline monopolist because they will not bring in many new passengers. Table 6.3 shows the return to innovation to Monopolists compared to non-monopolists. We define monopolist as those that have zero competitor. We show that the conventional wisdom is correct: after a monopolist innovates, its percentage of sales per worker increase is 90 percent (i.e. exp (-2.27)) lower than the percentage increase of non-monopolist. We expect the result to be stronger if we consider "upgraded products" alone, as we think that an improved product does not likely improve monopolist's profits, whereas a completely new product might.

6. 4. 2. The Return to Innovation with institution

In this section we focus on the question if the return to innovation is higher in countries with better institution quality. The argument is that in a better institutional environment, where the property right is protected, the courts are reliable, and regulatory uncertainty is small etc., firms' investment in bringing new products and services to the market will yield a good return. On the contrary, in an environment where a new product can easily be copied at little enforceable punishment or the government's policy is highly volatile, the return to innovation will likely be small. We proxy for institutional quality by Rule of Law and Regulatory Quality. Rule of law reflects ``*perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence*''. Regulatory quality reflects ``*perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development*''. These two variables are highly correlated, and commonly used to capture institutional quality.

We show that in general, in a country with better rule of law, the return to innovation is higher. Table 6.4 shows that if a country is placed 1 percentile higher in the world's rule of law ranking (i.e. better rule of law), the sale return to a new and improved product is 1.91 percent higher, and the sale per worker return -our focus- is 0.97 percent higher. Similarly, if a country is placed 1 percentile higher in the world's regulatory quality, the sales return to innovation is 1.77 percent higher, and the sale per worker return is 0.86 percent higher (Table 6.5).

The coefficients for "Innovation" variable become either negative or insignificant. The first rows in Tables 6.4 and 6.5 shows that the sales per worker return to innovation for the lowest ranked country is essentially zero.

Table 6.4. Returns of Innovation with rule of law: All countries

Variables	Δln(sales)		Δln(sales/labor)	
Innovation	-0.778*	-0.865**	-0.315	-0.330
	(0.443)	(0.407)	(0.256)	(0.234)
RuleofLaw*Innovation	0.0192**	0.0191***	0.00965**	0.00967**
	(0.00723)	(0.00682)	(0.00421)	(0.00388)
New Top Manager		-1.274***		-1.457***
		(0.371)		(0.389)
Exporter		0.0381		0.0187
		(0.0989)		(0.161)
More Competitors		-0.902***		-0.697***
		(0.170)		(0.0991)
Small Size		-1.480***		-0.540**
		(0.322)		(0.214)
Medium Size		-1.139***		-0.557***
		(0.167)		(0.158)
Constant	1.716*	4.463***	1.714	3.720***
	(0.946)	(1.180)	(1.033)	(1.283)
Year*Country FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
No of Obs	1,879	1,874	1,870	1,870
R-Squared	0.458	0.495	0.450	0.462

*** p<0.01, ** p<0.05, * p<0.1
Clustered robust standard errors by country in parentheses
Source: Authors' calculations

Table 6.5. Returns of Innovation with Regulatory Quality: All countries

Variables	Δln(sales)		Δln(sales/labor)	
Innovation	-0.848	-0.975*	-0.339	-0.360
	(0.621)	(0.572)	(0.348)	(0.312)
RegQual*Innovation	0.0172*	0.0177**	0.00846	0.00857*
	(0.00865)	(0.00802)	(0.00521)	(0.00472)
New Top Manager		-1.222***		-1.432***
		(0.424)		(0.414)
Exporter		0.0445		0.0222
		(0.0975)		(0.162)
More Competitors		-0.903***		-0.697***
		(0.170)		(0.0991)
Small Size		-1.485***		-0.542**
		(0.320)		(0.214)
Medium Size		-1.141***		-0.558***
		(0.166)		(0.158)
Constant	1.746*	4.461***	1.725	3.711***
	(0.941)	(1.203)	(1.027)	(1.295)
Year*Country FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
No of Obs	1,879	1,874	1,870	1,870
R-Squared	0.458	0.495	0.450	0.462

*** p<0.01, ** p<0.05, * p<0.1
Clustered robust standard errors by country in parentheses
Source: Authors' calculations

Focusing in LAC, the impacts of rule of law and of regulatory quality are both more significant and of a larger magnitude compared to the pooled sample (Tables 6.4b and 6.5b). If a LAC country is placed 1 percentile lower in the world's rule of law ranking, the sale return to innovation is 12.7 percent lower and the sale per worker return is 11.4 percent lower (Table 6.4b). If a LAC country is placed 1 percentile lower in the world's rule of law ranking, the sale return to innovation is 3.9 percent lower, whereas the sale per worker return is 5.98 percent lower. The results imply a more detrimental impact of "bad'' rule of law and regulatory quality on firms' incentive to innovate in LAC. However, the results should be taken with caution given the small number of countries covered in Latin America.[157]

[157] For sales and sales per workers, there are 5 countries in the sample: Honduras, Brazil, Nicaragua, Guatemala and Ecuador. For employment there are 6 countries: these 5 and Venezuela.

Table 6.4b. Returns of Innovation with rule of law: LAC

Variables	Δln(sales)		Δln(sales/labor)	
Innovation	-2.246***	-2.476***	-2.236***	-2.130***
	(0.268)	(0.355)	(0.220)	(0.247)
RuleofLaw*Innovation	0.126***	0.127***	0.114***	0.114***
	(0.0142)	(0.0136)	(0.0233)	(0.0225)
New Top Manager		-1.467***		-1.678***
		(0.196)		(0.224)
Exporter		0.179***		0.0424*
		(0.0355)		(0.0164)
More Competitors		-1.054***		-0.795***
		(0.00107)		(0.000567)
Small Size		-2.157***		-0.920***
		(0.0840)		(0.0383)
Medium Size		-1.266***		-0.713***
		(0.00977)		(0.00754)
Constant	0.495	5.303***	0.773	3.015***
	(0.340)	(1.147)	(0.367)	(0.494)
Year*Country FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
No of Obs	547	546	543	543
R-Squared	0.147	0.224	0.135	0.163

*** p< 0.01, ** p< 0.05, * p< 0.1
Clustered robust standard errors by country in parentheses
Source: Authors' calculations

Table 6.5b. Returns of Innovation with Regulatory Quality: LAC

Variables	Δln(sales)		Δln(sales/labor)	
Innovation	-1.220*	-1.427*	-1.851**	-1.718**
	(0.454)	(0.555)	(0.459)	(0.547)
RegQual*Innovation	0.0393**	0.0388**	0.0612***	0.0598***
	(0.00956)	(0.00974)	(0.00759)	(0.00860)
New Top Manager		-1.456***		-1.660***
		(0.209)		(0.245)
Exporter		0.185***		0.0505***
		(0.0311)		(0.00902)
More Competitors		-1.054***		-0.796***
		(0.000990)		(0.000442)
Small Size		-2.156***		-0.918***
		(0.0850)		(0.0397)
Medium Size		-1.266***		-0.714***
		(0.00955)		(0.00722)
Constant	0.605	5.343***	1.012*	3.224***
	(0.372)	(1.142)	(0.426)	(0.616)
Year*Country FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
No of Obs	547	546	543	543
R-Squared	0.147	0.224	0.135	0.164

*** p< 0.01, ** p< 0.05, * p< 0.1
Clustered robust standard errors by country in parentheses
Source: Authors' calculations

6. 4. 3. Return Innovation with property right protection

Since rule of law and regulatory quality is still too general to have specific policy recommendations, this section zooms in one particular component of institution that we think are most obvious in affecting the return to innovation. It is property right protection. For our analysis, we use the property right index by the Heritage Foundation[158] to proxy for the property right protection. Property rights assess the extent to which private economic activity is facilitated by an effective legal system and rule-based governance structure in which property and contract rights are reliably respected and enforced.

[158] http://www.heritage.org/index/property-rights

The property rights here include both intellectual property rights (IPR) and more general property right. While IPRs laws and enforcements provide necessary protection to the fruits of R&D (patent, copyrights, trademarks, etc.), broader property rights protection and contract enforcements protect investments that are complementary to R&D expenditures, especially during the post-R&D stage, and hence help realize the commercial values of R&D. In a country where property right is not well protected, a new product or service when deemed profitable will be easily copied, thus the return to the innovating firm is reduced. On the other hand, if property right is well protected, the firm can extract good return from its new products or services.

Table 6.6. Innovation with property right protection– All countries

Variables	Δln(sales)		Δln(sales/labor)	
Innovation	-0.635	-0.676	-0.307	-0.305
	(0.466)	(0.445)	(0.274)	(0.249)
PRP*Innovation	0.0163**	0.0153**	0.00937**	0.00909**
	(0.00748)	(0.00728)	(0.00428)	(0.00396)
New Top Manager		-1.274***		-1.454***
		(0.368)		(0.391)
Exporter		0.0406		0.0188
		(0.101)		(0.163)
More Competitors		-0.901***		-0.696***
		(0.170)		(0.0990)
Small Size		-1.477***		-0.538**
		(0.325)		(0.215)
Medium Size		-1.137***		-0.556***
		(0.169)		(0.159)
Constant	1.643	4.372***	1.698	3.694***
	(0.996)	(1.226)	(1.042)	(1.294)
Year*Country FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
No of Obs	1,879	1,874	1,870	1,870
R-Squared	0.458	0.495	0.450	0.462

*** p<0.01, ** p<0.05, * p<0.1
Clustered robust standard errors by country in parentheses
Source: Authors' calculations

Table 6.6 and 6.6b present the overall results across countries and those for Latin America. Overall, if a country is placed 1 percentile higher in the ranking, the sales per worker return to innovation for an innovating firm will be 0.91 percent higher and the sale return is 1.53 percent higher. Overall, the magnitude of the impact here is similar to that from the regulatory quality and rule of law regressions. Across Latin American countries, we do not see a significant impact of Property Right Protection on the sales return to innovation. However, we do see Property Right Protection have a positive and significant impact on the sales per worker return to innovation. In Latin America, if a country is place 1 percentile higher in the ranking, we expect the sales per worker

return to increase by 7.37 percent. The magnitude is also much larger than the one obtained from the world sample. However, it is only significant at 10 percent level.

Table 6.6b. Returns of Innovation with Property Right Protection: LAC

Variables	Δln(sales)		Δln(sales/labor)	
Innovation	-1.039**	-1.235**	-2.038***	-1.883**
	(0.349)	(0.350)	(0.420)	(0.463)
PRP*Innovation	0.0336	0.0325	0.0763*	0.0737*
	(0.0270)	(0.0277)	(0.0297)	(0.0311)
New Top Manager		-1.460***		-1.662***
		(0.205)		(0.243)
Exporter		0.183***		0.0504***
		(0.0320)		(0.00910)
More Competitors		-1.054***		-0.796***
		(0.00100)		(0.000442)
Small Size		-2.156***		-0.918***
		(0.0848)		(0.0398)
Medium Size		-1.266***		-0.714***
		(0.00957)		(0.00718)
Constant	0.481*	5.287***	0.881**	3.095***
	(0.204)	(1.106)	(0.249)	(0.449)
Year*Country FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
No of Obs	547	546	543	543
R-Squared	0.147	0.224	0.135	0.164

*** p< 0.01, ** p< 0.05, * p< 0.1
Clustered robust standard errors by country in parentheses
Source: Authors' calculations

6. 4. 4. Return Innovation with patent protection

In this section we squarely focus on the most arguably relevant factor that affects innovation: patent protection. The index is provided in Park (2008). It is "*the unweighted sum of five separate scores for: coverage (inventions that are patentable); membership in international treaties; duration of protection; enforcement mechanisms; and restrictions (for example, compulsory licensing in the event that a patented invention is not sufficiently exploited)*" (Park, 2008).

Table 6.7. Returns of Innovation with Index of patent rights – All countries

Variables	Δln(sales)		Δln(sales/labor)	
Innovation	-2.266	-2.584*	0.0674	0.0140
	(1.389)	(1.329)	(1.071)	(1.027)
PatentsRights*Innovation	0.0320	0.0349*	0.00197	0.00253
	(0.0183)	(0.0172)	(0.0148)	(0.0141)
New Top Manager		-1.484***		-1.700***
		(0.194)		(0.184)
Exporter		0.0407		-0.0374
		(0.112)		(0.169)
More Competitors		-0.918***		-0.709***
		(0.167)		(0.0961)
Small Size		-1.597***		-0.598**
		(0.355)		(0.222)
Medium Size		-1.209***		-0.598***
		(0.123)		(0.127)
Constant	1.575	3.014***	1.535	3.841**
	(1.057)	(0.377)	(1.186)	(1.294)
Year*Country FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
No of Obs	1,198	1,193	1,189	1,189
R-Squared	0.306	0.359	0.262	0.280

*** p<0.01, ** p<0.05, * p<0.1
Clustered robust standard errors by country in parentheses
Source: Authors' calculations

Table 6.7 shows the relationship between the return to innovation and patent rights ranking (where 1 is for the lowest ranked country, and 100 is for the highest ranked). We can see that the sale return for innovating firms is significantly smaller for countries with lower patent right protection: if a country is 1 rank lower, the sale return is 3.49 percent lower. The magnitude is relatively large, compared to findings for other institutional variables. However, the return in terms of sale per worker is not significantly correlated with the patent right ranking, although the sign is correct. It is possible that measurement errors inflate the standard errors, making the coefficient insignificant. It is also possible that patent right protection indeed has a smaller impact on the return than other components of property right protection. For example, if firms in developing countries do not habitually file for patent protection, the index would be irrelevant. We also repeat the exercise for LAC countries, however, probably due to the small size; the results are not significant with a wrong sign and therefore not shown here.

6. 5. Conclusion

Why firms do not innovate or adopt new technologies remains an important and interesting question. In this paper we do not go to the usual routes of examining the obstacles to firms' innovation, but focus on firms' incentives to innovate. We do that by estimating the return to innovation across countries, and comparing the return in countries with different levels of institutional quality, the return of innovation (in terms of sales per worker) for firms is lower. This means that in poorer countries, a large part of the lack of innovation is due to firms' unwillingness to innovate: bad institutional environment discourages firms to invest in researching new products.

The magnitude of the estimated gain is large. If a country can improve by 10 ranks in the world percentile ranking, the return to innovation in terms of sales per worker for firms in that country could be 8 percent to 10 percent higher. This finding calls for policies that go beyond addressing obstacles to firms' ability to innovate. They have to also place a strong focus on institutional factors (such as property right protection) in order to address firms' incentive problem.

6. 6. Appendix

Table A6.8. List of countries

Country Name	Number of Unique Firms	Percent (%)
Latin American Countries	1,229	32.73
Brazil	426	11.34
Ecuador	142	3.78
Guatemala	210	5.59
Honduras	194	5.17
Nicaragua	213	5.67
Venezuela	44	1.17
Europe & Central Asia Countries	2,526	67.27
Albania	48	1.28
Belarus	77	2.05
Georgia	68	1.81
Tajikistan	55	1.46
Turkey	391	10.41
Ukraine	173	4.61
Uzbekistan	93	2.48
Russian Federation	61	1.62
Poland	114	3.04
Romania	95	2.53
Serbia	90	2.40
Kazakhstan	86	2.29
Moldova	114	3.04
Bosnia and Herzegovina	51	1.36
Azerbaijan	107	2.85
Macedonia, FYR	88	2.34
Armenia	107	2.85
Estonia	87	2.32
Czech Republic	40	1.07
Hungary	75	2.00
Latvia	53	1.41
Lithuania	58	1.54
Slovak Republic	35	0.93
Slovenia	80	2.13
Bulgaria	131	3.49
Croatia	72	1.92
Montenegro	4	0.11
Kyrgyz Republic	73	1.94
Total	3,755	100.00

Source: Authors' calculations

Table A6.9. Percentile Ranking by Country for Different Variables

Country	Rule of Law	Regulatory Quality	Property Right Protection	Patent Right Protection
Brazil	56	56	67	60
Ecuador	14	16	17	64
Guatemala	15	48	37	44
Honduras	20	50	37	34
Nicaragua	30	40	10	34
Venezuela	2	7	1	48
Albania	38	59	37	-
Belarus	15	10	88	-
Georgia	51	74	62	-
Tajikistan	11	19	17	-
Turkey	58	66	67	71
Ukraine	23	32	37	62
Uzbekistan	6	4	10	-
Russian Federation	26	39	23	62
Poland	72	80	75	78
Romania	57	75	56	75
Serbia	47	53	56	-
Kazakhstan	32	43	49	-
Moldova	45	51	56	-
Bosnia and Herzegovin	46	52	17	-
Azerbaijan	22	38	23	-
Macedonia, FYR	49	60	49	-
Armenia	43	59	37	-
Estonia	86	91	89	-
Czech Republic	81	86	82	83
Hungary	73	82	78	88
Latvia	74	80	67	-
Lithuania	73	79	75	70
Slovak Republic	69	81	67	78
Slovenia	84	73	75	-
Bulgaria	52	71	37	90
Croatia	61	70	56	-
Montenegro	56	52	56	-
Kyrgyz Republic	10	45	17	-

Sources: The World Governance Indicators (for Rule of Law and Regulatory Quality), own elaboration based on the World Bank's Doing Business Survey (for the Cost of Starting a Business) and on the Heritage Foundation (for Property Right Protection).

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7. Convergence, Poverty, and Macroeconomic Volatility: A Latin American Perspective

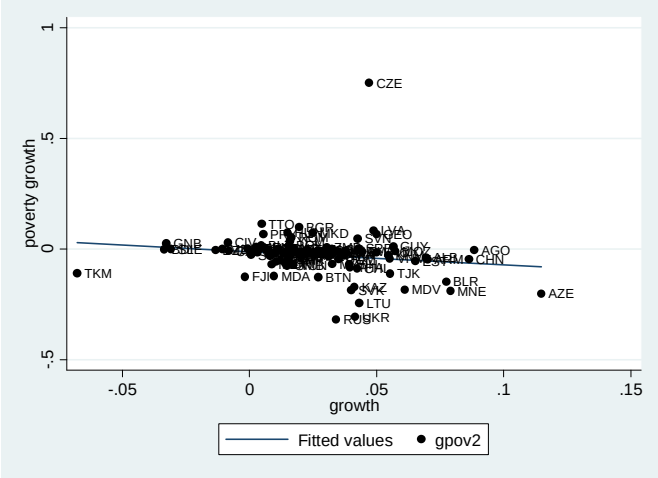
Konstantin M. Wacker[159]

Until recently, inequality was not seen as having major implications for macroeconomic developments. This belief is increasingly called into question. -- Olivier Blanchard[160]

7. 1. Introduction

A main motivation for asking about the factors that prevent LAC from converging towards high income levels is the assumed positive effect that income has on well-being. For example, the positive effect of growth on poverty reduction is well-documented in the literature (e.g. Dollar and Kraay, 2002; Ravallion, 2012; Dollar et al., 2013) and also depicted in Figure 7.1: on average, developing countries that saw higher aggregate growth saw higher reductions in the poverty gap.

Figure 7.1. Poverty developments and growth



Source: Authors' calculations
Note: Data sources are explained below. R-squared 0.02, robust t-statistic -1.53

While poverty in itself may severely reduce welfare, this paper re-addresses the issue of poverty being an impediment to growth, arguing that it is especially the interaction of initial poverty with economic volatility (and associated uncertainty) that prevents countries from converging. This builds on the findings of Crespo-Cuaresma, Klasen, and Wacker (henceforth CCKW, 2013) that macroeconomic volatility prevents "poverty convergence," i.e. that poor countries see faster

[159] The findings, interpretations, and conclusions expressed in this paper are those of the author. They do not necessarily represent the view of the World Bank, its Executive Directors, or the countries they represent. This paper largely benefited from related joint work with Jesús Crespo-Cuaresma and Stephan Klasen (2013) and from comments received at an authors' workshop and a concept note review meeting at the World Bank in 2014 and at a seminar at the University of Göttingen.
[160] Press Briefing on the World Economic Outlook, Washington, D.C., April 08, 2014

progress in poverty reduction (see also Ravallion, 2012). While CCKW (2013) already pointed out that the underlying channel for this finding is the effect of the volatility-poverty interaction on income convergence, this paper extends on our contribution in several ways. First, it gives a more elaborate theoretical motivation for the effect that poverty and volatility have on growth. Building on the derived intuition, it secondly looks at poverty gaps instead of poverty headcount ratios.[161] Third, the dataset used in this paper differs from Ravallion (2012) and CCKW (2013) by using conventional macro data. And finally, the paper interprets the findings from a LAC perspective, showing that conditional on their income level, LAC has historically suffered from over-proportionally high poverty gaps which might help explain why the region failed to converge towards high income levels over the long run.

With this contribution, the paper also bridges two stands in the literature that have previously coexisted peacefully without much interaction. Besides from Ravallion's (2012) contribution, a growing number of studies have emphasized the role of poverty and inequality for growth (e.g. Lopez and Servén, 2009; Berg et al., 2014; Berg et al., 2012). On the other hand, the importance of volatility for growth has been emphasized by the seminal paper of Ramey and Ramey (1995), and was confirmed by various contributions since (Hnatkovska and Loayza, 2005; Kose et al., 2006; Aghion et al., 2010; Berument et al., 2011 and 2012). However, the exact channel of volatility impacting growth remains opaque[162] and, similarly, there are various potential effects of poverty on growth (for a critical review see also Kraay and McKenzie, 2014). In the words of Ravallion (2012: 521): "[t]he policy implications of (…) poverty reduction depend on *why* countries starting out with a higher incidence of poverty tend to face worse growth prospects" (emphasis added). By bringing together these two strands of the literature, this paper highlights that volatility and poverty may mutually re-enforce each other in hampering growth.

7. 2. Poverty and volatility as a limitation to the advantages of backwardness

7. 2. 1. The argument for convergence

The most basic neoclassical growth model (Solow, 1956; Swan, 1956) assumes a Cobb-Douglas production function of output *Y*:

$$Y_t = K_t^{\alpha}(A_t L_t)^{1-\alpha}$$

which implies decreasing returns to capital *K*:

[161] Note that for the class of poverty measures $p = [(Y-r)/r]^{\alpha}$, the poverty headcount index is defined as $\alpha=0$, while for the poverty gap $\alpha=1$. The latter is hence "closer" to a distributionally sensitive (convex) poverty measure of the so-called Atkinson-class ($\alpha>1$) for which volatility will lead to an increase in expected poverty under less stringent assumptions that for the headcount index (see Ravallion, 1988).

[162] Ramey and Ramey (1995: 1148) attribute the negative effect of volatility on growth to uncertainty-induced planning errors in firms or, similarly, to the cost of shifting production factors across sectors, i.e. to an interaction of rigidities and uncertainty that imposes an ex post inefficiency. This is similar to the motivation given in this paper which argues that the uncertainty costs are higher for the poor. Kose et al. (2006: 199) conclude from their results about heterogeneity of the growth effects of volatility that there is need for "further research … to provide a better understanding of the roles played by various shocks in driving the relationship between volatility and growth."

$$\frac{\partial Y}{\partial K} = \alpha \left(\frac{A_t L_t}{K_t}\right)^{1-\alpha}$$

Assuming that countries share common features (such as the production function, technology and population growth), the model identifies a steady state level of capital per effective unit of labor, $k*$. Poorer countries with a lower capital stock will thus increase their capital stock to reach the steady state[163] and the model thus predicts that growth is related to the distance to the steady state level of income:

$$\frac{d\ \ln(y)}{d\ t} = \lambda[\ln(y*) - \ln(y_t)]$$

i.e. poorer countries should grow at higher rates than richer countries, the underlying rationale being that poor countries have a higher marginal return to capital. Empirically, it is well known that this unconditional convergence does not hold—or only for a very limited set of countries—but requires controlling for several factors ('conditional convergence').

7. 2. 2. Poor economics? Risk aversion of the poor in an uncertain environment: field evidence

Contrary to the intuition of decreasing returns to capital, we often observe in practice that those having the highest marginal return to investment, mostly the poor, do not undertake those highly profitable investments. For example, Bliss and Stern (1982: ch. 8) find that farmers in the north Indian state of Uttar Pradesh under-investment in highly productive fertilizers. While this might look like a poor economic decision, they explain this behavior by the fact that using less fertilizer contains investment losses in bad times. The authors' calculations suggest that the foregone expected profits are most plausibly explained by high levels of risk and risk aversion. Since then, various studies have found similar under-investment of poor households that would be expected to have the highest marginal returns on their investment (see Morduch, 1995, for an overview and the later contributions by Moser and Barrett, 2006; Yesuf and Bluffstone, 2009; Dercon and Christiaensen, 2011).

7. 2. 3. A simple intuition

To understand the problem more formally, assume households generate utility u from income Y, with the standard assumptions

$$\partial\, u/\partial Y > 0 \qquad (1a)$$
$$\partial^2\, u/\partial^2 Y < 0 \qquad (1b)$$

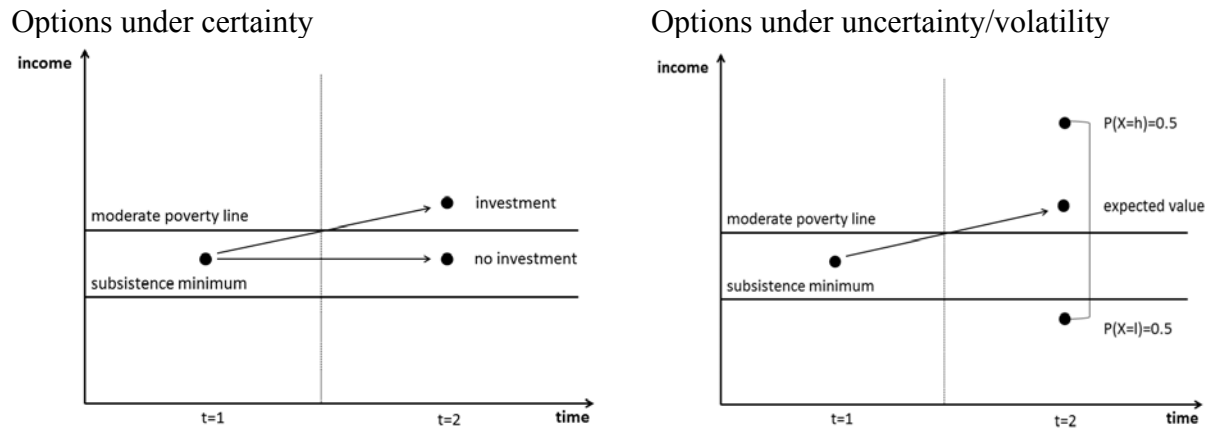
Suppose there is a moderate poverty line r at some level of income (e.g. at the 2 USD line) and some absolute poverty line that is equal to the subsistence minimum s (e.g. the 1.25 USD line).

[163] $\frac{d[k(t)-k*]}{dt} = -[1-\alpha(k*)](n+\delta+g)[k(t)-k*]$, i.e. the more negative [k(t)-k*], the higher the growth of k(t) over time (because of the negative prefix).

For the sake of the argument presented here, assume that the utility of falling below the subsistence minimum s is minus infinity, $u(Y<s) = -\infty$, but more generally any utility function that is sufficiently concave will suffice for the argument to hold.[164]

At time period t=1, a poor household with $s<Y<r$ faces the decision whether or not to make an investment (e.g. in fertilizer or education, or switching the sector of activity, e.g. by moving into the city) that might potentially allow the household to escape poverty. If there is no uncertainty about the state of the economy in the future (i.e. t=2), the payoffs of the investment are well known and the household will make the investment if it improves its lifetime income, which might potentially allow it to escape poverty. Otherwise, the household will not make the investment. This situation is depicted in the left panel of Figure 7.2..[165]

Figure 7.2. Escaping poverty through an investment decision



Source: Authors' calculations

Now let us assume the payoff to the investment is uncertain and can either be high, h, or low, l, according to the outcome of a Bernoulli trial (e.g. good vs. bad state of the economy, rain vs. no rain, political stability vs. instability). If the uncertainty becomes large enough for the "low" outcome to fall below the subsistence minimum s, the expected utility of the investment will become $\boldsymbol{E}(Y_{t=2}) = P(X=h)\, x_h + P(X=l)\, (-\infty)$, which in no case justifies the investment. This discrete case is intuitive but it is not hard to picture that a similar effect occurs in the continuous case with a sufficiently concave utility function of consumption due to the asymmetry of marginal utility around the expected value.[166]

[164] The literature sometimes considers the opposite case where the utility of income is bounded below, e.g. because of the existence of some social safety net (public or private). See e.g. Banerjee (2000). I will discuss some implications of this assumption below.

[165] Note that this simple intuition does not take into account that the household might be constrained to make the investment because the loss in consumption in period 1 might bring it below the subsistence minimum: $c_1=(Y-a)<s$. In my understanding, this is the view Ravallion (2012) provides for poverty not converging.

[166] Morduch (1994) formalizes a similar rationale in a two-period model where a poor agricultural household has to choose the share of safe (but on average less profitable) activity under a borrowing constraint. Due to the latter, less risk is taken and expected profits are sacrificed for greater self-protection against bad shocks for which financial market protection is unavailable.

For another, numerical example, consider a household with the isoelastic utility function

$$u(c) = \frac{c^{1-\eta}-1}{1-\eta}, \qquad (2)$$

maximizing consumption over two periods. The household can either stay in its business/sector in which case there will be no change in income: $Y = Y_1 = Y_2$. Or the household can invest a certain (discrete and predefined) amount $a>0$ in period 1 which increases its income in period 2 by $a+[1/(aY)]$. This reflects diminishing marginal returns to investment (or, income), which gives rise to convergence in the neoclassical growth model. The discrete and predefined size of a is motivated by assuming a lump-sum type of cost when switching business/sector. Suppose, however, that under this second option, the household faces a risk $q*$ to its income, which is given by:

$$q^* = \begin{cases} +q & with\ \boldsymbol{P} \\ -q & with\ (1-\boldsymbol{P}) \end{cases}$$

This uncertainty reflects that the relative desirability of a sector (or business) can repeatedly rise and fall (which induces hysteresis effects; see Dixit and Rob, 1994). Disregarding subjective intertemporal discounting or possibilities to transfer income across periods (i.e. there is neither insurance or lending, nor store of value - so individuals cannot achieve insurance indirectly by consumption smoothing over time), the household's utilities under these two options are then given by:

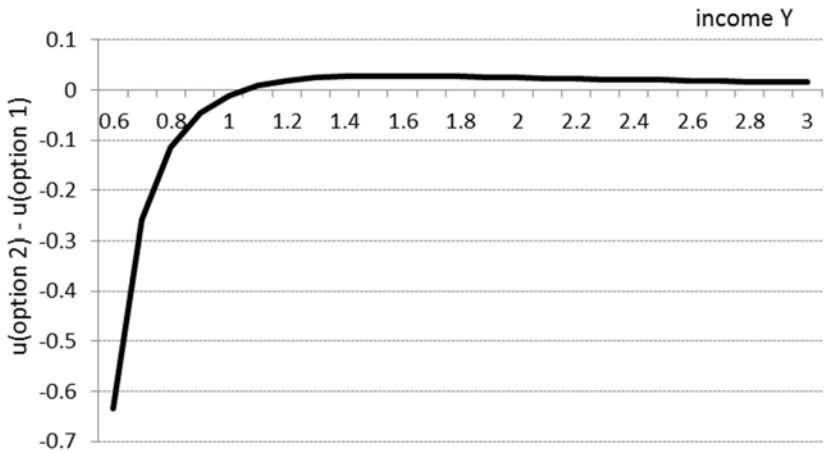
$$\boldsymbol{u(option\ 1)}:\ u(c_1) + u(c_2) = u(Y) + u(Y) = u(2Y)$$

$$\boldsymbol{u(option\ 2)}:\ u(c_1) + \boldsymbol{E}[u(c_2)] =$$

$$= u(Y-a) + \boldsymbol{P}u\left(Y + a + \frac{1}{aY} + q\right) + (1-\boldsymbol{P})u\left(Y + a + \frac{1}{aY} - q\right)$$

Let us parameterize this example by assuming $a=0.5$, $q=0.3$, $\boldsymbol{P}=0.5$, and a risk aversion $\eta=1$, in which case the utility function becomes the limiting case $u(c) = ln(c)$, so $u<0$ for $c<1$. I.e. $c=1$ can be interpreted as a poverty line below which utility is negative (e.g. because of starvation [absolute] or because of social exclusion [relative]). The difference in utilities of these two options with respect to different incomes under the given parameters is depicted in Figure 7.3., with a positive difference indicating that option 2 would be the optimal household choice.

Figure 7.3. Difference in utilities between options 2 and 1



Source: Authors' calculations

One can see that even though the expected two-period consumption under option 2,

$$\boldsymbol{E}(c_1 + c_2) = (Y - a) + Y + a + \frac{1}{aY} + \boldsymbol{E}(q^*) = 2Y + \frac{1}{aY} \quad > 2Y \quad \forall a, Y > 0, \tag{3}$$

would be higher than under option 1 (by a magnitude decreasing in Y as long as $Y>0$), it requires a certain income level for option 2 to provide a higher utility and become optimal. The intuition for this result is the aversion of the household of falling below a certain consumption level ("poverty line") which weighs stronger than the potential benefits of an investment which would otherwise deliver the highest payoffs for poor households (which is also reflected by the utility difference in Figure 7.3. falling again after reaching a peak at a certain income Y and approaching 0 as $Y \rightarrow \infty$ in the term $1/[aY]$ in equation 3). It is finally relevant to note that not only the uncertainty about consumption in period 2 detains the household from investing but that with uncertainty (q) rising, the optimum of option 2 requires a higher income level.

7. 2. 4. What does this imply for convergence?

If the above considerations were largely appropriate to describe actual income and convergence dynamics, one can derive some econometric hypotheses about income growth and convergence.

First and foremost, poverty will have a hampering effect on growth and convergence. More precisely, we would expect the poverty *gap* to exercise this effect, as it is a measure for how far the poor are away from the poverty line on average and thus, how close they are to the subsistence minimum s.[167] As they approach this subsistence minimum, they will no longer be able to reduce consumption and invest, i.e. they will no longer be able to benefit from the "advantages of backwardness" that are assumed to lead to overall convergence.

[167] Note that this differs from the results of Ravallion (2012) and CCKW (2013) who use the poverty *headcount ratio* instead of the poverty gap.

Secondly, this effect is expected to be re-enforced through volatility. For a given level of income with $s<Y<r$, the higher volatility, the deeper will the future level of income under a "bad state" of the economy ($X=l$) fall below the subsistence minimum (or, below $c_2=1$) and the less likely or meaningful it is for the poor to invest, although the marginal returns on their investment are expected to be high.

Finally, one should note that this reasoning implies a different aggregate production function because poverty and its interaction with volatility influences aggregate investment, which in turn defines the capital stock K that enters the aggregate production function Y. In other words, if poverty (and its interaction with volatility) is a serious impediment to convergence, one would expect that we see *convergence conditional on poverty* (and volatility), i.e. after controlling for the latter.

7. 2. 5. Pro poor economics: The example of China

Undoubtedly, China has been one of the most impressive cases of convergence in income and poverty rates over the last decades. Its PPP GDP per capita rose from merely 2 percent of the US level in 1980 to 17 percent in 2010. Over the same three decades its moderate poverty headcount ratio (at 2 PPP USD per day) fell from 98 percent of the population to 27 percent. Among other factors, the literature has pointed out the role of macroeconomic stabilization and pro-poor redistribute policies for achieving this tremendous progress.

While the high initial poverty rate[168] might seem to run against the above argument that poverty impedes convergence, Ravallion (2009) and Drèze and Sen (1995) have pointed out that initial inequality was low, especially when looking at access to basic health and education and that the pre-reform regime has thus left "advantageous initial conditions" for growth and poverty reduction" (Ravallion, 2009: 22). While the government has provided few direct redistributive interventions, it has still ensured a broad access to basic necessities and services, thus providing "equity of opportunity" and reducing the likelihood of households to fall below a critical threshold of income/consumption (s).

Furthermore, the government provided a relatively predictable outlook about the economic conditions in the near term future, which reduced uncertainty and volatility about the future payoffs of household investments.[169] This was achieved by both, components of central planning and a macroeconomic policy that was mostly successful in stabilizing market fluctuations which was beneficial for poverty reduction (see Ravallion, 2009).

From a sectoral perspective, poverty-reduction was mainly driven by the agriculture sector (Ravallion, 2009) but for income convergence to continue, it is also relevant to stress that China managed to absorb an increasing share of labor in more productive manufacturing activities. While the Chinese growth strategy and its focus on investment and exports caused a major rise in

[168] One should also remember to look at poverty conditional on the income level. China's poverty rate was not remarkably higher than the one of Bangladesh (90 percent in 1984) or Nepal (94 percent in 1985), countries with a similar income level at that time.

[169] In fact, Chamon et al. (2010) show that rising income variance can help explain a rise in precautionary savings observed in China after 2000, especially for younger households with lower buffer stocks of savings.

inequality (Lee, Syed, and Wang, 2013), it was nevertheless able to generate beneficial income opportunities for the poor and provided them access to opportunities which were supportive to promote the dynamic change that was necessary to sustain growth over an extended period of time.

7. 3. Empirical investigation

7. 3. 1. Econometric Model

The main model underlying this investigation is a standard neoclassical convergence specification, given by

$$\Delta \ln Y_{it} = \alpha_i + \beta_i \ln Y_{i,t-1} + \varepsilon_{it}, \qquad (4)$$

where Y_{it} denotes GDP in country *i* and period *t* and ε_{it} is a standard disturbance term assumed to fulfill the usual assumptions of the error term in linear regression models. If β_i is negative, countries converge in GDP levels, i.e. countries starting out with a lower initial GDP grow faster in subsequent periods, as discussed above.

Starting from there, one can add several control variables to the model, which are summarized in a matrix *X*:

$$\Delta \ln Y_{it} = \alpha_i + \beta_i \ln Y_{i,t-1} + X_i\theta_i + \varepsilon_{it}, \qquad (5)$$

where X_i includes interactions among variables and can in principle be measured at various points in time.

It should be noted that the interpretation of such interaction models might not be straightforward. For example, in the model

$$\Delta \ln Y_{it} = \alpha_i + \beta_i \ln Y_{i,t-1} + \theta_{i1}x_{i1} + \theta_{i2}x_{i2} + \theta_{i3}x_{i1} \times x_{i2} + \varepsilon_{it}, \qquad (6)$$

the marginal effect of x_{i1} on $\Delta \ln Y_{it}$ is given by

$$\frac{\partial \Delta \ln Y_{it}}{\partial x_{i1}} = \theta_{i1} + \theta_{i3}x_{i2}, \qquad (7)$$

i.e. it depends on the level of x_{i2}, and the statistical significance of the influence has to be evaluated over the relevant range of x_{i2}.

In line with the studies of Ravallion (2012) and CCKW (2013) we focus on OLS estimation of the outlined equations, well aware of the fact that this might induce severe endogeneity biases but hoping to thereby provide a first approximation to the effect of poverty and volatility on income convergence.

7. 3. 2. Data

While the studies of Ravallion (2012) and CCKW (2013) use data from household surveys and focus on the poverty headcount ratio (as a percentage of the population), this paper instead uses more aggregated macro data and looks at the poverty gap for reasons mentioned above. More specifically, GDP data is taken from PWT 7.1 as PPP converted GDP per capita at constant 2005 prices (PWT series rgdpl). Similar to CCKW (2013) the standard deviation over the last 5 years is calculated for each year. Aggregate data for the poverty gap at 2 PPP USD a day are retrieved from the World Bank WDI. It is worth noticing that this data is not available for every country in every year and only available for developing countries, so there are no industrialized economies in the sample.

For each country where data is available, I take the earliest and last observation that has a poverty data point. The resulting timespan ranges from 3 years (Czech Republic and Montenegro) to 32 years (India) and starts as early [late] as 1978 [2005] (India [Monenegro]) and ends as late [early] as 2010 [1992] (34 different countries [Trinidad and Tobago]). *Annual* real PPP GDP p.c. growth rates are calculated over these periods.

At this stage, no further control variables are added. This may certainly induce some omitted variable bias. For example, poverty might be correlated with poor institutions that are not able (or willing) to progressively redistribute resources. On the other hand, lack of institutional capacity might also have growth reducing effects on its own. By not controlling for institutional quality, poverty might pick up parts of the latter effect. However, there are qualified reasons to not control for other standard variables. First, the exact linkages and causalities between these variables and poverty are unclear. For example, is poverty high because institutional quality is low? Or do institutions not improve *because* the poor are systematically excluded from political participation? Similarly, are people poor because of low education? Or is it the case that poor people cannot invest in human capital *because* of a poverty trap as suggested above? By not controlling for other variables, the full impact of initial poverty will be captured, even though it might operate through various channels and capture effects of variables correlated with poverty. But the main aim of this investigation is not to exactly quantify the impact of poverty on growth in an unbiased manner. It rather suggests that poverty has an impact on the aggregate production function of output and hence asks if controlling for poverty is sufficient to obtain (conditional) convergence.

7. 3. 3. Results

Column (1) of Table 7.1 displays the estimation results of the unconditional convergence equation (4). As one can see, there are no signs of unconditional convergence among the 102 developing countries included, and this approach virtually explains nothing of the variation in growth rates among them (as indicated by the R-squared). When adding the initial poverty gap to the equation (column 2), the picture changes as that the explanatory power of the model increases (R-squared 6.7 percent), conditional convergence is present (and significant at the 10 percent level), and initial poverty exercises a statistically highly significant negative impact on subsequent growth. This suggests that poverty impedes growth, as already pointed out by previous studies. But it furthermore suggests that when controlling for this fact, countries would actually converge in income levels.

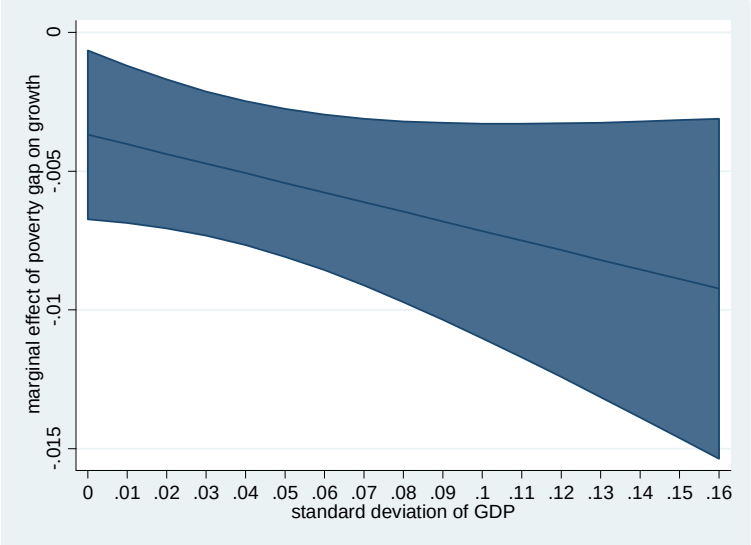
Table 7.1. Estimation results

VARIABLES	(1) Δln(Y)	(2) Δln(Y)	(3) Δln(Y)	(4) Δln(Y)	(5) Δln(Y)	(6) ln(povgap)
$\ln(GDP)_{t-1}$	0.000647	-0.00830*	0.000945	-0.00685*	-0.0164**	-1.826***
	(0.00288)	(0.00451)	(0.00266)	(0.00380)	(0.00797)	(0.184)
$\ln(povertygap)_{t-1}$		-0.00548***		-0.00368**	-0.0268	
		(0.00185)		(0.00185)	(0.0167)	
σ(GDP)			-0.161	-0.0607	-0.149	
			(0.136)	(0.0896)	(0.114)	
$\ln(povertygap)_{t-1}$ x σ(GDP)				-0.0347		
				(0.0272)		
$\ln(povertygap)_{t-1}$ x $\ln(GDP)_{t-1}$					0.00243	
					(0.00180)	
LAC dummy						1.292***
						(0.401)
Constant	0.0203	0.102**	0.0238	0.0914***	0.179**	16.09***
	(0.0230)	(0.0387)	(0.0223)	(0.0337)	(0.0721)	(1.293)
Observations	102	102	102	102	102	102
R-squared	0.001	0.095	0.032	0.126	0.133	0.572

Source: Authors' calculations
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

When volatility is added to the convergence equation instead of poverty (column 3), we see a negative effect of volatility—in line with the previous literature—that is not statistically significant though and the overall model does not fit the data as well as when including poverty instead. When adding both variables and allowing them to interact (column 4), it is poverty that exercises a statistically significant impact that is aggravated by volatility (although the interaction is not statistically different from 0). To better understand the effect implied by the estimated model, Figure 7.4 evaluates the impact of poverty on growth at different levels of volatility (following the rationale discussed for equations 6 and 7). As one can see, the effect of poverty becomes severely more negative, the higher volatility is, as suggested by the considerations above. Furthermore, column 4 highlights that once one controls for the effects of poverty, volatility, and their interaction, convergence in income levels is taking place.

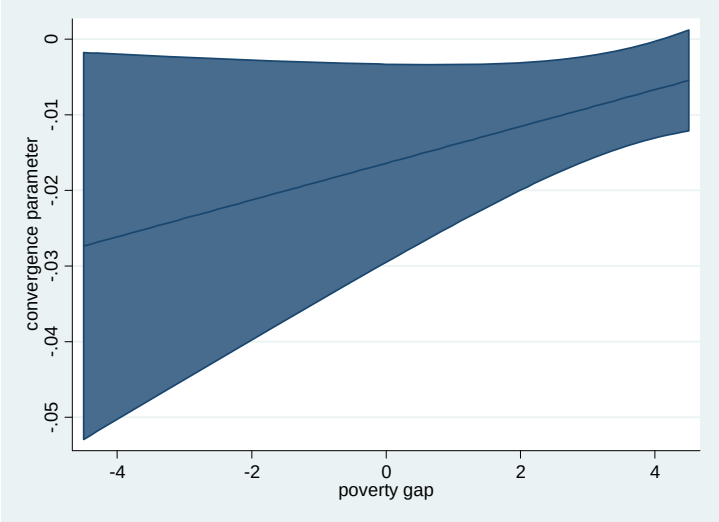
Figure 7.4. Marginal effect of poverty on growth for different levels of volatility



Source: WBG staff calculations based on WDI data.

Finally, I allow this convergence parameter to depend on the poverty gap by interacting the two relevant variables (column 5). The evaluation of the effect is depicted in Figure 7.5. It shows that the smaller the poverty gap is, the faster does a country converge in terms of the income level. Once the poverty gap increases, it becomes less likely for a country to converge. This is in line with the above consideration that poverty eats up the "advantages of backwardness," as poor people will find it hard to invest in assets even though they should provide a high marginal return.

Figure 7.5. Convergence parameter with respect to different poverty gaps



Source: WBG staff calculations based on WDI data.

Despite remaining fairly frugal, this empirical investigation highlights that it is sufficient to control for the poverty gap to observe statistically significant (conditional) convergence in income levels in a broad sample of 102 developing countries. The size of the poverty gap directly influences the convergence speed and the negative effect of poverty on growth increases with macroeconomic

volatility, in line with the findings of CCKW (2013). The negative effect of poverty on convergence may be driven through various channels related to poverty. For example, in the dataset above it is also sufficient to control for (log) initial primary school completion rates and/or life expectancy to obtain significant convergence. However, even with both these variables, inclusion of the log initial poverty gap still accelerates convergence (from a parameter of -0.015** to -0.018***).

7. 4. A Latin American Perspective

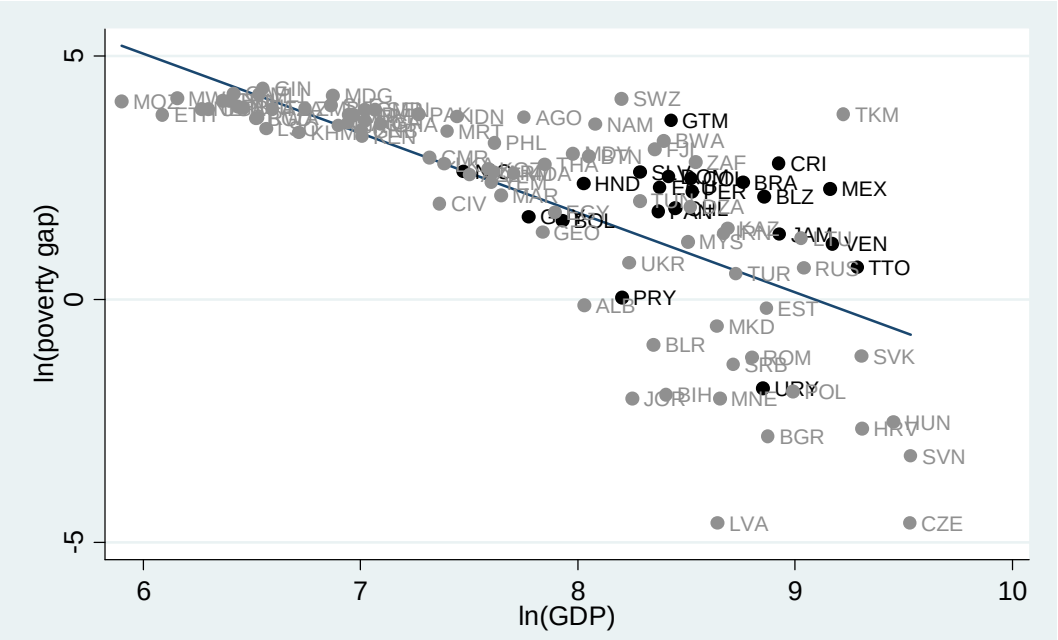
7. 4. 1. Lacking convergence in the past

What do these results imply for LAC and its convergence path?

The region is known for historically high levels of inequality and, relatedly, for a considerable poverty incidence considering the overall income level. This latter point is depicted in Figure 7.6. It shows (the logarithm of) the poverty gap on the vertical and (the logarithm of) GDP p.c. on the horizontal axis, outlining a clear negative relationship, as expected. Given this relationship, however, Latin American and Caribbean countries (depicted in full black) have larger poverty gaps than one would expect considering their income level. This is also confirmed parametrically in column (6) of Table 7.1 showing (with a LAC dummy variable), that LAC's poverty gap is significantly higher than in the rest of the developing world after controlling for the level of GDP p.c. This means that LAC is over-proportionally burdened with poverty given their income level, potentially preventing the region to benefit from "advantages of backwardness" relative to high-income countries.

Previous research has further pointed out the nature of volatilities in LAC and its macroeconomic linkages (e.g. Gavin, Hausmann, Perotti, and Talvi, 1996; Gavin and Hausmann, 1998) as well as its feedback loop on poverty (IDB, 1995; CCKW, 2013).

Figure 7.6. Relation between poverty and income



Source: WBG staff calculations based on WDI data.

Under these circumstances, a relatively large proportion of (poor) households might have been detained from investing into assets (such as education) that would have a potentially high return and would be in demand for a productivity-enhancing dynamic structural change in the sense of the contributions of Schiffbauer, Sahnoun, and Araujo and Brown, Crespi, Iacovone and Marcolin in this volume. The issue might be of special relevance for the Caribbean that experienced a considerable slowdown in growth rates in the last decades against the background of particularly high poverty levels and historically high exposure to volatility and shocks.

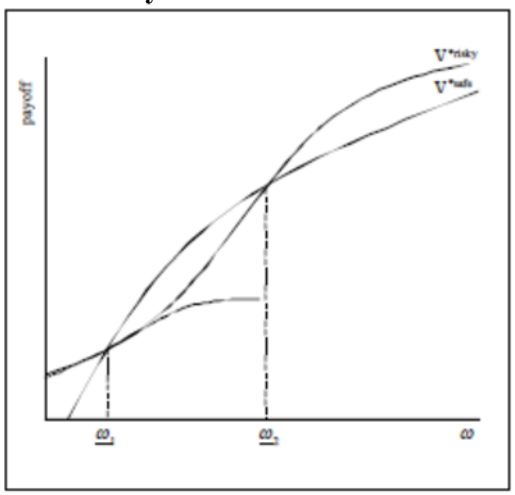
7. 4. 2. LAC looking ahead

Over the last decade LAC has seen a considerable decline in poverty mostly due to positive growth effects (see Dollar et al., 2013 and World Bank, 2014) and as CCKW (2013) show, LAC has in fact seen poverty convergence. This raises the hope that the potential drag of poverty on income convergence will be somewhat attenuated in the future. However, this will also depend on whether poverty reduction is mainly temporary, e.g. driven by the boom in the commodity and related sectors that have a high demand for unskilled labor, potentially benefitting poor households (see de la Torre, Messina, and Pienknagura, 2012), or has truly enlarged socio-economic opportunities of the poor, which would potentially allow them to move up the ladder towards higher-productivity activities over time. A recent World Bank (2014) study highlights that equality of access to basic childhood goods and services has improved in recent years while serious issues remain concerning the quality of those goods and services, particularly in education and housing infrastructure. Concerning volatility, the region has managed to stabilize output and inflation, and to support overall stability (see World Bank, forthcoming).

With a growing middle class in the region and extended basic social security nets amid fiscal windfall revenues, a paradox pointed out by Banerjee (2000: 137) might arise, however. Because

the safety net prevents effective income to fall below a certain threshold, the risk of investing for the poor is considerably reduced while the risk of investing shifts towards the middle class. This is depicted in Figure 7.7 which shows the payoff/utility V of a risky and a safe investment strategy for different levels of endowment (ω). For a certain ("middle-class") endowment level $\underline{\omega}_1 < \omega < \underline{\omega}_2$, the safe strategy (of not investing) leads to a higher payoff than investing. If such investment traps actually exist, the observed mobility of the poor towards the middle class in the region will not necessarily translate into increased investment in productive assets in the future—a "middle income trap" arises. However, this paradox is a very specific case and it is questionable if it captures households' investment behavior in the region appropriately. By and large, the observed developments with respect to poverty reduction and macroeconomic stabilization should give rise to a somewhat more optimistic growth outlook for the region going forward, besides from the intrinsic benefits of reducing poverty.

Figure 7.7. Payoffs for different endowments



Source: Banerjee (2000)

7. 5. Conclusion

This chapter has argued that poverty could deplete the "advantages of backwardness" that underlie neoclassical models of income convergence, i.e. the advantage that the marginal return to investment is higher in relatively poor countries. Especially in an environment where volatility and thus uncertainty is high, the poor might be distracted from investing because in a potentially "bad state" of the economy in the future (e.g. droughts, crisis, civil unrest or war), their disposable income might fall below a minimum level of consumption.

The hypotheses deriving from this reasoning are a negative impact of the poverty gap on growth that increases with the level of volatility and, accordingly, a convergence process that is slowed down by high initial poverty. These hypotheses are confirmed in a simplistic econometric estimation covering 102 developing countries. The empirical exercise further shows that unconditional convergence does not hold but controlling for initial poverty is sufficient to observe statistically significant (conditional) convergence.

This might be interpreted as a growth reducing effect of poverty on the aggregate production function. For example, economic misallocations (along firms or sectors) might take place because adjustment costs (i.e. rigidities) towards the most productive allocations are too high for the poor under credit constraints, particularly because uncertainty (i.e. volatility) might give rise to an ex post inefficiency that cannot be insured against (cf. Ramey and Ramey, 1991; Dixit and Rob, 1994; Bertola, 1995). Such a constraint would partially explain why efficiency concerns of mainly microeconomic nature or sectoral competitiveness considerations which both ranked high on the policy agenda of the LAC region in the 1990s, only painted an incomplete picture of the macroeconomic constraints of the region as it largely ignored equity and volatility considerations (cf. Birdsall, de la Torre, and Valencia Caicedo, 2010). Given the particularly high poverty levels in LAC, this 'incomplete agenda' might have overlooked a serious factor holding back income growth and convergence of the region.

Certainly, the present exercise is only a first approximation concerning the effect of poverty traps for income convergence in the presence of uncertainty and volatility. More elaborate estimation results are needed as much as different approaches to understand in more detail the exact channels that prevent countries with large poverty gaps from converging towards higher income levels.

7. 6. References

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