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Potential Drivers and Dynamics of Pro-Poor Growth in Latin American Countries

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Declaration

I hereby declare that the master thesis entitled "Potential Drivers and Dynamics of Pro-Poor Growth in Latin American Countries", submitted to GLODEP Consortium as thesis graduation requirement, is my original work and any theoretical and empirical literature, as well as all other data used in the proceedings of the study, have been explicitly acknowledged in the text and the list of references provided in the document.

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Zásady pro vypracování

Latin America and the Caribbean is the most unequal region in the world. However, in the past decades the region has experienced a significant decrease in income inequality and poverty. This process has been marked by a sustained increase in the mean income per capita and, more importantly, a higher increase in the income per capita among the poor. “Pro-poor growth” has been defined as a type of economic growth that enhances the welfare of the poor by increasing their participation and benefits from economic activities. More specifically, a pro-poor growth can be identify when the “poor” segment of the population benefits more, in relative or absolute terms, in comparison with the non-poor. The objective of the present study is to explore the potential drivers that determine the magnitude of the pro-poor element of economic growth and its dynamics for Latin American countries using regression techniques and data from the Socio-Economic Database for Latin America and the Caribbean (CEDLAS) and The World Bank.

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Abstract

Since the 1990s, growth in Latin America and the Caribbean [LAC] has been characterized by a sharp decline in inequality and poverty. This is often described as pro-poor growth, in which the poor are particularly benefited from the distribution of growth gains. Although this concept and its operationalization are still under debate, they result extremely useful to interlink the dynamics between growth, inequality and poverty.

The study analyzed the dynamics and potential drivers of pro-poor growth in 16 LAC countries using the latest available income and distribution data from the World Bank's PovcalNet. The characterization of the pro-poorness of growth was done using the decomposition of poverty changes (Kakwani, 2000), growth incidence curves and rates of pro-poor growth (Ravallion & Chen, 2003). The potential drivers were evaluated under a panel regression framework applying OLS, Fixed Effects and GMM estimators. The results suggest that LAC growth from 1991 to 2019 can be overall qualified as pro-poor as well as the specific growth pattern of each country except two. In addition to being heavily determined by income growth and changes in inequality, the magnitude of pro-poor growth is positively correlated with a larger government size.

Keywords: Latin America and The Caribbean**,** Pro-Poor Growth, Inequality, Poverty, Growth Incidence Curve, Rate of Pro-Poor Growth.

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List of Abbreviations

CEDLAS	Center for Distributive, Labor and Social Studies
FGT	Foster–Greer–Thorbecke
GDP	Gross Domestic Product
GIC	Growth Incidence Curve
GMM	Generalized Method of Moments
ILO	International Labour Organization
LAC	Latin American and the Caribbean
MDG	Millenium Development Goals
PEGR	Poverty Equivalent Growth Rate
PPG	Pro-Poor Growth
PPGI	Pro-Poor Growth Index
RPPG	Rate of Pro-Poor Growth
SDG	Sustainable Development Goals
SDGF	Sustainable Development Goals Fund
SEDLAC	Socio-Economic Database for Latin American and The Caribbean
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary Least Squares
UN	United Nations
UNDP	United Nations Development Program
WDI	World Development Indicators

Introduction

Persistent inequality has been a distinctive feature of Latin America and the Caribbean [LAC] for most of its history (Lustig et al., 2013). Although, since the 2000s, economic development in the region has been characterized by constant positive growth and a sharp decline in poverty and inequality, it remains the most unequal region in the world (Gasparini et al., 2007; Lustig et al., 2013). Even after a 14% decrease in the last two decades, the region's –unweighted– average Gini coefficient is still the highest in the world (0.44), 17% higher than the world's –unweighted– average Gini (0.38) and 10% higher than Sub-Saharan Africa (0.4) [1].

Interestingly, inequality appears to follow the same broad pattern, with some magnitude differences, in all LAC countries. Following an increase in inequality during the 1980 and 90s –after highly debated economic reforms–, inequality suffered a marked decrease in virtually all LAC countries (Gasparini et al., 2007). This is noteworthy especially considering the great diversity of countries included. All countries from large economies (like Brazil and Mexico) to small ones (Honduras and El Salvador), with initial high inequality (Paraguay and Brazil) to –comparatively– low inequality (Uruguay), with left-wing governments (Brazil, Bolivia) and right-wind governments (Mexico and Peru); have experienced a steady decline in their inequality and poverty measures since the 2000s (Lustig et al., 2013).

Even more remarkable, inequality declined regardless of the magnitude of the country's growth rate. Not only did the slow-growing countries (which experienced less than half the annual growth rate than the fast-growing ones) managed to reduce their inequality levels, but their reduction was even greater. From 2000 to 2019, the three fastest-growing economies (Panama, Dominican Republic and Peru) averaged a 4.95% GDP annual growth rate compared with the 2.11% of the three slowest growing economies (Argentina, El Salvador and Mexico). Nevertheless, during the same time, inequality not only decreased for both country groups, but there was an even slightly larger decline for the countries with the slowest growth rate (15% and 18% respectively) with practically the same initial inequality[2].

The sustained decline in both poverty and income inequality implies that not only has the mean per capita income risen steadily, but there also has been a higher increase in the per capita income among the poor. This is consistent with a bias in the distribution of gains during the economic process favoring the poor, referred to in development literature as 'pro-poorness' of growth (Shepherd et al., 2016). If the pro-poor growth [PPG] approach allows tilting the development process towards the poor, it will help maximize poverty reduction without compromising overall growth (Klasen, 2008). Among development literature, the study of pro-poorness of growth gained prominence as a key approach to understanding how inequality of distribution of economic gains affects poverty reduction during the development process.

[1] Calculation based on latest available data from World Bank estimates of Gini Index (2021) from the World Development Indicators [WDI] database.
[2] Based on WDI database for GDP growth data and Gini index (World Bank, 2021)

The dynamics between growth, inequality and poverty have been long studied. In LAC, the emphasis has mainly been on analyzing the persistence of inequality and its potential impacts on growth and subsequent poverty reduction. Nonetheless, a new approach has shifted the focus from characterizing some direct correlation between these two phenomena towards looking for potential factors that simultaneously influence both growth and inequality (Lundberg & Squire, 2003). This type of dynamic is consistent with PPG, such as that witnessed in the region in recent decades, in which there is a simultaneous sustained economic progress and inequality decrease.

Currently, there is still no consensus on what specifically pro-poor growth implies, even less on what drives this specific kind of dynamic (Kraay, 2004). Although there have been several attempts, the complexity of the processes involved, data comparability issues and substantial country-specific differences have made it highly challenging to identify what makes growth pro-poor and how[3]. Considering this, the empirical heterogeneity of economic performance and poverty reduction patterns of Latin American countries presents a promising opportunity to identify potential determinants of this pro-poor bias (Gasparini et al., 2007).

The present research work attempts to take advantage of this opportunity to contribute to the current gap in development literature by addressing the question: What factors have driven the pro-poorness bias of the growth experienced in Latin America and the Caribbean from 1991 to 2019? Accordingly, the main objective of the study is to analyze the growth and poverty dynamics of 16 LAC countries from 1991 to 2019 to determine whether growth during this period can be considered pro-poor and to identify potential drivers of the pro-poor bias of growth. Therefore, in order to answer the main research question, the specific objectives of the study are:

- To describe the general dynamics of income growth in 16 Latin-American countries from 1991 to 2019 in terms of their distribution dynamics and impact on poverty reduction.

- To determine whether growth can be considered pro-poor using 4-years growth spells from 1991 to 2019 for 16 Latin-American Countries.

- To identify potential drivers of the pro-poor bias of income growth using the rate of pro-poor growth (RPPG) as a proxy.

The document is divided into four chapters. Following this introductory section, the first chapter contains a review of the relevant literature on PPG and a brief summary of the debate over the definition, identification and measurement of PPG and its potential drivers. The second chapter consists of the methodological framework, including the delimitations of the study and a description of the data used. Chapter three presents the research findings with their respective discussion and, finally, chapter four closes with the conclusions and final remarks.

[3] See Lundberg and Squirre (2003), Kraay (2004), Pasha and Palanivel (2004), Son and Kakwani (2008) and Lustig et al. (2013) for some examples on attempts to identify potential determinants of pro-poor growth.

1. Literary Review

1.1 Growth and poverty

For decades the fight against poverty has been dominated by the dogma of growth. Poor countries just have to grow 'enough' to lift their population's living standards out of poverty –since growth is supposed to be unequivocally good for the poor– (Dollar & Kraay, 2002). The MDG's primary goal (MDG1. Eradicate extreme poverty) was achieved mainly by following this dogma with cases such as China's 'successful development' story (Besley & Burgess, 2003; UNDP, 2015). Paradoxically, China's development path lifted 470 million people out of poverty while dramatically increasing income inequality, making it one of the most unequal countries in the world (Jain-Chandra, 2018; UNDP, 2015). These mixed results raise some questions about the ideality of China's path towards poverty eradication, especially when moving from an absolute definition of poverty towards a relative one.

Beyond some inferred Kuznets Curve relationship between growth and inequality[4], the trends in inequality and poverty in China are explained by the combination of two factors. On the one hand, an impressive and sustained economic performance (averaging 9.8% GDP growth for 25 years) and, on the other, an extremely unequal distribution of the gains of this process (Gosh et al., 2011). Ravallion & Chen (2003) found that, during the 1990s, the income of the wealthiest percentiles in China was growing by 10% annually while the income of the poorest was barely growing by 3%. This implies that during the time of the "most successful anti-poverty push in history" (UNDP, 2015, para. 3), the distribution dynamic of growth gains was actually hindering poverty reduction.

This set-up is typically described as a 'trickle-down growth' in which the wealthy receive most of the benefits from economic progress, which later 'trickles down' to those below, thus generating an overall improvement in society (Greenwood & Holt, 2010). According to Kakwani and Pernia (2000), this kind of trickle-down growth is the expected resulting structure of a market-force-guided process. They argue that the rich have inherent advantages which allow them to benefit proportionally more than the non-rich. For a long time, this was part of the dominant development thinking and argued that the poor would automatically receive the indirect benefits once the rich spend their gains (Kakwani & Pernia, 2000; Kakwani & Son, 2003).

Consequently, according to this traditional theory and in agreement with the growth dogma, poverty would be reduced even if only a tiny fraction of the economic benefits went directly to the poor (Kakwani & Pernia, 2000). Under this logic, all types of growth are assumed to be suitable for poverty reduction, regardless of their inequality dynamics (Dollar & Kraay, 2002). Moreover, increasing inequality was considered acceptable as it would supposedly induce higher economic performance, and this resulting surplus would benefit everyone (Greenwood & Holt, 2010). However, further research on the income elasticity of the poor has argued that the income of the poorest is not as strongly related to mean growth rates as previously thought (Foster & Székely, 2008).

[4] It refers to the a relationship between inequality (typically measured with the Gini coefficient) and per capita income/GDP in which inequality first increases (at low levels of per capita income) to later fall describing a inverted-U or 'Kuznet curve' (Barro, 2000), although this has been highly contested among several authors and is still under debate (White & Anderson, 2001; Lundberg & Squire, 2003; Foster & Székely, 2008).

Another problem with this type of poverty-lifting mechanism is that, although proven to be effective, it is highly uncommon at this magnitude, as most developing countries are unable to achieve and sustain such high economic performance as China or India. Therefore, in the majority of cases, an unfavorable distributional dynamic of growth benefits not only hinders poverty reduction but prevents the poor from participating in and benefiting from the economic process enough to escape poverty (OECD, 2007). In other words, economic growth, although a necessary condition for poverty reduction (Kraay, 2004), is not sufficient since "in most cases is not sustained or equitable enough to lift the poorest and marginalized out of poverty" (UNDP, 2016, p. 19).

This implies that achievements in poverty reduction so far have been made not thanks to but despite the dominant distribution dynamic. If it had been accompanied by policies aimed at benefiting the poor, or at least avoiding policies that increase existing inequality, poverty reduction would have been even greater. In fact, inequality can reach a level in which its adverse impact on the poor completely offsets the beneficial effect of growth (Kakwani & Pernia, 2000). Although an extreme case, the reality is that if growth gains from 1980–2010 had been distributed with just a 2% gap in favor of the bottom 40 percent, global poverty incidence would have been reduced to 7.1% –instead of 20.6%–(Shepherd et al., 2016).

Currently, the most important development policy discussion is framed by the Sustainable Development Goals [SDGs]. As part of the transition, one of the most significant changes from the Millennium Development Goals [MDGs] to the SDGs was the shift from a quantitative targets approach to a more comprehensive concept of development (SDGF, n.d.). Specifically, Poverty Eradication (SDG 1) and Reduction of Inequality (SDG 10) goals have given greater relevance to the distribution dynamics of economic benefits. The "leave no one behind" commitment is inconsistent with an inequality increasing development (UNDP, 2016). If distributional changes are made without a detrimental impact on growth, it would be key in achieving the international development targets (White & Anderson, 2001). Moreover, it has been argued that the SDGs and World Bank's poverty eradication targets will not be achieved by 2030, even with a neutral distribution (Shepherd et al., 2016). Therefore, vital importance has been given to a new focus, moving away from pure growth, towards a 'pro-poor growth' approach (SDGF, n.d.).

1.2 Pro-Poor Growth: Concept

Pro-poor growth has been defined, in broad terms, as the type of growth that enhances the welfare of the poor by enabling their active participation and allowing them to benefit significantly from economic activities (UN, 2000; Kakwani & Pernia, 2000; OECD, 2007). It gained prominence in both research and policy papers in the early 2000s in the context of achieving the MDGs (Grosse et al., 2008) and became the main framework of donor's policy guidance with the strong equity focus of the SDGs (Shepherd et al., 2016). As the Chronic Poverty Advisory Network has repeatedly stated, PPG is necessary to eradicate extreme poverty and improve all poverty dynamics (Shepherd et al., 2014, 2019).

However, such a broad definition of PPG can imply a variety of situations in which the poor, even though benefiting from economic growth, might experience a worsening of their relative condition in society. Although there is still an open discussion on the exact definition of PPG (see, for example, Lopez, 2004a; Duclos, 2009; Klasen, 2008), several operationalizations of this concept have been carried out based on how the poor are affected by growth (Shepherd et al., 2016).

The line that has essentially divided the debate on the pro-poor concept is whether an absolute or relative approach should be used for its definition (Klasen, 2008). An absolute approach would look only at the end result of the growth process. In this case, it argues that PPG is all growth which benefits the poor, effectively reducing poverty (Ravallion & Chen, 2003; Ravallion, 2004). The main argument of this definition is that it focuses on improving the living conditions of the poor (Duclos, 2009). This approach gained somewhat importance, being World Bank's proposed definition; however, it is feeble as it completely disregards the distribution dynamics of growth gains under place. Ultimately, it results rather useless, as it would classify virtually all positive growth processes as pro-poor (Kakwani & Son, 2003).

A stronger absolute definition of PPG has been proposed as the one in which the poor sector of society receives larger absolute benefits than the non-poor (Grosse et al., 2008; Klasen, 2008). This implies that the –mean– absolute gain of the poor must be greater than the absolute gain in the mean of the distribution (Grosse et al., 2008). For this to occur, the poor's share of the incremental income would have to exceed their population share (White & Anderson, 2001). Consequently, this is the only definition that implies a reduction in absolute inequality (Lopez, 2004a). It could be argued that this approach implies an absolute growth bias towards the poor; hence it might be more suitable when considering poverty in non-income dimensions (Shepherd et al., 2016). However, it turns out to be of limited utility considering that this situation, as one might expect, is highly unlikely to occur (White & Anderson, 2001).

On the other hand, a relative definition of PPG would be when the poor benefit proportionally more than the non-poor from the economic process (McCulloh & Baulch, 1999; Kakwani & Pernia, 2000; Son, 2004). More specifically, when the growth rate of the income of the poor is greater than the average growth rate. This implies a larger poverty decrease than it would have occurred if all incomes have grown at the average growth rate and, thereby, a subsequent reduction of the relative gap between the poor and non-poor (Klasen, 2008). The main argument of this approach is that it implies an inherent distributional shift in favor of the poor (Ravallion, 2004). In other words, the distributional dynamic would need to be biased, in relative terms, in favor of the poor.

Even without a consensus over the concept of PPG, its use in policy literature and economic papers has spread in recent decades. All major development policy guidances advocate, to varying degrees, for PPG as the main path to follow for developing countries (e.g., UN, 2000; Pasha & Palanivel, 2004; OECD, 2007; UNDP, 2016). Despite this, there is a worrying gap yet to fill in identifying and measuring the appropriate policies to follow this path. In other words, there is still a long way to go on how to promote and sustain this kind of growth.

It must be pointed out that all the above characterizations are sensitive to the definition of 'the poor' (Grosse et al., 2008). Thus all classification of a given growth period as 'pro-poor inevitably depends on the arbitrary decision of who are the poor and how to define a 'bias' towards them (Gasparini et al., 2007). Although a further discussion is out of the scope of the present work, it is important to bear in mind that all further analysis is restricted to the income dimension of poverty and entails the fundamental arbitrariness of the definition of poverty used.

The discussion over the ideal concept of PPG, although beyond the objectives of the present work, offers a valuable starting point towards the analysis of development dynamics in pro-poor terms. It is important to note that all previous pro-poor definitions are based on the two primary underlying conditions of positive income growth of the poor and a bias of distributional change towards the poor (Klasen, 2008) [5]. Moreover, the changes in poverty are determined by changes in the mean income and changes in its distribution dynamic. Hence, it is possible to further analyze the impact of growth on poverty by separately examining the effects of changes in mean income and changes in its distribution on poverty.

1.3 Decomposition of Poverty Changes

As previously mentioned –and contrary to the classic neoliberal theory– growth does not unambiguously translate into poverty reduction. Economic growth, hereon interpreted as positive income growth, undoubtedly reduces poverty levels but with considerable variation (Shepherd et al., 2019). Many times, changes in the distribution of economic benefits hinder the poor and, on some occasions, this harmful effect might even overturn the benefits obtained from growth itself, resulting in an immiserizing growth (Kakwani & Pernia, 2000). To understand this dynamic, it is necessary to analyze how income growth impacts poverty.

Overall income growth can impact poverty in two mechanisms: (i) changes in average income and (ii) changes in the inequality of income distribution (Kakwani, 2000). Considering poverty quantified with an F-G-T metric[6] (e.g., poverty index and poverty gap) or Watts index based on an income/consumption variable[7]. This measure can be written as a function of the mean of the distribution on which it is based (income) and the Lorenz curve of that distribution (Ravallion, 2004). It is then possible to decompose income growth into these components and quantify the contribution of each to the total variation in poverty (Datt & Ravallion, 1992). This decomposition allows to allocate changes in poverty over time to growth and redistribution attributed components.

The growth attributed component of poverty changes refers to the change in the poverty level due to change in the mean income (μ_t) relative to the poverty line (Datt & Ravallion, 1992). When isolated, it measures the effect of growth on poverty if the income distribution had not changed (Kakwani & Pernia, 2000). It is called pure growth or income effect (G). The growth effect is always negative, implying that positive mean income growth will unambiguously reduce poverty, holding relative inequality constant (Kakwani & Pernia, 2000).

[5] Whether growth is still pro-poor – or to what extent – when only one of the two conditions is fulfilled is the base of the debate on relative or absolute approach (Klasen, 2008).

[6] Foster, Greer and Thorbecke poverty measures, in their general form: $FGT_\alpha = \frac{1}{N}\sum_{i=1}^{H}\left(\frac{z-y_i}{z}\right)^{\propto}$, where y_i is the income of the individual i, N is the total population and H is the number of people under the poverty line z (Foster et al., 1984).

[7] Referred from now on only as income.

The redistribution attributed component of poverty changes refers to the change in the level of poverty due to changes in relative inequality (L_t) (Datt & Ravallion, 1992). When isolated, it measures the effect of income redistribution on poverty if the mean income had not changed. (Kakwani & Pernia, 2000). It is called redistribution or inequality effect (D). The redistribution effect can be either negative or positive depending on whether the poor increase their share in the distribution of gains (Kakwani & Pernia, 2000).

The decomposition of changes in poverty first assumes a poverty measure in the form of $\theta = \big(z, \mu, L(p)\big)$; where z is an absolute poverty line, μ is the mean income/consumption and where $L(p)$ is the Lorenz function[8] of the distribution. Then, as pointed out by Kakwani (2000), a given percentage change in poverty will be given by

$$\theta_{01} = Ln\big[\big(z, \mu_1, L_1(p)\big)\big] - Ln\big[\big(z, \mu_0, L_0(p)\big)\big] \qquad [1]$$

where μ_0 and μ_1 are the mean income/consumption and $L_0(p)$ and $L_1(p)$ are the Lorenz functions for years 0 and 1, respectively. It considers a poverty line (z) which remains fixed between the two periods. Note that mean incomes must be adjusted by price changes over the period.

The total variation of poverty can be defined, using the rational axioms set approach proposed by Kakwani (2000) and Kakwani and Pernia (2000), into growth and redistribution attributed components as

$$\theta_{01} = G_{01} + D_{01} \qquad [2]$$

where G_{01} is the growth attributed component of poverty change and D_{01} is the redistribution attributed component of poverty change between years 0 and 1.
These components were defined by Kakwani (2000) into functional forms, similar to Datt and Ravallion's (1992), as the following expressions:

$$G_{01} = {}^{1}\!/_{2}\Big[Ln\big[\theta\big(z, \mu_1, L_0(p)\big)\big] - Ln\big[\theta\big(z, \mu_0, L_0(p)\big)\big] + Ln\big[\theta\big(z, \mu_1, L_1(p)\big)\big] - Ln\big[\theta\big(z, \mu_0, L_1(p)\big)\big]\Big] \qquad [3]$$

and

$$D_{01} = {}^{1}\!/_{2}\Big[Ln\big[\theta\big(z, \mu_0, L_1(p)\big)\big] - Ln\big[\theta\big(z, \mu_0, L_0(p)\big)\big] + Ln\big[\theta\big(z, \mu_1, L_1(p)\big)\big] - Ln\big[\theta\big(z, \mu_1, L_0(p)\big)\big]\Big] \qquad [4]$$

The first term G_{01}, growth effect, is the estimated change in poverty when there is a change in mean income (μ_0 to μ_1) while holding constant the Lorenz curve $L(p)$. The second term D_{01}, redistribution or inequality effect, is the estimated change in poverty when there is a change in the Lorenz curve ($L_0(p)$ to $L_1(p)$) while holding constant the mean income μ. As mentioned before, G_{01} is always negative, whereas D_{01} will only be negative (positive) if the shift in income distribution benefited (hindered) the poor.

[8] Introduced by Lorenz in 1905 it is widely spread for inequality studies to analyze the distribution of wealth or income, e.g.. It describes the corresponding share of income/wealth for the bottom p percent of the distribution. Its general form is $L(p) = \frac{1}{\mu}\int_0^x yf(y)dy$ with $p = f(y)$, where μ is the mean of the distribution and y is the income of the individual at the p percent with a probability density function $f(y)$ (Gasparini et al., 2014).

Datt and Ravallion (1992) had previously proposed that the total variation in poverty could be decomposed into growth in the mean, changes in the distribution and a residual, which captures the interaction between them. This decomposition, however, depends on the arbitrary decision –justify as somewhat 'natural'–to take the first year as the base distribution. More importantly, this decision results in a residual component that cannot be attributed to either growth or inequality effects, nor can it be statistically interpreted[9]. Kakwani and Pernia (2000) decided to decompose the total variation by taking the average growth/distribution components measured at the base and final distribution. Although still arbitrary[10], this method eliminates the residual term providing an exact breakdown of the changes in poverty (McCulloh & Baulch, 1999).

Going back to the absolute and relative approaches. Growth will be pro-poor, in the absolute sense, as long as the total variation of poverty (θ_{01}) is negative, regardless of whether both or only one of the terms is negative. Whereas in the relative sense, it will be pro-poor only if the redistribution component (D_{01}) is negative. Advocating for a more intuitive definition of PPG, it seems more reasonable to argue that the economic process has been in favor of (against) the poor whenever inequality decreases (rises) (McCulloh & Baulch, 1999). Although some might argue in favor of a greater emphasis on the absolute poverty fall, it is undeniable that, in the long term, growth accompanied by a decline in inequality will have a more sustained impact on poverty than if it would leave inequality unchanged (White & Anderson, 2001).

Some authors have insisted that the poor's income raises equiproportionally with the mean income, thus stating that growth benefits the poor to the same extent as the rest of society (Dollar et al., 2016; Dollar & Kraay, 2002). This analysis is fundamentally based on the apparent lack of correlation between the change in mean income and income share of the bottom 20 percent of the distribution. However, the absence of a systematic pattern between growth and income share of a given bottom percent of the distribution does not imply that the distribution effect itself does not change between countries or across time (White & Anderson, 2001).

If considering the direct impact of the growth dynamic (as defined above) instead, the redistribution (inequality) effect on poverty becomes highly relevant. White and Anderson (2001), using a database of 29 countries and 143 growth spells, found that the change in income share played a significant role in determining changes in the income of the poor. They estimated that, in over 25% of the growth spells, the change in distribution was more important than overall growth. Similarly, Lustig, Lopez and Ortiz (2013) determined, using a Datt-Ravallion decomposition, that the redistribution effect accounted for 50% of changes in poverty for 17 Latin American countries during the first decade of the 2000s. Likewise, considering the sustained effect due to inequality decrease, it is possible to argue that even small changes in the distribution dynamics can substantially impact poverty reduction (White & Anderson, 2001).

[9] The correct interpretation of this residual is that it captures the difference between the growth (redistribution) component evaluated using the initial and terminal Lorenz curve (mean income), respectively. If the either the Lorenz curve or mean income remains unchanged the residual is equal to zero (Datt & Ravallion, 1992).
[10] By taking the averages of the effects the residual component is 'arbitrary' allocated in the growth and redistribution components (McCulloh & Baulch, 1999).

1.4 Pro-Poor Growth: Identification and Measurement

Although there is still an ongoing discussion over the ideal concept of pro-poor growth, several indicators and measures of PPG have been proposed and operationalized. In recent years the use of these indicators has become widespread, especially in growth-inequality studies. Previous approaches to identify and quantify the impact of growth on poverty were focused mainly on measuring the changes in the poor's income. Traditionally this was measured by the growth rate in the mean income of the poor or the growth rate of the income of the poorest quintiles (e.g., Dollar & Kraay, 2002; Dollar et al., 2016). However, these types of measurements lack any information on the inequality dynamics in place. Hence, the use of a pro-poor focus has presented scholars with a 'fresh' approach to the long-running debate over the growth-inequality relationship.

Pro-poor Growth Index

Kakwani and Pernia (2000) proposed a characterization of PPG focusing on the changes in poverty. They argued that to fully understand the impact of growth on poverty, it is necessary to take into account the components of these changes. As discussed in the previous section, changes in poverty depend on both the magnitude of growth (growth component) and changes in inequality (redistribution component) so that $\theta = \theta_G + \theta_D$. They defined δ as the proportional change in poverty, when there is a positive growth rate of 1 percent, such as

$$\delta = \eta + \zeta \qquad [5]$$

where δ is the sum of the percentage change in poverty when the distribution does not change (pure growth effect η) and the change in poverty when inequality changes in the absence of growth (redistribution/inequality effect ζ) (Kakwani & Pernia, 2000). Using this approach, they proposed a pro-poor growth index [PPGI] defined as:

$$\text{PPGI}\ (\varphi) = \frac{\delta}{\eta} \qquad [6]$$

In this case, growth is said to be strictly pro-poor (relative sense) when PPGI > 1, meaning the real change in poverty is greater than the pure growth effect or, in other words, the inequality effect (ζ) is negative. When 0 < PPGI < 1, growth is classify as trickle-down (weak absolute sense). Meaning that there still occurred a poverty reduction, although accompanied by an inequality increase. If PPGI < 0, it means that growth dynamics actually increased poverty. This is considered as immiserizing growth (Kakwani & Son, 2003). Although the PPGI provides a good base to identify PPG, it is inefficient in terms of quantifying the magnitude of the benefits received by the poor.

Growth Incidence Curve

Ravallion and Chen (2003) took a different approach and, instead of the traditional measurement of the mean growth of a fixed poorest percent, decided to expand the idea of Penn's parade[11] to growth rates. They proposed a growth incidence curve [GIC], defined as the growth rates of each centile of the distribution ranked by income. More specifically,

[11] Pen's parade (proposed by Pen in 1971) is a comparison between mean income across the population distribution ranked by income (Ravallion & Chen, 2003).

they used as a base the inverse of the cumulative distribution function[12] of income or quantile function (Q_t), such that:

$$Q_t(p) = F_t^{-1}(p) = L'(p)\mu_t \qquad (Q_t'(p) > 0) \qquad [7]$$

where, $F_t(p)$ would be the cumulative distribution function and $L_t(p)$ is the Lorenz curve, with slope $L'_t(p)$, and μ_t is the mean of the income distribution at time *t*.
Now comparing the changes in income between time *t* and *t-1*

$$g(p) = \left[\frac{Q_t(p)}{Q_{t-1}(p)}\right] - 1 = dLn\big(Q(p)\big) \qquad [8]$$

Then $g(p)$ is the growth rate of the income of the *p-th* quantile between times $t-1$ and t. Letting p vary from 0 to 1 provides what Ravallion and Chen (2003) named as growth incidence curve, which can be conveniently expressed in terms of the Lorenz curve:

$$g(p) = \frac{L_t'(p)}{L_{t-1}'(p)}(\gamma + 1) - 1 \qquad [9]$$

where γ is the growth rate in the mean income (μ_t) such that $\gamma = \left(\mu_t/\mu_{t-1}\right) - 1$.

If the entire GIC lies above zero ($g_t(p) > 0$ for all p), meaning income growth was positive for all quantiles, then growth can be considered pro-poor in the weak absolute sense. If $g_t(p)$ is a decreasing function for all p, it would be unambiguously pro-poor in a relative sense since it implies a fall in inequality over time for all inequality measures (Ravallion & Chen, 2003). Moreover, this is a stricter condition than the standard relative approach as it requires that the benefits received from the economic process are a decreasing function of income. Although, this particular situation –described by Gasparini et al. (2007) as progressive growth– is, once again, highly unlikely to occur.

Rate of Pro-poor Growth

Extending the aforementioned approach, Ravallion and Chen (2003) proposed a PPG measure closely related to the properties of the GIC. They suggested that any accurate measure of pro-poor growth should satisfy the following set of axioms:

i. Focus. Its measure must be invariant to changes in income of the non-poor.
ii. Monotonicity. Any income loss of the poor must reflect an increase in poverty and vice versa.
iii. Transfer. Progressive transfers (decrease in inequality) lead to poverty reduction.
iv. Additive decomposability. The measure can be calculated by the population-weighted average of disjoint subgroups.
v. Subgroup consistency. An increase in inequality in any subgroup leads to an increase in poverty.
vi. Direction. The measure should be consistent in direction with the direction of the change in poverty, meaning any positive (negative) sign implies a reduction (increase) in poverty.

[12] The cumulative distribution function CDF(x) defines the *p*-th probability of a random variable taking a value $\leq x$. Thus, the inverse of this function, also called quantile function, Q(p) = CDF^{-1} returns the value *x* such that there is a *p* probability that *f(x)* takes a value $\leq$ x (Gasparini et al., 2014).

This are the set of five widely agreed fundamental axioms of poverty indicators in addition to one axiom (*direction*) proposed by the authors for any PPG measure (Ravallion & Chen, 2003). Now considering as the poverty measure the Watts poverty index (defined in terms of the quantile function)[13], which satisfies all poverty axioms. Then, the change in poverty will be given by

$$\theta_{01} = -\frac{dW_t}{dt} = \int_0^{H_t} \frac{d \log Q_t(p)}{dt} \, dp = \int_0^{H_t} g_t(p) \, dp \qquad [10]$$

Taking into account that $Q_t(H_t) = z$, it is possible to conclude from the previous equation that the area under the GIC up to the headcount index ($\int_0^{H_t} g_t(p) \, dp$) is equal to minus one times the change in the Watts index (Ravallion & Chen, 2003). Thus Ravallion and Chen's proposed rate of pro-poor growth [RPPG] is defined as the area under the GIC up to the headcount index divided by the headcount index (H_t) as follows:

$$RPPG = \frac{\int_0^{H_t} g_t(p) \, dp}{H_t} \qquad [11]$$

This 'mean growth rate of the poor'[14] is the actual (mean) growth rate adjusted by the ratio of the changes in the Watts index to the changes that would have occurred with the same growth rate but with constant inequality (Ravallion & Chen, 2003).

Poverty Equivalent Growth Rate

In accordance with the characterization of PPG by Kakwani and Pernia (2000) and Son's poverty growth curve (2004), Kakwani and Son (2003, 2008) proposed a new measure (under the relative approach). It takes into account both the growth in the mean income and the distribution of its benefits.

Assuming the income of an individual (μ_i) is a random variable with a distribution function $f(\mu_i)$ and considering a general class of additive poverty measure[15]. Then defining the growth elasticity of poverty (δ) as the ratio of proportional changes in poverty (θ) to the proportional changes in the mean income (μ) (Kakwani & Son, 2008). It is obtained by the total change in poverty divided by mean growth rate (γ) given by:

$$\delta = \frac{dLn(\theta)}{\gamma} = \frac{1}{\theta\gamma} \int_0^{z} \frac{\partial P}{\partial \mu_i} \mu_i(p) \, g(p) \, dp \qquad [12]$$

where $\gamma = dLn(\mu)$ is the growth rate in the mean income and g(p) is the income growth rate at the pth percentile. δ is the percentage change in poverty resulting from a growth rate of 1 percent in the mean income (Kakwani & Son, 2008).

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[13] Proposed by Watts in 1968, written in terms of quantile function: $W_t = \int_0^{H_0} \log\,[z/Q_t(p)] dp$, where H_0 is the poverty headcount at time t, Q_t is the quantile function for the pth percentile (Ravallion & Chen, 2003).

[14] Which is not the same as the growth rate in the mean income of the poor (Ravallion, 2004).

[15] The general class additive poverty measures, considered also by Son (2004), written as $\theta = \int_0^{z} P(z, \mu_i) \, f(\mu_i) \, d\mu_i$.

This can be decomposed, as showed in equation [5], in an inequality/redistribution component (ζ) and a pure growth component (η). This η or neutral growth elasticity was first derived by Kakwani as

$$\eta = \frac{1}{\theta} \int_{0}^{z} \frac{\partial P}{\partial \mu_i} \mu_i(p)\, dp \qquad [12]$$

This is the percentage change in poverty resulting from a growth rate of 1 percent in the mean income, given that relative inequality does not change(Kakwani & Pernia, 2000). In these terms, growth would be considered pro-poor if the actual growth elasticity of poverty is greater than the neutral relative elasticity of poverty[16] (Kakwani & Son, 2008).

Using the previous properties of poverty elasticity, Kakwani and Son proposed the idea of a poverty equivalent growth rate [PEGR]. This is the growth rate that would produce the same poverty reduction as the actual growth rate in the hypothetical situation that inequality remains constant (Kakwani & Son, 2003). It is estimated by

$$PEGR = \left(\frac{\delta}{\eta}\right)\gamma \qquad [13]$$

which is the actual growth rate γ (of the mean income) adjusted by the ratio of the total poverty elasticity (δ) to the neutral growth elasticity of poverty (η). Note that this ratio equals the PPGI previously proposed by Kakwani and Pernia (2000), thus $PEGR = \varphi\gamma$. If the PEGR > γ, then growth is pro-poor in the relative sense (relative inequality has been reduced). If 0 < PEGR < γ, it is considered to be trickle-down. If PEGR < 0, then it is considered as a situation of immiserizing growth (Kakwani & Son, 2003).

All previously described instruments have both merits and limitations. In terms of graphical representation, the GIC is easily understood and interpreted and it allows a more in-depth analysis of the income dynamics along the whole distribution, as it is directly based on disaggregated data. On the other hand, it is subject to data source errors and the estimations on the extremes of the distribution tend to be highly unstable (Son, 2004). In terms of academic use, the application of GIC in inequality-growth analysis has become widely extended in research papers in the past 15 years (examples include Gasparini et al., 2007; Grosse et al., 2008; Gasparini et al., 2014; Iniguez-Montiel, 2014; and Ferreira et al., 2019).

Considering the axiom approach, the RPPG and the PEGR are the best available measures for the magnitude of PPG. They both satisfied the direction axiom and have a monotonical relationship with poverty reduction. Whether or not they fulfilled all axioms is still debatable. Kakwani and Son (2003) argued, with a hypothetical example, that the RPPG would not fulfill either direction axiom or subgroup consistency axiom if the RPPG is estimated under a different sub-group decomposed method[17]. Although, if this is the case, it would also apply for the PEGR for the Watts index, given that the PEGR using the Watts index as the poverty measure is, in fact, the RPPG proposed by Ravallion and Chen.

[16] Considering that PPGI > 1 if and only if δ > η, that is to say, whenever ζ is positive on equation [7].

[17] Is important to note that a different (consistent) result is obtained for the same hypothetical example if the RPPG is calculated with the original equation and for the whole population, instead of the individual-decomposed averaged method used by Kakwani and Son (2003).

Moreover, although the RPPG suffers from the limitation of being bound to the absolute weak approach, as a measure, it still exhibits several unique properties. Its definition is directly related to the GIC, and it is based on arguably the strongest poverty measure. The Watts index, for example, has the convenient property of being equally sensitive in all percentiles below the poverty line (Kraay, 2004). Additionally, the RPPG offers a direct interpretation based on an actual occurrence (change in poverty), while the PEGR value is interpreted based on a hypothetical situation (neutral growth rate). For this reasons, the magnitude of the pro-poorness of growth is measured throughout this work using the RPPG:

Identification-wise, the underlying logic of the PPGI is the one that provides clearer classification criteria corresponding to the relative definition of poverty. Moreover, it integrates the more profound analysis of growth and inequality changes to which the decomposition of poverty changes refers. In consequence, following this logic, growth spells are classified as pro-poor when the redistribution component of the decomposition of poverty changes is poverty reducing (negative).

1.5 Potential Drivers of Pro-Poor Growth

Although positive growth is vital for poverty reduction, there is a significant variation in the magnitude of the reduction produced by a given growth rate (Ravallion & Datt, 1999). Beyond the difficulties and limitations of identifying PPG, it is even more critical –and challenging– to identify the determinants of such characteristics. Identifying PPG drivers is essential for effective strategies and policies to enhance the poverty-reducing impact of the economic process (Kakwani & Pernia, 2000; Shepherd et al., 2016).

The two inherent factors that drive poverty reduction during a given period are income growth and change in inequality. As analyzed in subsection 2.3, it is possible to decompose the impact of a given growth rate on poverty in these two components. Nevertheless, the growth and redistribution effects vary significantly between countries and over time (Datt & Ravallion, 1992; Ravallion & Datt, 1999). Therefore, it is necessary to explore what other factors might influence the pro-poor (or anti-poor) bias of economic processes.

Employment growth

Employment is one of the main channels through which the economic benefits flow directly to the poor (Pasha & Palanivel, 2004) and, subsequently, the main scape route out of poverty (OECD, 2009). As argued by the OECD (2009), a surge in productive employment (sometimes referred to as job 'creation') and decent work increase the benefits going to the poor sectors. They also act as a self-reinforcing mechanism towards PPG. Hence, different employment levels could have a different impact on poverty reduction with a given growth rate.

Changes in employment/unemployment rates might hint at intrinsic characteristics about the sectoral composition of economic growth. When it happens to be concentrated in low-technology/labor-intensive sectors, where most of the formal jobs of the poor are, it is likely, *ceteris paribus*, to have a greater poverty reduction impact (Pasha & Palanivel, 2004). It has been argued that the expansion of employment due to a fast economic recovery (Lustig et al., 2013) and large investment in labour-intensive manufacturing (Shepherd et al., 2019) effectively reduce labor income inequality and contribute to faster poverty reduction. Consequently, employment dynamics might be directly related to both increases in the income of the poor and decreases in the inequality in labor income, which subsequently affects poverty reduction.

Even though a direct measure of job creation would be the ideal proxy for employment growth, it is not widely available nor consistently measured. A far more realistic approach is to consider the change in unemployment rates during the given period. Once more, as there is no specific measure of unemployment levels among the poor, the overall unemployment rate of the total work labor force is used instead.

Government size

Government size, typically measured as government consumption adjusted by the size of the economy (GDP), presents an interesting relationship with economic growth and inequality changes. Although several authors have found it to be negatively correlated to growth (Barro, 2000; Kraay, 2004), or did not find a direct relationship with the income of the bottom percentiles (Dollar & Kraay, 2002), there is evidence that suggests that it is positively correlated with pro-poor distributional changes (Kraay, 2004) and inequality reduction (Anderson et al., 2018). In this sense, the implicit logic is that countries with larger governments have better transfer mechanisms, which results in a decrease in inequality and a larger redistribution component (Kraay, 2004).

Moreover, several arguments have been made against the negative correlation between government spending and economic growth. As Forbes (2000) argues, higher government spending in public health and primary education, and better quality in public education in general, all tend to be negatively related to inequality and positively related to growth. In an in-depth analysis of the growth-inequality dynamics for Argentina, Brazil and Mexico, Lustig et al. (2013) found that progressive government transfers have a key equalizing effect through their impact on both labor and non-labor income. Finally, Anderson et al. (2018) carried out a meta-analysis on 19 studies about the relationship between government spending and poverty reduction. They found an overall negative relationship and not negligible in size, especially with poverty. Although they concluded that a publication bias potentially magnifies it and, after adding several controls, it was not overall statistically significant (Anderson et al., 2018).

Following previous studies (e.g., Barro, 2000; Dollar & Kraay, 2002; Kraay, 2004), the government size is proxied as the ratio of total government final consumption expenditure to GDP. This evidently contains administrative and bureaucratic costs and other government expenses not related to the before-mentioned transfer channels. A more accurate measurement would be to consider only the expenses related to welfare and social transfer programs (*e.g.*, health, education and social assistance) (Anderson et al., 2018). Nevertheless, such a standard instrument is not available for the whole sample.

Agricultural productivity

As mentioned before, not only overall economic performance is important for poverty reduction but also its pattern and sectoral composition. It has been argued that traditional sectors, such as agriculture, play a crucial role in determining the development pattern (Son & Kakwani, 2008). Considering that poverty is traditionally concentrated in rural areas, the evolution of poverty reduction could be closely related to agricultural progress (Pasha & Palanivel, 2004). In accordance with this, several authors have tried to evaluate it by studying the relationship between general agricultural production and poverty reduction

(Datt & Ravallion, 1992), agricultural productivity and growth and distributional changes (Dollar & Kraay, 2002; Kraay, 2004) and agricultural growth and income of the poorest quintiles (White & Anderson, 2001).

The dominant argument in the literature emphasizes the importance of the overall performance of the agricultural sector for poverty reduction (Dollar et al., 2016; Pasha & Palanivel, 2004). Nevertheless, there have been conflicting results when testing this relationship. As early as 1992, Datt and Ravallion argued that India's negative growth episodes due to bad agricultural performance were associated with modest improvement in inequality. Similarly, Kraay (2004) found that relative productivity in agriculture was uncorrelated with growth and 'surprisingly' higher relative productivity tended to be related to poverty-increasing changes. On the other hand, Pasha and Palanivel (2004), studying the experiences of Asian countries, determined that cases of rapid economic and agricultural surges were accompanied by sharp poverty decreases. Other studies have included either overall agricultural growth (White & Anderson, 2001), share (importance) of the agricultural sector in the economy (Son & Kakwani, 2008; Dollar et al., 2016) or measures of relative productivity (Dollar & Kraay, 2002) without finding any significant relationship.

In this case, like the approach of Dollar and Kraay (2002) and Kraay (2004), the relative productivity growth of agriculture is included. It is proxied as the value-added per worker in the sector. This measure aims to capture both changes in agricultural output and a broad indication of expected wage dynamics in the sector. It is favored instead of measures of the importance of the agricultural sector in the economy as the selection of a unique stationary value would imply an unavoidable arbitrariness in the choice, and the potential effects due to changes during the period would be lost.

Openness to trade

It has been broadly sustained that a general improvement in openness to trade, considered as an expansion in exports and imports, contributes to economic progress (Barro, 2000; Pasha & Palanivel, 2004). The main arguments pro liberalization are that higher trade openness enhances growth and raises incomes in the country (Dollar & Kraay, 2002). However, the impact on poverty reduction, once controlled for the overall growth rate, is still unclear (Pasha & Palanivel, 2004; White & Anderson, 2001).

Different studies have found diverse interactions between trade openness, growth and poverty reduction. Barro (2000) stated that trade openness, although enhances economic growth, is correlated with an increase in inequality. When exploring the factors determining the bottom quintile's share of income, Dollar and Kraay (2002; 2016) determined that trade openness does not affect the poor's share of income. Similarly, White and Andersson (2001) stated that an increase in trade openness benefits growth with no apparent effect on the poor's share of income.

Several approaches have been taken on how to measure trade openness, of which the ratio of imports plus exports to GDP is the most commonly used (see, for example, Barro, 2000; Dollar & Kraay, 2002; Kakwani & Son, 2008). In this case, the change in trade openness is considered as the change in the ratio of the sum of exports and imports of goods and services to the total value of GDP over the whole period. In accordance with White and Anderson (2001), the change is used instead of the initial or average value as it provides more information about the trade dynamics the country underwent in the given period.

2. Data & Methodology

As discussed in the previous chapter, although PPG in Latin America has been extensively studied, there still exists a significant gap in the academic literature regarding the identification of its determinants. This chapter presents the methodological framework used to answer the main research question: What factors have driven the pro-poorness bias of the growth experienced in Latin America from 1991 to 2019? First, the research framework, including the scope and limitations of the study, is defined in section 3.1, followed by a definition of variables and a description of data sources (section 3.2). Finally, the methodology is thoroughly described in section 3.3.

2.1 Research Framework

PPG in Latin America has been studied and measured under different conceptual approaches. Although there is an agreement in the existing literature on the presence of a common pattern of poverty and inequality reduction since the late 1990s, there has not been a concrete response to what is driving this PPG in the region. This remarkable heterogeneity of development patterns and poverty-inequality reduction patterns presents a unique opportunity to identify the determinants of growth's pro-poorness and its magnitude (Gasparini et al., 2007). This work, therefore, aims to help fill the literature gap related to the factors that determine PPG and its dynamics.

The study uses a panel data set including 16 Latin American countries, for which enough income survey data were available, in an average period of 29 years (1991 to 2019). Growth is analyzed in terms of 4 year periods (or growth spells), rather than annual changes, to capture systematic dynamics instead of yearly variations. Additionally, lower frequency observations help to minimize potential measurement errors of data sources (Barro, 2000; Lundberg & Squire, 2003). The panel data set results from household survey microdata processing carried out by the World Bank's PovcalNet database. It should be noted that household survey methodologies are not uniform across the included countries; thus, all comparisons made based on this data will inevitably contain a degree of variability. The selection of countries and years was made to minimize any potential bias, although a trade-off between accuracy and coverage is unavoidable. After selection, all data underwent the same consistent processing method to avoid further variability.

The scope of the present work is to analyze PPG restricted to the income dimension of poverty. Consumption is often regarded as a better proxy for well-being, but almost all country-level surveys in Latin America are based on income questionaries, and only a few include consumption/expenditure questions (Gasparini et al., 2007). All income and survey information contained in the panel is nationally representative, except for Argentina[18]. Although these surveys are known to have a consistent absence of the extremely wealthy (Gasparini et al., 2014), this does not generate a problem for the current analysis since it will affect (relatively) all countries and periods. Additionally, the pro-poor measures used focus only on the poor sector, thus should not be affected by this absence.

[18] EPH survey in Argentine covers only urban population which still represent more than 85% of the total population (CEDLAS & World Bank, 2021)

Although national definitions of poverty incorporate inherent society features that might depict a better image of the poor, they also add a considerable disparity between countries (Gasparini et al., 2007). For comparison purposes, the absolute international poverty line of $1.90 (2011 PPP) is used as the standard poverty definition for all countries in all periods. This successfully eliminates the variability between countries but entails an unavoidable arbitrariness in defining the poor (Grosse et al., 2008).

2.2 Data

The study covers the period from 1989 to 2019 for 15 Latin American Countries and 1 Caribbean country. The included countries are urban Argentina (1991–2019), Bolivia (1992–2019), Brazil (1990–2019), Chile (1990–2017), Colombia (1992–1996), Costa Rica (1991–2019), Dominican Republic (1992–2019), Ecuador (1994–2019), El Salvador (1991–2019), Honduras (1991–2019), Mexico (1989–2018), Nicaragua (1995–2015), Panama (1991–2019), Paraguay (1990–2019), Peru (1994–2019) and Uruguay (1992–2019). Together they represent approximately 96% of the total population of Latin American and the Caribbean[19]. The data set consists of observations every four years, with minimal discrepancies (in years and time intervals) between countries due to the date and frequency in which the surveys are conducted. Therefore, nearly every country has eight observations[20] each four years, seven time-periods[21], for a total of 109 observations. Period adaptations, although not ideal, should not represent a major impediment for the comparison analysis. The income data, from which the main pro-poor measures are estimated, and the five explanatory variables are described below.

Income and pro-poor variables

All the income and distribution data used in this study was taken from the latest available data from the World Bank's PovcalNet database. This database is build directly from the national household surveys and includes income distribution and mean monthly income information reported in 2011 PPP$. Following PovcalNet's guidance, only survey-year estimates are taken into account (World Bank Group, 2018). Consequently, observation years and periods have been adapted, to the nearest available survey-year, for those countries where a survey was not conducted that specific year.

PovcalNet's national aggregated distributional data (by percentile) on income and mean monthly income (2011 PPP$) were used for all countries and all years. The only two exceptions are Argentina, for which only urban data is available, and Peru, in 1994, in which consumption data is used to avoid missing the first eight years of the study period of the country. All other income and poverty-related data (including F-G-T poverty measures and pro-poor measures) used in the study were estimated by first disaggregating the percentile distributional data into a household level and then proceeding with the respective calculations. All data processing and analysis were carried out in STATA Statistical Software 14 (StataCorp, 2015), and the disaggregation procedures and pro-poor estimations were done using the Distributive Analysis Stata Package [DASP] developed by Araar and Duclos (2007).

[19] Estimation base on the most recent population data from the WDI (World Bank, 2021).
[20] With the exception of Nicaragua (5 observations), Peru (6 obs.) and Ecuador (6 obs.).
[21] 5 for Nicaragua and 6 for Peru and Ecuador.

Regarding the pro-poor measures, the rate of pro-poor growth (RPPG), proposed by Ravallion and Chen (2003) and the decomposition of poverty changes into growth G_θ and redistribution D_θ components, proposed by Kakwani (2000), were estimated using the DASP program. The mean growth, Gini coefficient[22], RPPG, and D_θ and G_θ components for the three F-G-T poverty measures, poverty headcount (P_0), gap (P_1) and squared gap (P_2), are estimated for each country in each period.

Explanatory variables

In accordance with the literary review, a total of six explanatory variables are evaluated as potential determinants of PPG. They include changes in inequality, income growth, changes in the unemployment rate, government size, agriculture productivity growth and changes in trade openness. Inequality changes (measured as the change in the Gini coefficient) and mean income growth are the total change for the whole period and are directly estimated from the income distribution data; therefore, they coincide with the WorldBank's reported estimates (World Bank Group, 2018). The data for the other four variables is extracted from the World Development Indicators [WDI] of the World Bank (2021) and the International Labour Organization [ILO] modeled estimates (2021).

It has been argued that using the same survey data for the dependent and explanatory variables could pass any measurement errors from the original data source (Dollar & Kraay, 2002; Ravallion, 2004). This could potentially lead to an overestimation of the correlation due to an endogeneity problem. Additionally, as mentioned above, the expected absence of the wealthiest in survey data also implies an unavoidable underestimation of inequality (Gasparini et al., 2014). However, there is no reason to think that this varies substantially between countries or over time; thus, it would not produce a significant bias on the results[23].

While an instrumental approach has been used previously to correct for biases due to measurement errors and potential endogeneity, the available instruments' adequacy remains a major concern (Forbes, 2000). For example, using national accounting data as a proxy for growth incorporates a further measurement error (from national accounts). Additionally, some countries show significant differences between the two, which generates an inconsistent estimate (Ravallion & Chen, 1997; Ravallion, 2004). In this study, a methodological approach is proposed to address potential endogeneity and measurement bias (see section 3.3), which is expected to provide consistent estimates even with measurement errors in both variables (Dollar & Kraay, 2002; Ravallion & Chen, 1997).

In the absence of a more accurate (widely available and consistently measured) indicator, the change in the unemployment rate is considered as a proxy for the employment dynamic. The data used comes from the International Labor Organization estimates for "Total unemployment rate (% of the total labor force)" (2021), and the changes are calculated as the absolute change in the rates for the whole period, in harmony with the dependent variable. The database of modeled ILO estimate starts from 1991, thus for countries with initial observation dates prior to that year (Mexico 1989, Brazil, Colombia and Paraguay 1990), the value from 1991 is used instead of the initial value.

[22] Proposed by Gini in 1912 is the most widely spread measurement of income/wealth inequality, written in terms of the Lorenz function as $Gi = 1 - 2\int_0^1 L(p)d(p)$ where *Gi* goes from 1 to 0 (perfect equality) (Gasparini et al., 2014).

[23] Specially considering that the change in inequality levels are used as explanatory variable instead of the absolute levels.

The "General government final consumption expenditure (% of GDP)" from the WDI (World Bank, 2021) is considered as a proxy for government size and the value at the initial year of each period is used. This includes all government expenditure for purchases of goods and services and compensation for employees, which provides a somewhat gross estimate of the transfer mechanisms that the variable intends to capture. However, it is regarded as the best available option for such a measure. The only cases of missing data are for Honduras in the years 1991, 1995 and 1999. The data is reported missing for the first two years and for 1999 it is replaced with the value of the following year.

Agricultural productivity growth is measured as the percentual change in the "Agriculture, value-added per worker (constant 2010 US$)" of the WDI (World Bank, 2021). It corresponds to the added value of net outputs minus intermediate inputs divided by the ILO estimate of the corresponding employment in the sector. The data for the estimations starts from 1991, thus for countries with initial observation dates before that year (Mexico 1989, Brazil, Colombia and Paraguay 1990), the value of 1991 is used instead of the initial value.

Changes in trade openness are proxied as changes in the "Trade (% GDP)" indicator of the WDI (World Bank, 2021) from the initial year to the final year of each period. It measures the variation in the total value of exports plus imports of goods and services as a share (%) of the GDP during the growth spell. The dataset has no missing values. Table 1 summarizes each regressor variable's source and short description, while the complete descriptive statistic of all variables can be found in Appendix A.

Table 1.
List of explanatory variables

Symbol	Description	Source
Yg	Growth rate in mean income (%).	Income data*
INQc	Change in Gini coefficient.	Income data*
UNPc	Change in unemployment rate (% total labor force).	ILO (2021)
GSZ	General government consumption expenditure (% of GDP).	WDI (2021)
$AGRP_g$	Growth (%) in agricultural productivity (value added per worker).	WDI (2021)
TRDc	Change in the rate (%) of the value of export plus imports to total GDP.	WDI (2021)

*Calculated from the data of World Bank's PovcalNet database (2021).

2.3 Econometric Framework

To analyze the PPG dynamics, the income and distribution data are processed, and all general measures (income growth, inequality changes and poverty levels for all FGT metrics and Watts index) are estimated for each country and subperiod. Then the rate of pro-poor growth (RPPG) of Ravallion and Chen (2003) is calculated, and the changes in all poverty measures are decomposed according to the method proposed by Kakwani (2000) for each subperiod.

The identification of pro-poor growth spells is done using the underlying condition of the PGI, proposed by Kakwani and Pernia (2000). Growth spells are classified as pro-poor (or anti-poor) using, as a necessary condition, that the redistributional component of poverty changes (D_{01}) is negative (Kakwani and Pernia, 2000). The three F-G-T poverty measures for each given period are considered, meaning that growth spells are classified as pro-poor if and only if $D_{\theta(H0)} > 0$ and $D_{\theta(H1)} > 0$ and $D_{\theta(H2)} > 0$; and anti-poor other wise.

The evaluation of potential drivers is done under a regression approach using the RPPG as a proxy for the magnitude of the pro-poorness of growth. The value is the estimated RPPG for the total period. Assuming a relationship between RPPG and income growth, changes in inequality and a set of x unknown factors in the form

$$RPPG = F(Growth, \Delta Inequality, X) \qquad [14]$$

Now further including the considered determinants of pro-poor growth in the following model specification under panel regression settings:

$$RPPG_{it} = \beta_0 + \beta_1\, Yg_{it} + \beta_2\, INQc_{it} + \beta_3\, UNPc_{it} + \beta_4\, GSZ_{it} + \beta_5\, AGRg_{it} + \beta_6\, TRDc_{it} + \varepsilon_{it} \qquad [15]$$

where RPPG is the estimated rate of pro-poor growth, Y_g is the growth rate of mean income, INQ_c is the change in the Gini coefficient, UNP_c is the change in the unemployment rate, GSZ indicates government size, AGR indicates the agricultural productivity growth, TRD_c is the change in trade openness, β_0 is constant, ε_{it} represents the error term, and i and t are individual (country) and time (period) indicators.

As a first step, the study applies a pooled Ordinary Least Squares [OLS] regression on equation [15], ignoring cross-country time-invariant characteristics. In this situation, nevertheless, a simple OLS estimation is likely to return inconsistent estimates of the parameters due to unobserved country-specific effects and a failure in meeting strict exogeneity assumptions (Dollar & Kraay, 2002).

To take these country-specific effects into consideration, a second step incorporates the time-invariant characteristics of countries by applying a panel fixed effect regression to the following model specification:

$$RPPG_{it} = \beta_{0i} + \beta_1\, Yg_{it} + \beta_2\, INQc_{it} + \beta_3\, UNPc_{it} + \beta_4\, GSZ_{it} + \beta_5\, AGR_{it} + \beta_6\, TRDc_{it} + \varepsilon_{it} \qquad [16]$$

where β_{0i} is a country-specific intercept for individual i, which captures the differences between countries. The OLS regression is then applied expressing each variable as deviation from their respective within-group mean to obtain the respective coefficient estimates. The adequacy of fixed effect specification, compared to the pooled OLS approach, is verified with the respective F test[24].

[24] In this case the F-test evaluates if all individual intercepts are equal to 0. If they are not, the Ho is rejected and it implies that the individual differences are significant and a fixed effect (or random effect) model fits the data better (Gujarati & Porter, 2009).

As mentioned in subsection 3.2, the inclusion of income growth and inequality changes from the same survey data gives rise to problems with some of the assumptions for the models in steps 1 and 2. This means that, even under the relatively safe assumptions, that the measurement error from the same source will not lead to inconsistent coefficient estimates (see Dollar & Kraay, 2002; Ravallion & Chen, 1997), there are still serious concerns about potential endogeneity. Suppose income growth or inequality changes and the dependent variable are simultaneously determined. In that case, it would imply that models in equations [15] and [16] produce inconsistent estimations due to endogeneity of one or more explanatory variables (Arellano & Bond, 1991).

The third step, thus, consists of the application of a system panel Generalize Method of Moments [GMM] to control for such potential endogeneity in the following form:

$$\begin{aligned} RPPG_{it} = \beta_0 + \beta_1 RPPG_{\,i\,(t-1)} + \beta_2\, Yg_{it} + \beta_3\, INQc_{it} + \beta_4\, UNPc_{it} + \beta_5\; GSZ_{it} \\ + \beta_6\, AGR_{it} + \beta_7\, TRDc_{it} + \varepsilon_{it} \end{aligned} \qquad [17]$$

The one-step difference GMM estimator, first proposed by Arellano and Bond (1991), includes lagged dependent variables as internal instruments while it uses a differencing operator on explanatory variables to eliminate country-specific differences. It is designed for panel data with T total time periods and N total individuals, where N > T and T ≥ 3. It uses all lags available of the dependent variable, as well as the differential equation of the rest of the variables as instruments to control for potential endogeneity and eliminate the unobserved country-specific error (Arellano & Bond, 1991; Zsohar, 2012).

This procedure is very similar to the methodology applied by Zaman and Shamsuddin (2018) to study the linear and non-linear relationship between growth and inequality in panel data. Analogously, Dollar and Kraay (2002) used the GMM estimator to control for measurement errors, omitted variables and endogeneity in similar panel data. The Arellano and Bond estimator is also used to control for the potential bias due to simultaneity in the determination of growth and inequality by Forbes (2000) when including both initial income and inequality as regressors. Lopez (2004b) also applied it to analyze the trade-off dynamics between inequality changes and growth.

The respective diagnostic tests are run for Arellano-Bond model specification. The Sargan-Hansen J-statistic test the validity of instruments while the AR(1) and AR(2) tests serve to detect serial correlation in the difference estimator (Arellano & Bond, 1991; Zaman & Shamsuddin, 2018). Complementary, robust standard errors are used to control for potential heteroskedasticity in the error term.

3. Results and Discussion

3.1 Income and Poverty: Descriptive Statistics

During the period of study (1989–2019), the region was characterized by moderate income growth of 3.03% per year (unweighted annualized average) and an 11% decrease in the average Gini coefficient (from 0.51 to 0.45). Furthermore, as seen in the detailed country summary (Table 2), poverty was reduced in all but two countries when considering the Watts index. More importantly, the few countries for which there was no reduction in poverty already had considerably low initial poverty levels (Argentina, Paraguay and Uruguay).

The above overall patterns do not imply that there were no substantial differences between countries. For example, while Panama had a period average annual income growth ($\bar{g}^a$) of 5.87 % and achieved a reduction of 13 points in the Gini index, Mexico experienced a 0.39% $\bar{g}^a$ and a Gini index decreased by 9 points. As a result, Panama experienced a reduction in Watts index of 0.49, with overall poverty incidence going from 22% (P_0) in 1991 to 1% in 2019, while Mexico's Watts index (although considerably lower) was reduced by 0.02 and poverty incidence went from 8% (1989) to 2% (2018).

Table 2.
Poverty and Income, levels and changes per country

Country	Period	Income		Gini	Poverty	
		Total growth	Annualized growth[a]	Gini Δ	Watts Δ	P_0 Δ
Argentina	1991–2019	14 %	0.51 %	- 0.04	- 0.01	0.07%
Bolivia	1992–2019	110 %	4.06 %	- 0.07	- 0.10	- 11.74%
Brazil	1990–2019	127 %	4.37 %	- 0.07	- 0.13	- 16.90%
Chile	1990–2017	114 %	4.23 %	- 0.13	- 0.05	- 7.65%
Colombia	1992–2019	50 %	1.86 %	- 0.03	- 0.18	- 8.69%
Costa Rica	1991–2019	172 %	6.16 %	0.02	- 0.15	-10.95%
Dominican Rep.	1992–2019	50 %	1.86 %	- 0.09	- 0.02	- 4.82%
Ecuador	1994–2019	85 %	3.42 %	- 0.08	- 0.13	-13.70%
El Salvador	1991–2019	68 %	2.43 %	- 0.15	- 0.33	- 19.80%
Honduras	1991–2019	85 %	3.05 %	- 0.04	- 0.14	- 19.29%
Mexico	1989–2018	11 %	0.39 %	- 0.09	- 0.02	- 5.27%
Nicaragua	1993–2014	83 %	3.97 %	- 0.04	- 0.09	- 19.09%
Panama	1991–2019	164 %	5.87 %	- 0.08	- 0.49	- 20.76%
Paraguay	1990–2019	23%	0.79 %	0.05	0.00	-0.21%
Peru	1994–2019	113%	4.53 %	-0.03	- 0.05	- 12.58%
Uruguay	1992–2019	26 %	0.95 %	- 0.02	0.00	- 0.49%

Source: Own calculations based on $1.9 per day (2011 PPP$) poverty line.
[a] Calculated by dividing the total income growth of the period by the number of years. It does not correspond to average annual income growth.
Δ Total change is equal to the value of the last year minus the value of the first year.

Although suggestively consistent, this pattern does not imply that poverty and inequality were unambiguously reduced throughout the entire period. It is important to remark that gross average period statistics tend to lose important information of the real dynamics in place. The further analysis takes a look at more specific pro-poor estimates to describe and analyze such dynamics.

3.2 Pro-Poor Growth: RPPG and Poverty Changes Decomposition

Similar to the previous examination, a closer look at pro-poor average-period statistics of the region (summarized in Table 3) indicates a broad pattern of positive moderate growth accompanied by a substantial decrease in inequality and poverty reduction. The unweighted annual average rate of pro-poor growth (RPPG) for the region was 2.89% for the whole period. This implies that the poor experienced a 'mean growth rate' of 2.89% per year in their income – for the whole region and period–, compared to the overall 3.03% growth in the mean income. Notably, there is a sizable variation in the RPPG, with values ranging from 0.42% for Paraguay to 7.92% for Panama.

Table 3.
Rate of pro-poor growth per country

Country	Period	$\bar{g}$[a]	RPPG	
			Total	Annual
Argentina	1991–2019	0.51 %	52 %	1.87 %
Bolivia	1992–2019	4.06 %	67 %	2.47 %
Brazil	1990–2019	4.37 %	62 %	2.14 %
Chile	1990–2017	4.23 %	60 %	2.23 %
Colombia	1992–2019	1.86 %	159 %	5.89 %
Costa Rica	1991–2019	6.16 %	127 %	4.53 %
Dominican Republic	1992–2019	1.86 %	31 %	1.16 %
Ecuador	1994–2019	3.42 %	78 %	3.12 %
El Salvador	1991–2019	2.43 %	159 %	5.67 %
Honduras	1991–2019	3.05 %	95 %	3.38 %
Mexico	1989–2018	0.39 %	36 %	1.23 %
Nicaragua	1993–2014	3.97 %	40 %	1.89 %
Panama	1991–2019	5.87 %	222 %	7.92 %
Paraguay	1990–2019	0.79 %	12 %	0.42 %
Peru	1994–2019	4.53 %	34 %	1.34 %
Uruguay	1992–2019	0.95 %	25 %	0.91 %

Note. RPPG is the rate of pro-poor growth.
[a] Annualized mean income growth for reference (same as in Table 2).
Source: Own calculations based on $1.9 per day (2011 PPP$) poverty line.

As mentioned above, these general patterns hide substantial differences between countries and within countries over time. For some countries, income growth during the period was particularly high among the poor, such as Mexico (1.23 % annual RPPG compared to 0.39% $\bar{g}^{a}$) and El Salvador (5.67% and 2.43%, respectively). In others, poor's income lagged significantly behind mean growth, for instance, Brazil (2.14% annual RPPG compared to 4.37% $\bar{g}^{a}$) and Peru (1.34% and 4.53%, respectively).

Equivalently, looking at the growth pattern of a given country divided into shorter periods leads to even more significant differences. For example, in the Dominican Republic case, from 1992–1996, although there was a positive mean income growth (11% over the whole period), the poor experience a reduction in their income (- 27% RPPG). Similarly, between 1996–2000, the poor's income, although growing, lagged significantly behind mean income (10% RPPG compared to 18% $\bar{g}$). Nevertheless, since the 2003–2007 period, the poor have been experiencing a higher or equal rise in their income (25% RPPG to 3% $\bar{g}$) which continued for all subsequent periods (17, 15 and 21% RPPG compared to 4, 15 and 13% $\bar{g}$). The complete estimates for all sub-periods can be found in Appendix B.

Analysis of the sub-periods PPG using the RPPG results of exceptional help to identify how different development patterns affect the poor. Iniguez-Montiel (2014), for example, described a drastic change in Mexico's development pattern from 1992–2008 using the growth rates of the poorest percentiles. They found that, during the first period from 1992–2000, growth was - 0.2% $\bar{g}^{a}$ while the income of the bottom 20 decreased by -1.3% per year. This is confirmed by the sub-period analysis in Appendix B. From 1989 to 1994, Mexico experienced a general fall in incomes (- 1.7% $\bar{g}^{a}$ and - 0.2% RPPG[a]), which worsened and particularly affected the poor from 1994 to 1998 (- 5.2% $\bar{g}^{a}$ and - 9.8% RPPG[a]). After this period, however, the pattern changed, and for the 1998–2002 and 2002–2006 periods, Mexico's mean income grew considerably (5.2% and 3.6% $\bar{g}^{a}$, respectively) and the poor were particularly benefited (6.1% and 4.6% RPPG[a]). Almost the exact change in pattern as the one described by Iniguez-Montiel (2014) for 1998 to 2008, in which the estimated $\bar{g}^{a}$ for the period was 1.6%, while the income of the bottom 20 percent grew by 3.7%.

A more detailed analysis of poverty patterns is carried out by decomposing poverty changes into growth (G_{θ}) and redistribution effect (D_{θ}). As mentioned in section 3.3 –and consistent with a relative definition of PPG–, all periods were classified as pro-poor (antipoor) if the redistribution effect of the poverty change decomposition was poverty reducing (increasing) for all considered measures. As shown in Table 4, the growth pattern during the whole period can be classified as pro-poor for all countries except for Argentina and Paraguay. This means that the overall changes in inequality over the entire period had a poverty-reducing effect on all poverty measures for all countries except these two. However, it must be noted that for these two countries, poverty remained virtually unchanged (Table 4)[25].

The complete decomposition for all countries and all sub-periods for poverty headcount (P_0), gap (P_1) and squared gap (P_2) measures and subsequent classification of sub-periods as pro-poor or anti-poor can be found in Appendix C.

[25] In the case of Uruguay and Peru, although not negative for P_2, the D_{θ} is virtually zero while there is still a poverty reduction so it can still be considered as pro-poor.

Table 4.
Decomposition of changes in poverty measures per country (1989-2019)

Country	Poverty headcount			Poverty gap			Poverty squared gap		
	Δ	$G_{\theta(P_0)}$	$D_{\theta(P_0)}$	Δ	$G_{\theta(P_1)}$	$D_{\theta(P_1)}$	Δ	$G_{\theta(P_2)}$	$D_{\theta(P_2)}$
Argentina	0.00	- 0.00	0.01	0.00	- 0.00	- 0.00	0.00	- 0.00	- 0.00
Bolivia	- 0.12	- 0.10	- 0.02	- 0.04	- 0.03	- 0.01	- 0.02	- 0.02	- 0.01
Brazil	- 0.17	- 0.13	- 0.04	- 0.07	- 0.05	- 0.02	- 0.04	- 0.03	- 0.01
Chile	- 0.08	- 0.04	- 0.04	- 0.03	- 0.01	- 0.02	- 0.02	- 0.01	- 0.01
Colombia	- 0.09	- 0.06	- 0.03	- 0.08	- 0.01	- 0.07	- 0.14	0.03	- 0.17
Costa Rica	- 0.11	- 0.08	- 0.03	- 0.05	- 0.03	- 0.03	- 0.04	- 0.01	- 0.03
Dominican Republic	- 0.05	- 0.02	- 0.02	- 0.01	- 0.01	- 0.01	- 0.01	- 0.00	- 0.00
Ecuador	- 0.14	- 0.09	- 0.05	- 0.07	- 0.03	- 0.03	- 0.04	- 0.02	- 0.03
El Salvador	- 0.20	- 0.07	- 0.13	- 0.10	- 0.03	- 0.08	- 0.07	- 0.01	- 0.06
Honduras	- 0.19	- 0.19	- 0.00	- 0.09	- 0.09	0.00	- 0.05	- 0.05	0.00
Mexico	- 0.05	- 0.01	- 0.04	- 0.02	- 0.00	- 0.01	- 0.01	- 0.00	- 0.01
Nicaragua	- 0.19	- 0.15	- 0.05	- 0.06	- 0.05	- 0.02	- 0.03	- 0.02	- 0.01
Panama	- 0.21	- 0.10	- 0.11	- 0.14	- 0.04	- 0.09	- 0.11	- 0.03	- 0.08
Paraguay	0.00	- 0.01	0.01	0.00	- 0.00	0.00	0.00	- 0.00	0.00
Peru	- 0.13	- 0.11	- 0.01	- 0.04	- 0.04	- 0.00	- 0.02	- 0.02	0.00
Uruguay	0.00	- 0.00	- 0.00	0.00	0.00	- 0.00	0.00	0.00	0.00

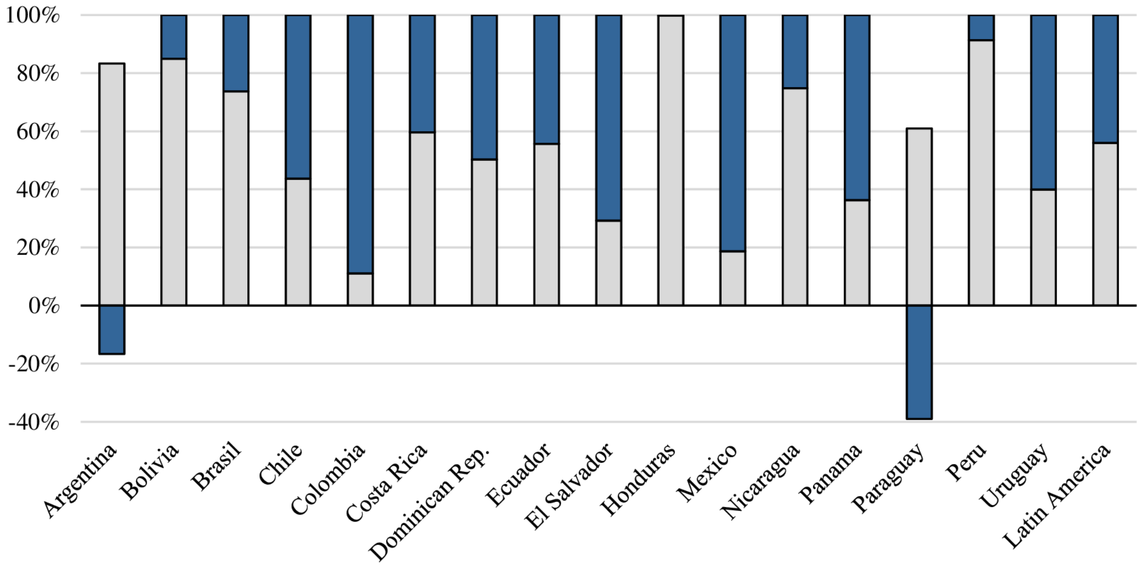
Note. Δ Total change in poverty level is the value of the last year minus the value of the first year. G_θ and D_θ are growth component and redistribution component of poverty changes, respectively. P_0, P_1 and P_2 are poverty headcount, poverty gap and poverty squared gap, respectively.
Source: own calculations using Kakwani (2000) decomposition of poverty changes based on \$1.9 per day (2011 PPP\$) poverty line.

This requirement, although somewhat strict since it considers all three F-G-T measures, is fulfilled by most growth spells considered in the study. Of the 108 growth spells, 67 (62%) are classified as pro-poor. Among the remaining 38%, 14 (12%) have a negative D_θ in at least one of the measures. While none of the countries were unambiguously pro-poor, for all sub-periods and all poverty measures, Panama and Chile were pro-poor in all sub-periods but one, and half the sample countries had an anti-poor growth only in two or less sub-periods.

Moreover, the classification accuracy is, to a certain degree, confirmed by what has been described in previous inequality and poverty studies in the region. During the first two sub-periods (1991–1999), only 26% (5) of the countries experienced a PPG. As described by Gasparini et al., this decade was rather disappointing as "almost none of the LAC countries experiences strong sustainable growth along with significant equalizing distributional changes" (2007, p. 217). After this, from 1999 to 2015, 75% (10) of the countries experienced a pro-poor growth pattern. This coincides with the sharp declined in inequality and poverty described by Lustig et al. (2013) for a similar sample of Latin American countries during the same approximate period.

It is important to remark that the redistribution effects were of substantial importance in the magnitude of poverty reduction. In 46% of the cases displayed in Table 4 D_θ were the dominant component in poverty changes and in another 4% they were equally important as G_θ. By giving higher importance to the depth of poverty, when considering P_2 for example, D_θ becomes the dominating factor (56%). Contrary to the conclusion proposed by Dollar et al. (2016) that G_θ is the indisputable determinant of income of the poor, this implies that changes in inequality have an equally important effect on poverty changes. Figure 1 shows the overall averages of the composition of changes in poverty for all measures P_0, P_1 and P_2, per country and the region average for the whole period.

Figure 1.
Importance of Growth and Redistribution components of poverty changes per country (1989–2019)



Source: elaborated based on data from Table 4.

As shown in the Latin American aggregate of Figure 1, D_θ accounted, on average, for 44% of the overall decline in poverty in the region for all measures. This is consistent with the results of Lustig et al. (2013), who found, using the Datt and Ravallion decomposition, that the D_θ accounted, on average, for 50% of poverty reduction for 11 Latin American countries from 1999 to 2009. Specifically, for the three sub-periods corresponding to that particular time (1999–2011), the Kakwani decomposition shows that reduction in inequality (D_θ) accounted for more than 60% of the reduction of poverty in all indicators (60% for P_0, 62% for P_1 and 62% for P_2)[26].

Considering the decomposition for all growth spells and all measures, the growth and distribution components were practically equally important. In fact, in 49% of the cases, the D_θ was larger than G_θ. A figure containing the relative importance for each poverty measure for all countries can be found in Appendix D.

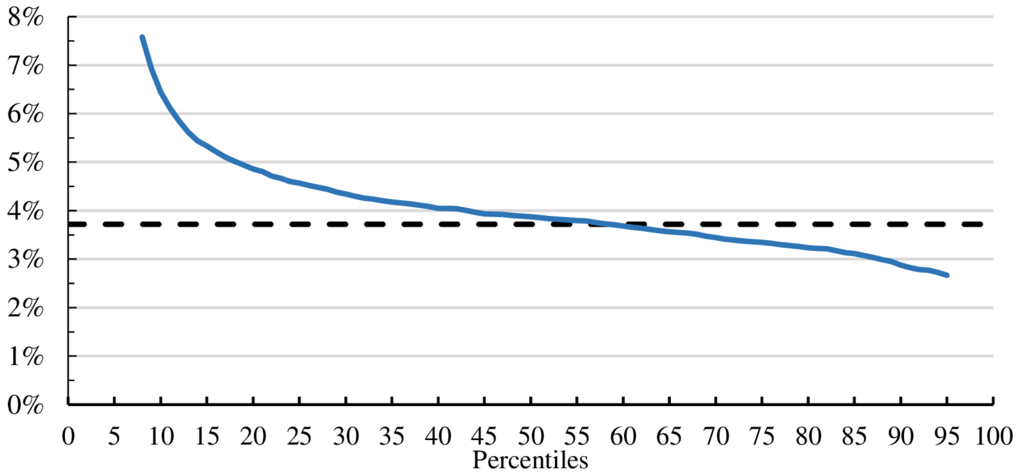
[26] Calculations based on data from Appendix C.

3.3 Pro-Poor Growth: Growth Incidence Curves

The Growth Incidence Curves (GIC) present a simple picture of the overall changes in income throughout the distribution. They are handy to summarize the dynamics in place to which the RPPG refers. In section 4.2, for instance, it is mentioned that the poor's income, on average, rose at 2.89% per year (RPPG) compared to the 3.03% $\bar{g}^{a}$. This might not sound as the benefits were flowing towards the poor; nonetheless, we can see what kind of dynamic was actually taking place when looking at the GIC of the period (Figure 2.).

Figure 2.

Growth Incidence Curve (GIC) on household per capita income from 1989 to 2019 for LAC



Note. Mean per capita income growth (dotted) of the period for reference.
Source: author's calculations of unweighted annualized average growth of the 16 countries in the sample[27].

As we can observe in Figure 2, although the unweighted average RPPG was far from impressive (when compared to $\bar{g}^{a}$), the GIC shows a clearly progressive dynamic. In fact, from 1989 to 2019, while the income of the top 20% increased at (approx.) 2.99% per year, the income of the bottom 20% increased at (approx.) 5.72%[28]. Not only the poor benefited more, but the curve for all percentiles below any of the typical 'poor percentiles' (10, 20 or 40) is substantially above the mean growth. The interpretation of this curve is that, although not decidedly pro-poor, growth dynamics benefited more the lowest percentiles of the distributions during this period.

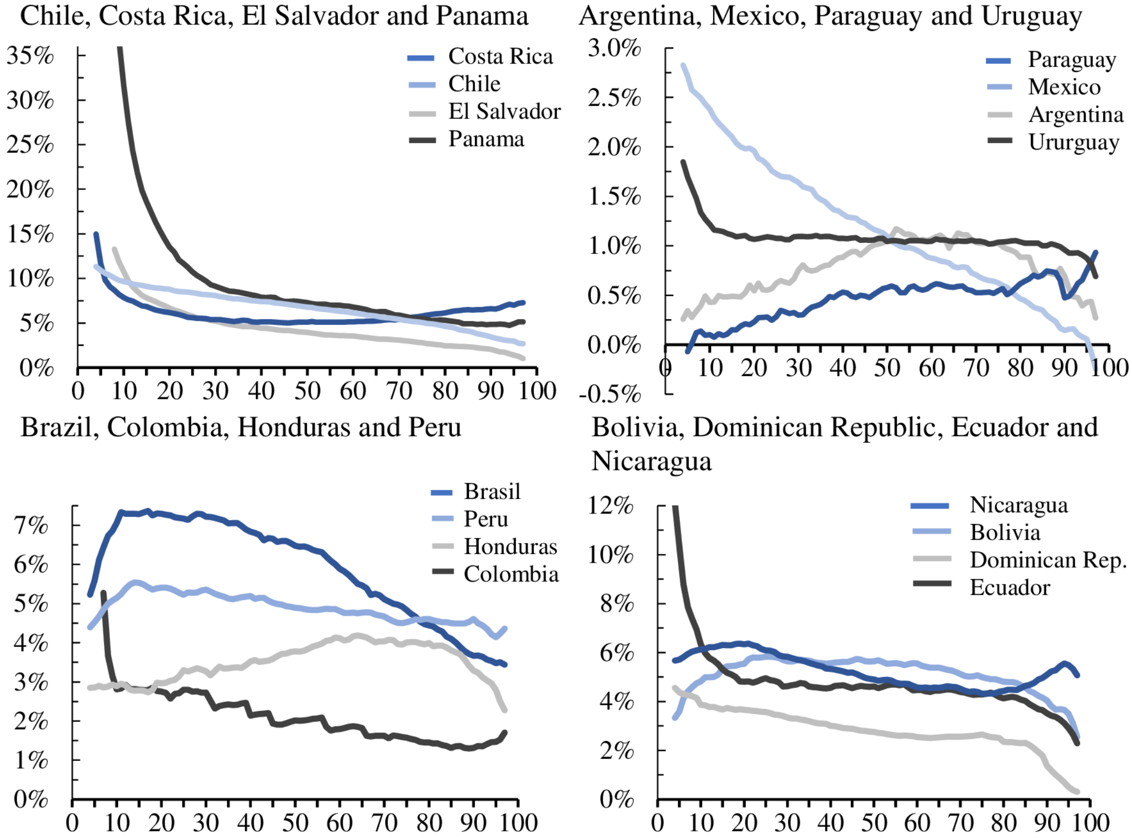
It must be noted that few conclusions should be drawn directly and solely from this graph since it is a gross estimation of the region's dynamics. As discussed previously, averages tend to hide different stories and, even more importantly, unweighted averages, although useful for general explanations, do not provide accurate information of the dynamics in place. The countries' GICs for the entire period are displayed in Figure 3.

[27] Must be noted that for this and all further GICs graphics the 5 to 3 upper and bottom percentiles and other extreme values neighboring these cuts are left out as GICs tend to be extremely volatiles in the limits of the distribution (see CEDLAS, 2014; Gasparini et al., 2007).

[28] This estimates are clearly affected by both bias and correcting procedure explained in the previous footnote.

Figure 3.

Growth Incidence Curves (GIC) on household per capita income per country

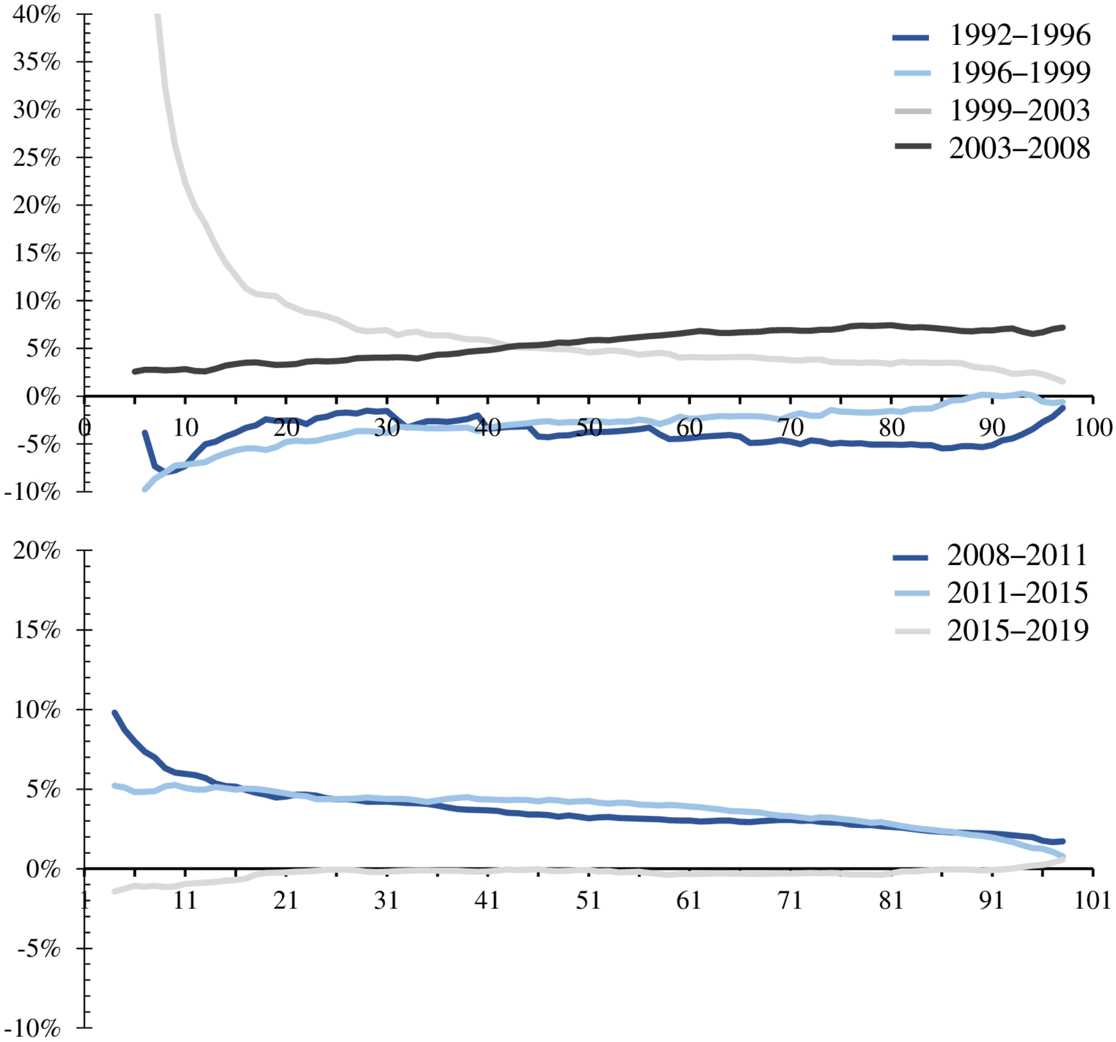


Note. Growth is the total per capita income growth over the whole period considered for each country (see Table 3 for details on periods per country).
Source: elaborated based on own estimates from the disaggregation of income and distribution data.

Although the region's average pattern can be described as pro-poor, this does not imply that growth was equally pro-poor in all countries nor that it was pro-poor at all. Panama's GIC, for example, is not only above all other curves, but the growth in the poorest percentiles is six times higher than in the richest percentiles. Similarly, Mexico presents an almost perfectly progressive GIC, in which growth is monotonically decreasing in income (see section 2.4). On the opposite side, both Argentina and Paraguay present a pro-rich behaviour, in which growth appears to be low or even negative (Paraguay) for the poorest of the poor and increases as it moves towards the richest percentiles. Nicaragua and Uruguay present what could be described, with some variations, as an overall neutral growth with peaks on both extremes of the distribution.

The GICs displayed in Figure 3 are extremely useful for describing the long-term processes graphically, and it contains important information about overall patterns. However, sometimes the changes over time, often observed in middle term analysis, are even more valuable to study how patterns evolve within the same country. In Figure 4 we can observe the evolution of growth patterns for Colombia throughout all sub-periods.

Figure 4.
Growth Incidence Curves (GIC) on household per capita income for Colombia per sub-period



Note. Growth is the total per capita income growth over each period.
Source: elaborated based on own estimates from the disaggregation of income and distribution data.

Although Colombia's overall growth pattern (1992–2019), described by the GIC in Figure 3, has a pronounced pro-poor shape, it does not mean that it was pro-poor in all sub-periods. In fact, the first eight years (1992–1996 and 1996–1999) were particularly bad for the poor. While mean income suffered a general decrease of - 2.25% and - 1.33% per year, respectively, the income of the bottom 20% decreased approximately - 4.9 and - 6.4% per year.

This pattern, however, suffered a dramatic change in the subsequent sub-periods. From 1999–2003 the poor were benefited not only of a general improvement of growth (2.75% $\bar{g}^a$) but also from a high concentration of income growth in the bottom 20%. The RPPG shifted from – 13.6% to 38.5% per year. Afterward, from 2003–2008, the income of the poor almost stagnated (virtually 0% RPPG for the overall period), even though mean income kept growing.

For the period from 2008–2011, Colombia's income growth was positive and pro-poor; the GIC almost perfectly decreases as it moves towards the highest (richest) percentiles. While in the 2011–2015 sub-period, growth continued to be, in less degree, pro-poor but more moderate (RPPG fell from 12 to 3.25% per year). Finally, from 2015–2019, although income growth was negative (- 2.5% per year) for the first time since the second sub-period, it did not particularly affect the poor. In fact, it was almost perfectly neutrally distributed, with RPPG barely negative at - 0.075% per year. The GICs for all countries in each sub-period can be found in Appendix E.

3.4 Drivers of Pro-Poor Growth

The potential drivers of PPG were evaluated, as described in section 3.3, by estimating their fitness as factors determining the magnitude of the RPPG. Table 3 shows the estimates of the three steps taken to evaluate the potential factors. The first two columns contain the results of the pooled OLS regression, which ignores differences in time and between countries. The third and fourth columns contain the fixed effects model to control for such differences. The last two columns contain the Generalized Method of Moments (GMM) estimates using the first lag of the dependent variable and all other explanatory variables in differenced equations as instruments.

The results of the pooled OLS regression reveal that income inequality and trade changes have a significant negative relationship (at 1 and 5%, respectively) with RPPG, while the size of the government also has a highly significant (1%) but positive relationship with RPPG. Changes in the unemployment rate were negatively related to the RPPG and almost significant at a 5% level (p-value 0.056). Similar results are obtained if considering the country-specific effects by applying a fixed effect model. Inequality changes, trade and unemployment changes remain negative and significant (at 1, 10 and 10%, respectively). The government size is positive and significant at 5%. However, when evaluating the entire model, the post-estimate F-test suggests that the differences between groups are not significant; thus, the pooled OLS estimates should be preferred over fixed effects.

Finally, the results of the one-step GMM estimator show that income growth is now significant at a 5% level, while changes in inequality and government size remain significant (at 1 and 5% levels). Additionally, agricultural productivity growth becomes relevant (and negative) but only at a 10% level. The added lagged dependent variable turns out not significant, which suggests that past realizations of the RPPG are not correlated with present ones. For these final estimates, in addition to the instrumentalizing differentiation used to control for potential endogeneity, robust standard errors are used to control for heteroskedasticity[29].

[29] Presence of heterokedasticity confirmed by OLS post-estimates test (Appendix F). Alternatively, robust std. error OLS was carried out -without controlling for endogeneity- and the only substantial change was for agricultural productivity which became significant at a 10% (Appendix F).

Table 5.
Results of pooled OLS regression, panel fixed effect and panel GMM estimator for potential determinants of pro-poor growth (RPPG)

	Pooled OLS		Fixed Effects		GMM (one-step)	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error[a]
$RPPG_{t-1}$	–	–	–	–	0.038	0.036
Yg	0.91	0.587	0.70	0.672	1.014**	0.396
INQc	- 15.82***	2.220	- 15.20***	2.320	- 7.458***	1.942
UNPc	- 0.06**	0.033	- 0.06*	0.036	- 0.010	0.025
GSZ	0.06***	0.021	0.08**	0.039	0.093**	0.033
AGRPg	- 0.04	0.205	0.07	0.240	- 0.218*	0.122
TRDc	- 0.01**	0.006	- 0.01*	0.006	- 0.006	0.004
Constant	- 0.92***	0.281	- 1.20**	0.517	- 1.146**	0.474
Statistical tests						
R-squared	0.483		0.474		–	
Adjusted R-sq	0.452		–		–	
F-statistics	15.43***		13.38***		16.81***	
F-test ($u_i = 0$)[b]	–		0.689		–	
Nº obs.	106		106		91	
Nº instruments	–		–		12	
AR(1)	–		–		0.260	
AR(2)	–		–		0.139	
Hansen test	–		–		6.94	(0.139)

Note. For GMM (one-step) procedure, the lagged dependent variable and differenced explanatory variables are used as instruments. $RPPG_{t-1}$ = lagged of RPPG; Yg = Mean income growth; INQc = change in Gini index; UNPc = change in unemployment rate; GSZ = share of government expenditure; AGRPg = growth in agricultural productivity; TRDc = change in share of trade.
*, ** and *** indicate 10, 5 and 1% level of significance, respectively.
[a] Robust standard errors are used to control for heteroskedasticity.
[b] The overall F-test cannot reject Ho such that all individual (differential) intercepts equal 0; thus the pooled OLS is preferred (Gujarati & Porter, 2009).
Source: Complete output for all regression procedures can be found in Appendix F.

The diagnostic tests confirm the overall validity of the model (p-value < 0.001), and the serial correlation tests (AR(1) and AR(2)) ensure that there is not a correlation between the explanatory variables and the error term. The Sargan-Hansen statistic confirms the instruments' validity (difference equations of the explanatory variable.). Although ideally, this model should include time controls, they are left out as the inclusion of these extra controls brings the number of instruments above the number of groups, severely weakening the model (Sargan-Hansen statistic) (Arellano & Bond, 1991). However, this addition does not change the overall estimates and can be found in Appendix F.

These results imply that, in addition to changes in inequality and income which expectedly express similar changes as the RPPG[30], the government size was the only regressor that remained significant (at least at 5%) for all specifications. The fact that income growth was not statistically different from zero (bordering 10% significance) for the first configurations is one of the reasons to believe there is endogeneity among the regressors. Although significant for initial configurations, changes in trade and unemployment rate changes become not significant in the last configuration. Therefore it is difficult to discern a particular relationship or overall role for this two variables.

There are compelling arguments to consider the initial level of inequality instead of –or in addition to– the change in inequality (see, for example, Ravallion & Datt, 1999; White & Anderson, 2001; Duclos, 2009). The reason for using the change instead is that it provides more information about the dynamics taking place during the specific period. Besides, using the absolute difference in the Gini coefficient instead of the original (initial) value is a way to minimize any potential bias from the measurement error of the income and distribution data source (Dollar & Kraay, 2002).

Changes in the unemployment rates of the labor force are always negative and, although slightly significant in the initial configurations, become not different from zero, coincidentally, once the effect of income growth becomes relevant. This could hint that the increase in employment is not significant once the overall effect of economic growth is adequately taken into account. Pasha and Palanivel (2004) argued otherwise using average changes in poverty incidence and poverty elasticity of growth, although their results do not carry any statistical certainty. In a more in-depth country comparison analysis, Lustig et al. (2013) stated that the contribution of changes in employment varies substantially depending on which sector benefited the most from job creation during the period.

To accurately determine whether or not changes in employment have a significant impact on poverty, once control for the effect of economic growth, it would be necessary to consider a specialized indicator. Following this logic, changes in employment would be relevant if they directly affect the poor (Lustig et al., 2013) or critical specific sectors (Shepherd et al., 2016). It is still possible that more specific employment dynamics, closely related to the sectors mentioned above, could have a significant effect on the RPPG.

Government size is always positive and significant in all configurations, implying that, even without more specific measures of social transfer programs, public spending tends to be positively related to the RPPG for the current sample. This relationship has been and remains a highly debated subject, with studies supporting both negative and positive aspects of government spending (see section 2.4). This result, however, is consistent with those of Kraay (2004), who found that government size tended to be negatively correlated with all measures of the distributional effect of poverty changes.

This result would add up with those of Anderson et al (2018) meta-regression analysis that found a negative and sizable relationship between government size and poverty reduction across 169 estimates from 19 studies. However, it was not statistically significant after several controls and accounting for publication bias. Overall, they concluded that the estimated relationship between government spending and income poverty, or inequality

[30] The RPPG is in fact the growth rate adjusted by the ratio of the actual changes in the Watts index to the changes that would have occurred with the same growth rate but constant inequality (see section 2.4).

changes, is heavily affected by the regional composition of the sample, control variables included and type of spending considered (Anderson et al., 2018). Therefore, although it is not possible to strongly affirm that government size unequivocally increases the pro-poorness of growth, evidence in the sample suggests that it is positively correlated with a higher magnitude of the RPPG.

Growth in agricultural productivity was not statistically different from zero, even changing sign when accounting for country-effects, except for the last configuration, when it becomes slightly significant at a 10% level (p-value 0.093). Pasha and Palanivel (2004) related periods of high income growth and high agricultural growth with a sharp decline in poverty. Nevertheless, in the cases of moderate income changes, the poverty decrease was considerably lower. Numerous attempts to test this agriculture–growth or agriculture–poverty relationship have resulted in a lack of significance (for agricultural productivity, growth or importance) using this or similar proxies (examples include White & Anderson, 2001; Dollar & Kraay, 2002; Son & Kakwani, 2008; Dollar et al., 2016). Thus, there is no substantial evidence to support that this relationship is overall significant. Similar results are obtained if agricultural growth or the share of the agricultural sector is considered instead (see Appendix F).

Although consistently negative and relevant in initial specifications, changes in trade are not significant in the last GMM regression, bordering the 10% level (p-value 0.118). It must be considered that the effects, which this variable aims to capture, can be of a complex nature as they might affect growth and inequality in either way (positive or negative). As argued by Barro (2000), trade openness is expected to have a different effect (increasing or decreasing) on the income inequality of a country depending on its human and physical capital. Nevertheless, and consistent with this result, they also found a positive relationship between greater trade openness and inequality, while positive with overall growth (Barro, 2000). Other studies have come to different conclusions, determining that trade openness, although it might benefit economic growth, is not related to changes in income of the poor or poverty reduction (White & Anderson, 2001; Dollar & Kraay, 2002; Pasha & Palanivel, 2004). Again, although the data suggest a certain negative influence of trade openness in the RPPG, there is insufficient evidence to support or contradict this argument.

The overall results imply that the RPPG, for LAC countries (1989–2019), was heavily determined by the income growth and change in inequality. The data suggest that a larger government size, measured as the ratio of total expenditure to GDP, is significantly related to higher RPPG. While there is not a definite pattern, it appears that changes in unemployment rates and changes in trade could also be potential determinants of the magnitude of the RPPG. However, this relationship is not statistically significant after controlling for heteroskedasticity and potential endogeneity. Growth in agricultural productivity is only slightly significant (at 10%) in one of the specifications, with no improvement when replaced with similar proxies. Therefore, it is not possible to conclude about its relevance in determining RPPG. In general, these results should always be considered in the context they are drawn from, as many of the interpretations might be valid only for the region and period considered.

4. Conclusions

The key emphasis on the "leave no one behind" commitment of the Sustainable Development Goals marked an important shift in the international development agenda. It changed the focus, away from the broad economic performance, towards a more comprehensive approach to the development process. The pursuit of more egalitarian societies implies that not only the final outcome of the growth process matters but also the pattern it takes. In this context, the concept of pro-poor growth gained importance as that which enhances the welfare of the poor by allowing them to participate and significantly benefit from economic activities. Even while the exact concept and implications are still under debate, this focus has been of essential utility to analyze the effect of diverse growth patterns on the livelihood of the poor.

The debate of PPG has been characterized by two main approaches, relative and absolution definition. The absolute approach of PPG focuses on the direct impact that growth has on the poor, specifically on their income and overall poverty reduction. The relative definition pays special attention to the distribution dynamics of the economic gains and their interaction with the growth impact on poverty. Although there are good arguments to support both absolute and relative approaches, the relative has the strongest implications. Furthermore, only the inequality reduction implied by the relative definition of PPG is consistent with the type of inclusive growth pattern that the development agenda aims to achieve.

Even without consensus on the concept, several useful indicators and techniques have been developed to analyze the pro-poorness of growth. Although of limited scope about underlying processes, the decomposition of changes in poverty helps to identify and measure the relevance of inequality changes for poverty reduction. The Growth Incidence Curve (GIC) is one of the most valuable tools to graphically represent and analyze the pattern of growth that occurred during a given period. Complementary, in terms of identification, the Pro-Poor Growth Index (PPGI) presents the clearest logic and criteria according to the relative approach of PPG. The Rate of Pro-poor Growth (RPPG), on the other hand, excels in measuring the magnitude of PPG. It not only presents a straightforward interpretation, while based on a robust set of axioms, but it is also linked with both poverty headcount and Watts index poverty measures.

Latin America, although it remains the most unequal region in the world, has made substantial progress in both poverty and inequality reduction. The region's growth pattern from 1989 to 2019 has been marked by a sharp decline in inequality and poverty for the 16 countries included in the study. During the study period, all countries experienced a significant reduction in inequality (- 0.06 Gini index), except for Costa Rica and Paraguay, and poverty incidence (- 0.12 in the Watts index and - 0.11 in poverty headcount). Even though the region's overall per capita household income growth was not outstanding (3.03% per year), it still accomplished a substantial increase in the income of the poor (2.89% measured by the RPPG). Although with considerable variations, it was positive for all countries.

The decomposition of poverty changes revealed that changes in inequality (redistribution component) accounted, on average, for a remarkable 44% of the poverty reduction during the whole period. Even more impressing, for the specific subperiods from (2009 – 2011), it accounted for more than 60% of the decrease in all poverty measures considered. As a result, using the proposed classification requisite, the overall growth pattern from 1989 to 2019 for Latin America is deemed pro-poor and for each country except for Argentina and Paraguay. Consequently, of the 108 growth spells analyzed, 62% were classified as pro-poor. Although no country was unambiguously pro-poor in all sub-periods, half the countries of the sample had an anti-poor growth only in two or less sub-periods. Furthermore, only in 24% of the growth spells the poor experienced an actual decrease in their income measured by the RPPG.

Finally, to answer the main research question about what are the drivers of the pro-poorness bias, a one-step GMM estimation was applied to the proposed model to determine which factors determine the rate of pro-poor growth for all growth spells. The overall results imply that the RPPG for LAC countries from 1989 to 2019, besides being heavily determined by the household per capita income growth and changes in inequality, was positively related to the government size. The data suggest that a larger ratio of total expenditure government to GDP, is significantly related to higher RPPG. As for the rest of the factors considered, changes in unemployment rates and changes in trade openness, although they appeared to have some negative relationship in initial configurations, were not statistically significant after controlling for all other factors. Growth in agricultural productivity is significant (at 10% level) only in the final specification; thus, it is not possible to make a definite conclusion about its relevance in determining PPG.

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Appendix A.
Descriptive Statistic of Variables Considered

	RPPG	Yg	INQc	UNPc	GSZ	$AGRP_g$	TRDc	AGR_g	AGR_{shr}
Nº observations	108	108	108	108	122	110	108	110	124
Mean	0.59	0.94	- 0.01	0.82	12.97	0.14	0.72	0.12	8.92
Median	0.16	0.99	- 0.01	0.02	12.93	0.11	1.55	0.11	7.48
Std. deviation	1.02	0.14	0.34	2.48	3.49	0.37	12.81	0.11	4.61
Variance	1.03	0.19	0.01	6.17	12.17	0.14	164.10	0.01	21.24
Maximum	2.92	0.45	0.17	13.36	22.16	3.18	34.88	0.45	23.96
Minimum	- 8.12	- 0.25	- 0.08	-7.26	3.32	-0.50	- 62.55	- 0.19	2.13
Skewness	- 5.15	0.13	1.72	1.26	0.71	5.47	- 1.11	- 0.01	0.98
Kurtosis	42.53	3.01	10.28	11.19	3.21	43.54	8.30	3.79	3.46

Note. RPPG = rate of pro-poor growth, Yg = Mean income growth; INQc = change in Gini index; UNPc = change in unemployment rate; GSZ = share of government expenditure; AGRPg = growth in agricultural productivity; TRDc = change in share of trade; AGRg = agricultural growth; AGRshr = share of agriculture to GDP.

Appendix B.
Poverty, Income and Pro-Poor Measures per Country per Sub-Period

Country	Period	RPPG	Income growth	Gini Change	Pro-poor	Period	RPPG	Income growth	Gini Change	Pro-poor
Argentina	1991–1995	- 378%	- 5%	0.02	AP	2007–2011	34%	16%	- 0.04	PP
	1995–1999	- 17%	- 5%	0.01	AP	2011–2015	6%	-3%	- 0.01	PP
	1999–2003	43%	- 10%	0.01	AP	2015–2019	-14%	-7%	0.01	AP
	2003–2007	43%	35%	- 0.05	PP					
Bolivia	1992–1997	- 55%	45%	0.09	AP	2007–2011	45%	22%	- 0.08	PP
	1997–1990	- 103%	- 18%	0.03	AP	2011–2015	1%	9%	0.01	AP
	2000–2003	103%	19%	- 0.07	PP	2015–2019	54%	- 1%	- 0.05	PP
	2003–2007	- 2%	13%	- 0.00	AP					
Brazil	1990–1995	26%	34%	- 0.01	AP	2007–2011	24%	17%	- 0.02	PP
	1995–1999	- 1%	- 4%	- 0.01	PP	2011–2015	34%	14%	- 0.01	PP
	1999–2003	26%	8%	- 0.01	PP	2015–2019	- 37%	4%	0.01	AP
	2003–2007	21%	17%	- 0.03	PP					
Chile	1990–1994	17%	20%	- 0.01	PP	2006–2011	30%	16%	- 0.01	PP
	1994–1998	26%	16%	- 0.01	PP	2011–2015	23%	26%	- 0.02	PP
	1998–2003	- 41%	- 15%	- 0.04	AP	2015–2017	10%	11%	0.00	PP
	2003–2006	73%	12%	- 0.04	PP					
Colombia	1992–1996	- 74%	- 9%	0.02	AP	2008–2011	36%	13%	- 0.02	PP
	1996–1999	- 41%	- 4%	0.02	AP	2011–2015	13%	9%	- 0.03	PP
	1999–2003	154%	11%	- 0.05	PP	2015–2019	- 10%	0%	0.00	AP
	2003–2008	0%	26%	0.02	AP					

Country	Period	RPPG	Income growth	Gini Change	Pro-poor	Period	RPPG	Income growth	Gini Change	Pro-poor
Costa Rica	1991–1995	23%	33%	- 0.01	PP	2007–2011	0%	13%	- 0.01	AP
	1995–1999	89%	9%	0.02	AP	2011–2015	8%	7%	- 0.00	AP
	1999–2003	48%	35%	0.02	AP	2015–2019	22%	3%	- 0.00	PP
	2003–2007	57%	13%	- 0.00	PP					
Dominican Republic	1992–1996	- 27%	11%	- 0.03	AP	2007–2011	17%	4%	- 0.01	PP
	1996–2000	10%	18%	0.04	AP	2011–2015	15%	15%	- 0.03	PP
	2000–2003	- 10%	- 17%	0.01	PP	2015–2019	21%	13%	- 0.03	PP
	2003–2007	25%	3%	- 0.03	PP					
Ecuador	1994–1999	- 15%	3%	0.05	AP	2007–2011	28%	5%	- 0.07	PP
	1999–2003	36%	15%	- 0.05	PP	2011–2015	23%	12%	0.00	PP
	2003–2007	30%	35%	- 0.00	PP	2015–2019	11%	- 1%	- 0.00	AP
El Salvador	1991–1995	110%	15%	- 0.04	PP	2007–2011	2%	- 10%	- 0.03	PP
	1995–1999	- 114%	6%	0.02	AP	2011–2015	19%	15%	- 0.02	PP
	1999–2003	46%	1%	- 0.02	PP	2015–2019	10%	18%	- 0.02	AP
	2003–2007	106%	12%	- 0.05	PP					
Honduras	1991–1995	11%	32%	0.04	AP	2007–2011	- 9%	- 1%	0.00	AP
	1995–1999	- 43%	7%	- 0.00	AP	2011–2015	19%	- 12%	- 0.06	PP
	1999–2003	28%	8%	0.03	AP	2015–2019	7%	5%	- 0.02	PP
	2003–2007	45%	33%	- 0.02	PP					
Mexico	1989–1994	- 1%	- 9%	- 0.02	PP	2006–2010	- 14%	- 5%	- 0.02	AP
	1994–1998	- 39%	- 21%	- 0.01	AP	2010–2014	18%	3%	0.02	PP
	1998–2002	25%	21%	- 0.02	PP	2014–2018	23%	14%	- 0.03	PP
	2002–2006	18%	15%	- 0.01	PP					

Country	Period	RPPG	Income growth	Gini Change	Pro-poor	Period	RPPG	Income growth	Gini Change	Pro-poor
Nicaragua	1993–1998	- 42%	2%	0.04	AP	2005–2009	5%	- 2%	- 0.05	PP
	1998–2001	45%	18%	- 0.02	PP	2009–2014	23%	37%	0.02	AP
	2001–2005	32%	14%	- 0.04	PP					
Panama	1991–1995	- 139%	28%	- 0.00	PP	2007–2011	37%	37%	- 0.01	PP
	1995–1999	292%	4%	- 0.01	PP	2011–2015	16%	15%	- 0.01	PP
	1999–2003	185%	4%	- 0.01	PP	2015–2019	5%	14%	- 0.01	AP
	2003–2007	38%	6%	- 0.03	PP					
Paraguay	1990–1995	- 812%	- 6%	0.17	AP	2007–2011	13%	21%	- 0.01	AP
	1995–1999	27%	- 2%	- 0.04	PP	2011–2015	38%	12%	- 0.05	PP
	1999–2003	26%	- 6%	0.00	PP	2015–2019	15%	2%	- 0.02	PP
	2003–2007	6%	3%	- 0.02	AP					
Peru	1994–1999	- 34%	35%	0.11	AP	2007–2011	30%	17%	- 0.05	PP
	1999–2003	32%	6%	- 0.02	PP	2011–2015	11%	8%	- 0.01	PP
	2003–2007	0%	10%	- 0.03	AP	2015–2019	17%	6%	- 0.02	PP
Uruguay	1992–1995	0%	2%	- 0.01	AP	2007–2011	16%	27%	- 0.04	PP
	1995–2000	3%	0%	0.02	PP	2011–2015	5%	11%	- 0.02	AP
	2000–2003	- 12%	- 25%	0.02	PP	2015–2019	10%	- 1%	- 0.00	PP
	2003–2007	14%	18%	0.01	PP					

Source: Own estimations based on $1.9 per day (2011 PPP$) poverty line.

Appendix C.
Decomposition of Changes in Poverty Measures per Country per Period

Country	Period	Pro-poor	Poverty headcount (P_0) Total Δ	$G_{\theta(H0)}$	$D_{\theta(H0)}$	Poverty gap(P_1) Total Δ	$G_{\theta(H1)}$	$D_{\theta(H1)}$	Poverty squared gap (P_2) Total Δ	$G_{\theta(H2)}$	$D_{\theta(H2)}$
Argentina	1991–1995	AP	0.036	0.002	0.034	0.019	0.001	0.018	0.014	0.000	0.014
	1995–1999	AP	0.006	0.003	0.003	0.002	0.001	0.001	0.002	0.001	0.001
	1999–2003	AP	0.022	0.011	0.011	0.000	0.004	- 0.004	- 0.006	0.002	- 0.008
	2003–2007	PP	- 0.052	- 0.027	- 0.025	- 0.019	- 0.010	- 0.010	- 0.011	- 0.005	- 0.006
	2007–2011	PP	- 0.015	- 0.005	- 0.010	- 0.005	- 0.002	- 0.004	- 0.003	- 0.001	- 0.002
	2011–2015	PP	- 0.001	0.001	- 0.001	- 0.000	0.000	- 0.001	- 0.000	0.000	- 0.000
	2015–2019	AP	0.003	0.002	0.001	0.001	0.001	0.000	0.001	0.000	0.000
Bolivia	1992–1997	AP	0.041	- 0.085	0.126	0.052	- 0.033	0.085	0.042	- 0.019	0.062
	1997–1990	AP	0.094	0.039	0.055	0.075	0.021	0.055	0.064	0.015	0.049
	2000–2003	PP	- 0.149	- 0.038	- 0.112	- 0.115	- 0.017	- 0.098	- 0.097	- 0.012	- 0.085
	2003–2007	AP	- 0.013	- 0.018	0.004	- 0.000	- 0.009	0.008	0.002	- 0.006	0.008
	2007–2011	PP	- 0.052	- 0.021	- 0.031	- 0.029	- 0.010	- 0.019	- 0.020	- 0.007	- 0.013
	2011–2015	AP	- 0.008	- 0.008	- 0.001	- 0.002	- 0.003	0.001	- 0.000	- 0.002	0.002
	2015–2019	PP	- 0.030	0.001	- 0.031	- 0.018	0.000	- 0.018	- 0.012	0.000	- 0.013
Brazil	1990–1995	AP	- 0.085	- 0.069	- 0.016	- 0.034	- 0.030	- 0.004	- 0.017	- 0.017	0.000
	1995–1999	PP	0.003	0.008	- 0.005	0.001	0.003	- 0.002	0.000	0.002	- 0.001
	1999–2003	PP	- 0.023	- 0.015	- 0.008	- 0.011	- 0.006	- 0.005	- 0.009	- 0.003	- 0.006
	2003–2007	PP	- 0.042	- 0.022	- 0.020	- 0.015	- 0.008	- 0.006	- 0.007	- 0.005	- 0.003

			Poverty headcount			Poverty gap			Poverty squared gap		
Country	Period	Pro-poor	Total Δ	$G_{\theta(H0)}$	$D_{\theta(H0)}$	Total Δ	$G_{\theta(H1)}$	$D_{\theta(H1)}$	Total Δ	$G_{\theta(H2)}$	$D_{\theta(H2)}$
Brazil	2007–2011	PP	- 0.020	- 0.013	- 0.007	- 0.008	- 0.005	- 0.003	- 0.005	- 0.003	- 0.002
	2011–2015	PP	- 0.016	- 0.008	- 0.008	- 0.009	- 0.003	- 0.006	- 0.006	- 0.002	- 0.004
	2015–2019	AP	0.015	- 0.002	0.017	0.007	- 0.001	0.008	0.004	- 0.001	0.005
Chile	1990–1994	PP	- 0.030	- 0.025	- 0.005	- 0.009	- 0.007	- 0.002	- 0.004	- 0.003	- 0.001
	1994–1998	PP	- 0.014	- 0.013	- 0.001	- 0.005	- 0.004	- 0.001	- 0.004	- 0.002	- 0.002
	1998–2003	AP	0.006	0.012	- 0.006	0.004	0.004	0.001	0.004	0.002	0.002
	2003–2006	PP	- 0.026	- 0.006	- 0.020	- 0.012	- 0.002	- 0.011	- 0.009	- 0.001	- 0.008
	2006–2011	PP	- 0.006	- 0.003	- 0.003	- 0.003	- 0.001	- 0.002	- 0.002	- 0.001	- 0.001
	2011–2015	PP	- 0.005	- 0.003	- 0.001	- 0.001	- 0.001	- 0.000	- 0.001	- 0.000	- 0.000
	2015–2017	PP	- 0.001	- 0.001	- 0.000	- 0.000	- 0.000	- 0.000	- 0.000	- 0.000	- 0.000
Colombia	1992–1996	AP	0.031	0.019	0.012	- 0.011	0.006	- 0.016	- 0.086	- 0.002	- 0.083
	1996–1999	AP	0.036	0.008	0.027	0.019	0.004	0.015	0.014	0.002	0.012
	1999–2003	PP	- 0.081	- 0.024	- 0.058	- 0.065	- 0.009	- 0.056	- 0.059	- 0.005	- 0.054
	2003–2008	AP	- 0.018	- 0.042	0.024	- 0.005	- 0.016	0.012	- 0.000	- 0.009	0.009
	2008–2011	PP	- 0.040	- 0.018	- 0.022	- 0.018	- 0.006	- 0.012	- 0.012	- 0.003	- 0.008
	2011–2015	PP	- 0.018	- 0.009	- 0.009	- 0.006	- 0.003	- 0.003	- 0.003	- 0.002	- 0.001
	2015–2019	AP	0.004	0.000	0.004	0.002	0.000	0.002	0.001	0.000	0.001
Costa Rica	1991–1995	PP	- 0.050	- 0.039	- 0.011	- 0.020	- 0.013	- 0.007	- 0.013	- 0.007	- 0.006
	1995–1999	AP	- 0.004	- 0.008	0.004	- 0.007	- 0.003	- 0.004	- 0.007	- 0.002	- 0.005
	1999–2003	AP	- 0.020	- 0.025	0.005	- 0.011	- 0.009	- 0.002	- 0.009	- 0.005	- 0.004

Country	Period	Pro-poor	Poverty headcount			Poverty gap			Poverty squared gap		
			Total Δ	$G_{\theta(H0)}$	$D_{\theta(H0)}$	Total Δ	$G_{\theta(H1)}$	$D_{\theta(H1)}$	Total Δ	$G_{\theta(H2)}$	$D_{\theta(H2)}$
Costa Rica	2003–2007	PP	- 0.028	- 0.006	- 0.022	- 0.013	- 0.002	- 0.011	- 0.009	- 0.001	- 0.008
	2007–2011	AP	- 0.001	- 0.004	0.003	- 0.000	- 0.001	0.001	0.000	- 0.001	0.001
	2011–2015	AP	- 0.002	- 0.002	0.001	- 0.001	- 0.001	0.000	- 0.001	- 0.000	- 0.000
	2015–2019	PP	- 0.005	- 0.000	- 0.005	- 0.002	- 0.000	- 0.002	- 0.001	- 0.000	- 0.001
Dominican Republic	1992–1996	AP	- 0.004	- 0.011	0.007	0.004	- 0.004	0.008	0.005	- 0.002	0.007
	1996–2000	AP	0.004	- 0.015	0.019	- 0.000	- 0.006	0.005	- 0.002	- 0.003	0.001
	2000–2003	PP	0.013	0.020	- 0.008	0.004	0.007	- 0.003	0.002	0.004	- 0.002
	2003–2007	PP	- 0.025	- 0.003	- 0.022	- 0.010	- 0.001	- 0.009	- 0.006	- 0.000	- 0.005
	2007–2011	PP	- 0.014	- 0.004	- 0.010	- 0.005	- 0.001	- 0.004	- 0.003	- 0.000	- 0.002
	2011–2015	PP	- 0.011	- 0.009	- 0.001	- 0.003	- 0.002	- 0.001	- 0.001	- 0.001	- 0.000
	2015–2019	PP	- 0.011	- 0.004	- 0.008	- 0.003	- 0.001	- 0.002	- 0.001	- 0.000	- 0.001
Ecuador	1994–1999	AP	0.045	- 0.007	0.052	0.021	- 0.003	0.023	0.012	- 0.002	0.013
	1999–2003	PP	- 0.069	- 0.034	- 0.035	- 0.040	- 0.014	- 0.026	- 0.028	- 0.008	- 0.019
	2003–2007	PP	- 0.063	- 0.054	- 0.009	- 0.026	- 0.021	- 0.005	- 0.015	- 0.012	- 0.004
	2007–2011	PP	- 0.039	- 0.006	- 0.033	- 0.014	- 0.002	- 0.012	- 0.008	- 0.001	- 0.007
	2011–2015	PP	- 0.012	- 0.009	- 0.003	- 0.005	- 0.003	- 0.002	- 0.004	- 0.002	- 0.002
	2015–2019	AP	0.001	0.001	0.000	- 0.001	0.000	- 0.002	- 0.002	0.000	- 0.002
El Salvador	1991–1995	PP	- 0.084	- 0.030	- 0.054	- 0.050	- 0.013	- 0.037	- 0.040	- 0.007	- 0.033
	1995–1999	AP	0.038	- 0.010	0.048	0.035	- 0.004	0.039	0.033	- 0.002	0.035
	1999–2003	PP	- 0.013	- 0.002	- 0.011	- 0.012	- 0.001	- 0.012	- 0.012	- 0.001	- 0.012

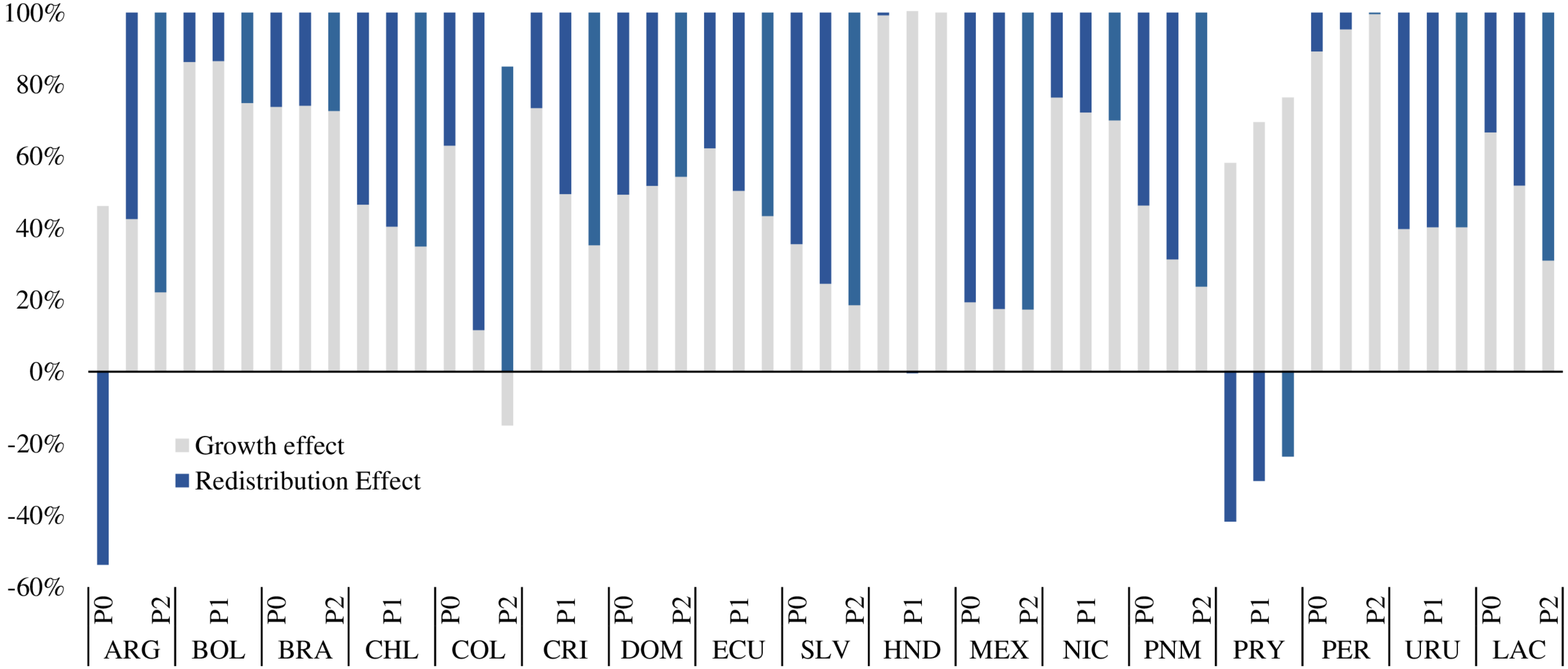
Country	Period	Pro-poor	Poverty headcount			Poverty gap			Poverty squared gap		
			Total Δ	$G_{\theta(H0)}$	$D_{\theta(H0)}$	Total Δ	$G_{\theta(H1)}$	$D_{\theta(H1)}$	Total Δ	$G_{\theta(H2)}$	$D_{\theta(H2)}$
El Salvador	2003–2007	PP	- 0.105	- 0.017	- 0.088	- 0.066	- 0.006	- 0.060	- 0.050	- 0.003	- 0.047
	2007–2011	PP	0.001	0.014	- 0.013	- 0.000	0.004	- 0.004	- 0.000	0.002	- 0.002
	2011–2015	PP	- 0.027	- 0.013	- 0.014	- 0.007	- 0.003	- 0.004	- 0.003	- 0.001	- 0.001
	2015–2019	AP	- 0.008	- 0.009	0.001	- 0.002	- 0.002	0.000	- 0.001	- 0.001	0.000
Honduras	1991–1995	AP	- 0.058	- 0.102	0.044	- 0.024	- 0.051	0.028	- 0.013	- 0.031	0.018
	1995–1999	AP	- 0.015	- 0.018	0.003	0.018	- 0.010	0.028	0.025	- 0.006	0.032
	1999–2003	AP	0.017	- 0.021	0.038	- 0.003	- 0.011	0.009	- 0.011	- 0.007	- 0.003
	2003–2007	PP	- 0.109	- 0.075	- 0.034	- 0.062	- 0.038	- 0.023	- 0.042	- 0.024	- 0.018
	2007–2011	AP	- 0.002	0.003	- 0.004	0.004	0.001	0.003	0.006	0.001	0.005
	2011–2015	PP	- 0.011	0.031	- 0.042	- 0.013	0.013	- 0.027	- 0.012	0.008	- 0.020
	2015–2019	PP	- 0.015	- 0.010	- 0.005	- 0.008	- 0.005	- 0.003	- 0.004	- 0.003	- 0.001
Mexico	1989–1994	PP	0.004	0.015	- 0.011	0.001	0.005	- 0.004	0.000	0.002	- 0.002
	1994–1998	AP	0.056	0.047	0.009	0.020	0.016	0.004	0.010	0.008	0.002
	1998–2002	PP	- 0.064	- 0.035	- 0.029	- 0.022	- 0.012	- 0.010	- 0.011	- 0.006	- 0.005
	2002–2006	PP	- 0.024	- 0.014	- 0.010	- 0.008	- 0.005	- 0.003	- 0.004	- 0.002	- 0.002
	2006–2010	AP	0.004	0.005	- 0.000	0.003	0.002	0.002	0.002	0.001	0.001
	2010–2014	PP	- 0.008	- 0.002	- 0.006	- 0.005	- 0.001	- 0.004	- 0.003	- 0.000	- 0.003
	2014–2018	PP	- 0.020	- 0.008	- 0.012	- 0.006	- 0.003	- 0.004	- 0.003	- 0.001	- 0.002
Nicaragua	1993–1998	AP	0.019	- 0.006	0.025	0.035	- 0.002	0.038	0.032	- 0.001	0.033
	1998–2001	PP	- 0.076	- 0.048	- 0.028	- 0.050	- 0.021	- 0.029	- 0.036	- 0.012	- 0.024

Country	Period	Pro-poor	Poverty headcount Total Δ	$G_{\theta(H0)}$	$D_{\theta(H0)}$	Poverty gap Total Δ	$G_{\theta(H1)}$	$D_{\theta(H1)}$	Poverty squared gap Total Δ	$G_{\theta(H2)}$	$D_{\theta(H2)}$
Nicaragua	2001–2005	PP	- 0.084	- 0.032	- 0.052	- 0.034	- 0.011	- 0.023	- 0.018	- 0.005	- 0.013
	2005 -2009	PP	- 0.011	0.004	- 0.015	- 0.003	0.001	- 0.004	- 0.001	0.001	- 0.002
	2009–2014	AP	- 0.039	- 0.039	- 0.000	- 0.012	- 0.012	0.000	- 0.005	- 0.005	- 0.000
Panama	1991–1995	PP	- 0.057	- 0.034	- 0.024	- 0.029	- 0.016	- 0.013	- 0.020	- 0.011	- 0.009
	1995–1999	PP	- 0.031	- 0.004	- 0.026	- 0.026	- 0.002	- 0.024	- 0.023	- 0.001	- 0.022
	1999–2003	PP	- 0.021	- 0.005	- 0.016	- 0.038	- 0.002	- 0.036	- 0.042	- 0.001	- 0.041
	2003–2007	PP	- 0.034	- 0.007	- 0.026	- 0.019	- 0.004	- 0.016	- 0.014	- 0.002	- 0.012
	2007–2011	PP	- 0.047	- 0.031	- 0.015	- 0.018	- 0.011	- 0.007	- 0.010	- 0.005	- 0.004
	2011–2015	PP	- 0.010	- 0.009	- 0.001	- 0.003	- 0.003	- 0.001	- 0.002	- 0.001	- 0.001
	2015–2019	AP	- 0.008	- 0.006	- 0.002	- 0.001	- 0.001	0.000	- 0.000	- 0.001	0.001
Paraguay	1990–1995	AP	0.109	0.005	0.104	0.048	0.002	0.045	0.029	0.001	0.027
	1995–1999	PP	- 0.022	0.003	- 0.025	- 0.012	0.002	- 0.013	- 0.008	0.001	- 0.009
	1999–2003	PP	- 0.021	0.009	- 0.030	- 0.013	0.004	- 0.017	- 0.009	0.002	- 0.011
	2003–2007	AP	- 0.004	- 0.004	0.000	- 0.003	- 0.001	- 0.002	- 0.002	- 0.001	- 0.001
	2007–2011	AP	- 0.027	- 0.025	- 0.003	- 0.008	- 0.008	0.000	- 0.003	- 0.004	0.001
	2011–2015	PP	- 0.029	- 0.010	- 0.020	- 0.011	- 0.002	- 0.009	- 0.006	- 0.001	- 0.005
	2015–2019	PP	- 0.008	- 0.001	- 0.007	- 0.002	- 0.000	- 0.002	- 0.001	- 0.000	- 0.001
Peru	1994–1999	AP	0.024	- 0.073	0.098	0.027	- 0.029	0.056	0.020	- 0.016	0.036
	1999–2003	PP	- 0.052	- 0.015	- 0.037	- 0.030	- 0.006	- 0.025	- 0.020	- 0.003	- 0.017
	2003–2007	AP	- 0.009	- 0.020	0.010	- 0.001	- 0.008	0.007	0.000	- 0.004	0.004

Country	Period	Pro-poor	Poverty headcount			Poverty gap			Poverty squared gap		
			Total Δ	$G_{\theta(H0)}$	$D_{\theta(H0)}$	Total Δ	$G_{\theta(H1)}$	$D_{\theta(H1)}$	Total Δ	$G_{\theta(H2)}$	$D_{\theta(H2)}$
Peru	2007–2011	PP	- 0.058	- 0.023	- 0.036	- 0.023	- 0.009	- 0.014	- 0.012	- 0.004	- 0.007
	2011–2015	PP	- 0.016	- 0.008	- 0.007	- 0.004	- 0.002	- 0.002	- 0.002	- 0.001	- 0.001
	2015–2019	PP	- 0.015	- 0.005	- 0.010	- 0.004	- 0.001	- 0.003	- 0.002	- 0.001	- 0.001
Uruguay	1992–1995	AP	0.000	- 0.000	0.000	0.000	- 0.000	0.000	0.000	- 0.000	0.000
	1995–2000	PP	- 0.001	- 0.000	- 0.000	- 0.000	- 0.000	- 0.000	- 0.000	- 0.000	- 0.000
	2000–2003	PP	0.003	0.006	- 0.003	0.000	0.001	- 0.001	0.000	0.001	- 0.000
	2003–2007	PP	- 0.004	- 0.004	- 0.000	- 0.001	- 0.001	- 0.000	- 0.000	- 0.000	- 0.000
	2007–2011	PP	- 0.002	- 0.002	- 0.000	- 0.000	- 0.000	- 0.000	- 0.000	- 0.000	- 0.000
	2011–2015	AP	- 0.000	- 0.001	0.000	- 0.000	- 0.000	0.000	- 0.000	- 0.000	0.000
	2015–2019	PP	- 0.000	0.000	- 0.000	- 0.000	0.000	- 0.000	- 0.000	0.000	- 0.000

Source: Own estimations based on $1.9 per day (2011 PPP$) poverty line.

Appendix D.
Relative Importance of Growth and Redistribution Effects per Country

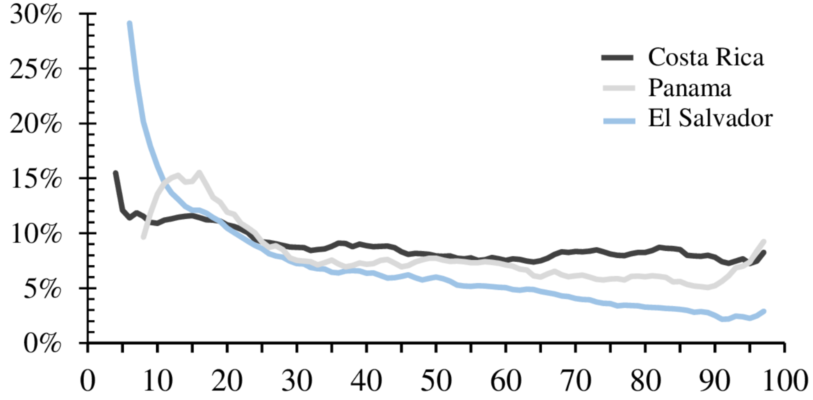


Note. P0 = Poverty headcount; P1 = Poverty gap; and P3 = Poverty squared gap. ARG = Argentina; BOL = Bolivia; BRA = Brazil; CHL = Chile; COL = Colombia; CRI = Costa Rica; DOM = Dominican Republic; ECU = Ecuador; SLV = El Salvador; HND = Honduras; MEX = Mexico; NIC = Nicaragua; PNM = Panama; PRY = Paraguay; PER = Peru; URU = Uruguay; and LAC = Latin American and the Caribbean unweighted average.
Source: own calculations based on poverty changes decomposition for the complete periods (Appendix C).

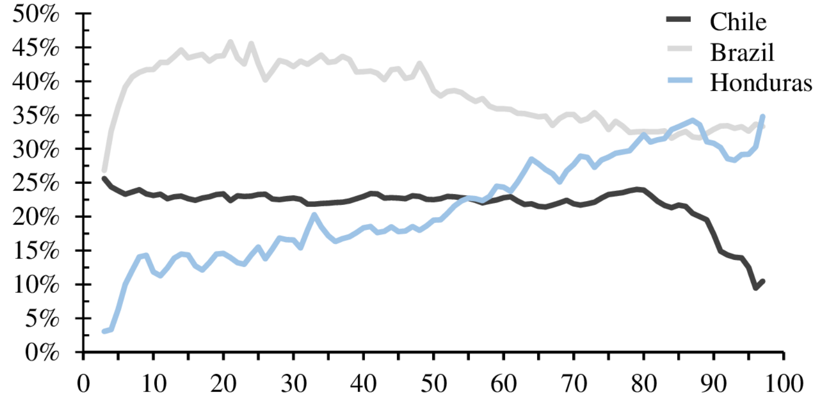
Appendix E.
Growth Incidence Curves per Country per Period

Figure E1. *Growth incidence curves corresponding to sub-period 1.*

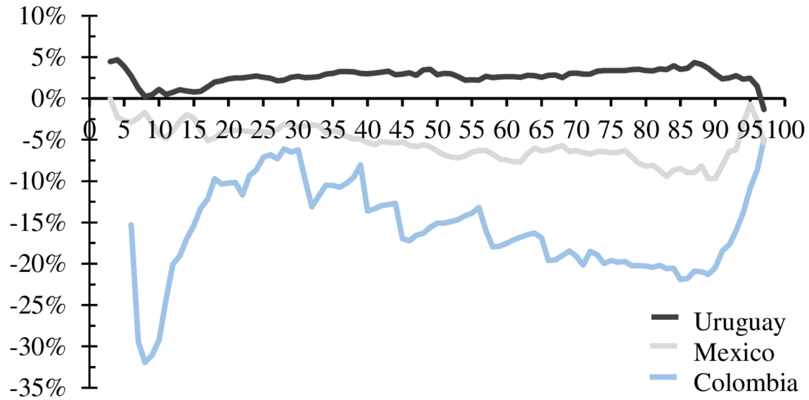
Costa Rica, Panama and El Salvador (19991–1995)



Chile (1990–1994), Honduras (1991–1995) and Brazil (1990–1995)



Bolivia (1992–1997), Dominican Republic (1992–1996) and Argentina (1991–1995) & Paraguay (1990–1995)



Uruguay (1992–1995), Mexico (1989–1994), and Colombia (1992 – 1996)

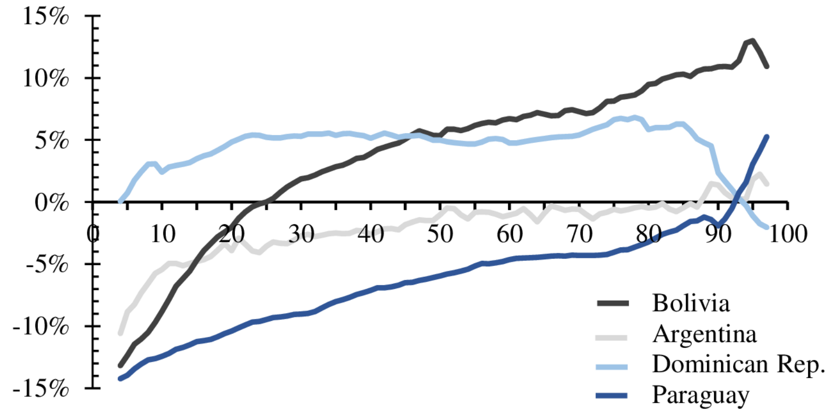
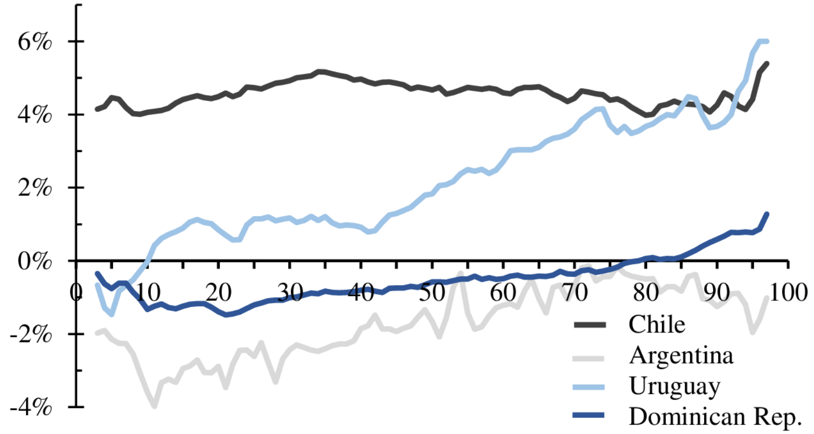
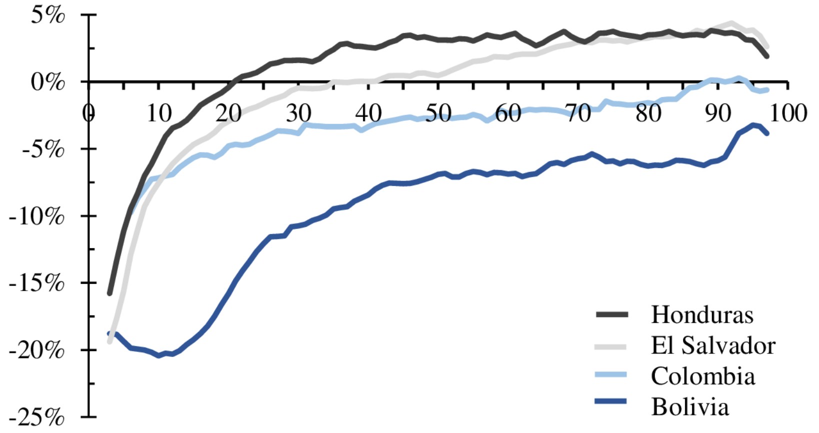


Figure E2. *Growth incidence curves corresponding to sub-period 2.*

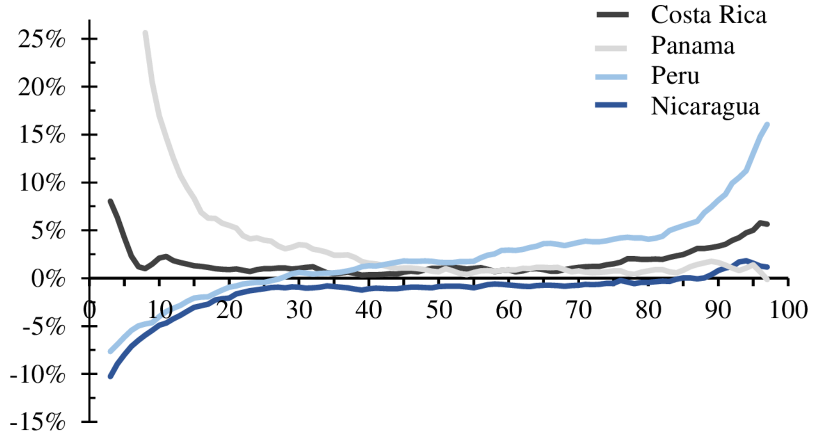
Chile (1994–1998), Argentina (1995–1999), Uruguay (1995–2000) and Dominican Republic (1996–2000)



Honduras & El Salvador (1995–1999), Colombia (1996–1999) and Bolivia (1997–1990)



Costa Rica & Panama (1995 - 1999), Peru (1994–1999) and Nicaragua (1993–1998)



Paraguay & Brazil (1995–1999), Mexico (1994–1998) and Ecuador (1994–1999)

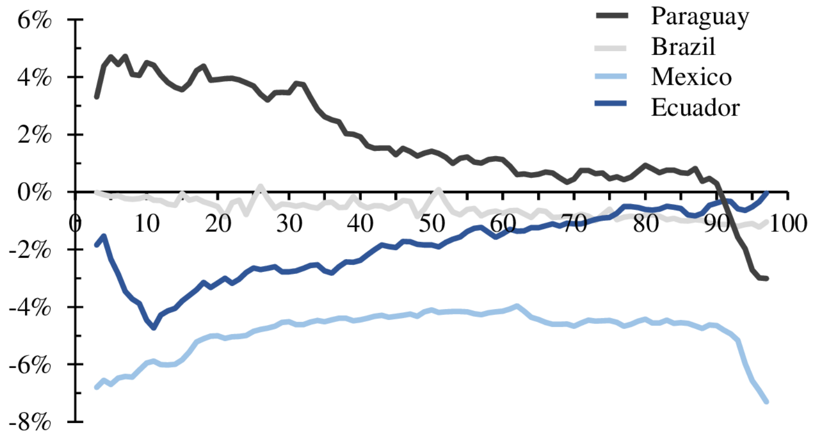
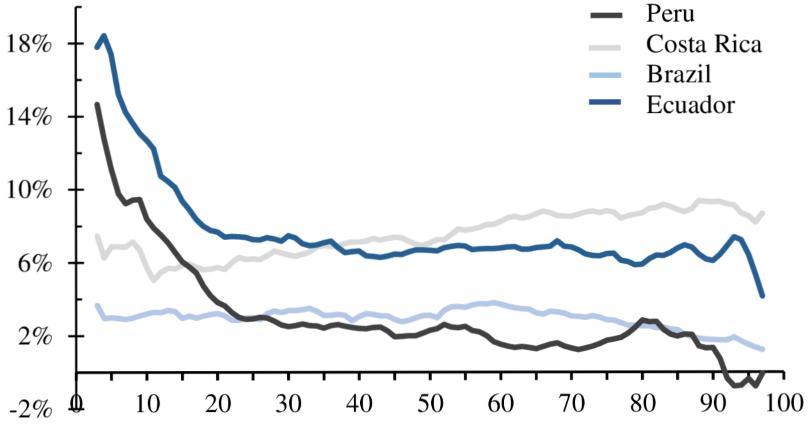
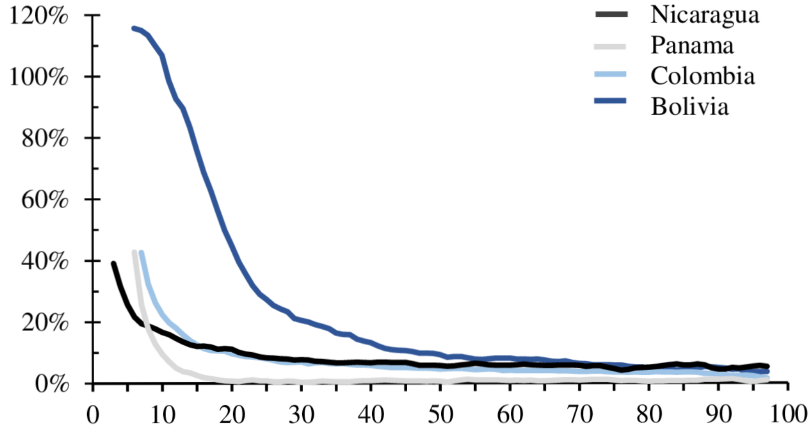


Figure E3. *Growth incidence curves corresponding to sub-period 3.*

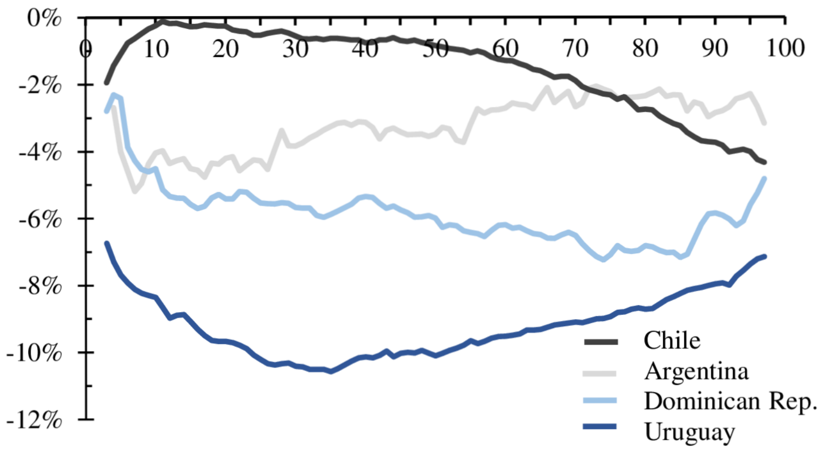
Peru, Costa Rica, Brazil and Ecuador (1999–2003)



Nicaragua (1998–2001), Panama & Colombia (1999–2003) and Bolivia (2000–2003)



Chile (1998–2003), Argentina (1999–2003) and Dominican Republic & Uruguay (2000–2003)



Honduras, Paraguay & El Salvador (1999–2003) and Mexico (1998–2002)

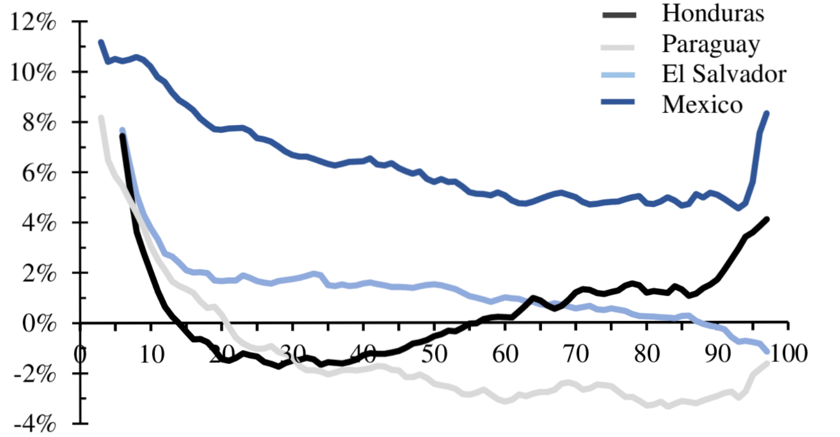
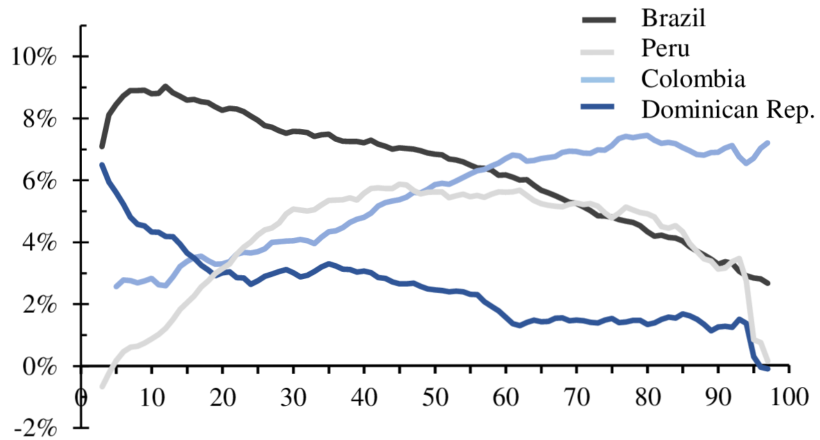
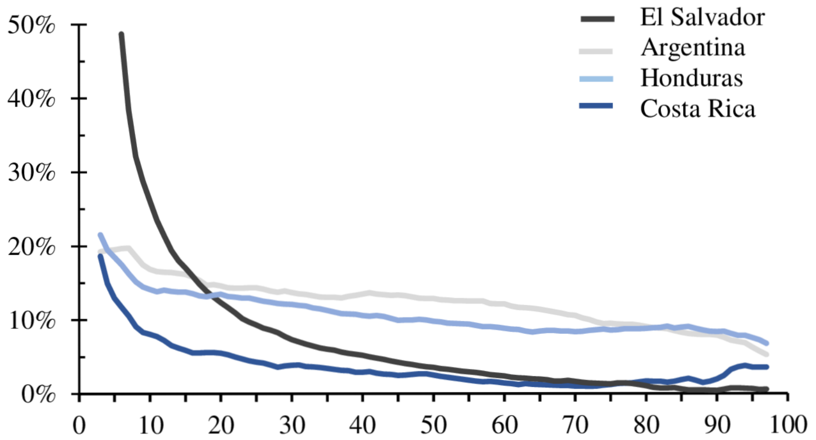


Figure E4. *Growth incidence curves corresponding to sub-period 4.*

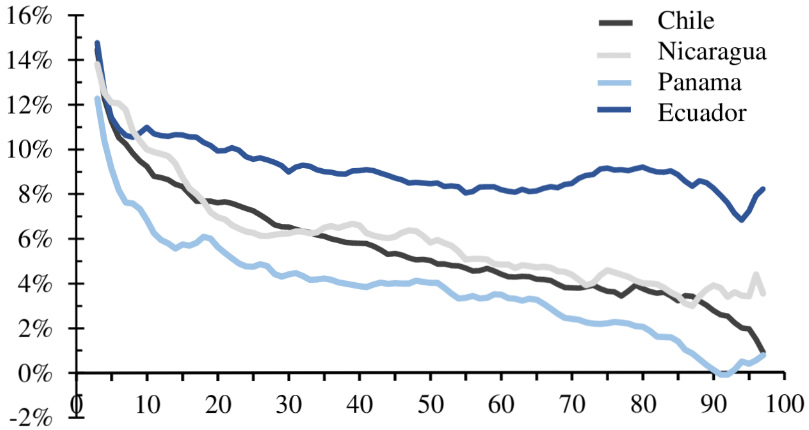
Brazil, Peru & Dominican Republic (2003–2007) and Colombia (2003–2008)



El Salvador, Argentina, Honduras and Costa Rica (2003–2007).



Chile (2003–2006), Nicaragua (2001–2005) and Panama & Ecuador (2003–2007)



Uruguay, Bolivia & Paraguay (2003–2007) and Mexico (2002–2006)

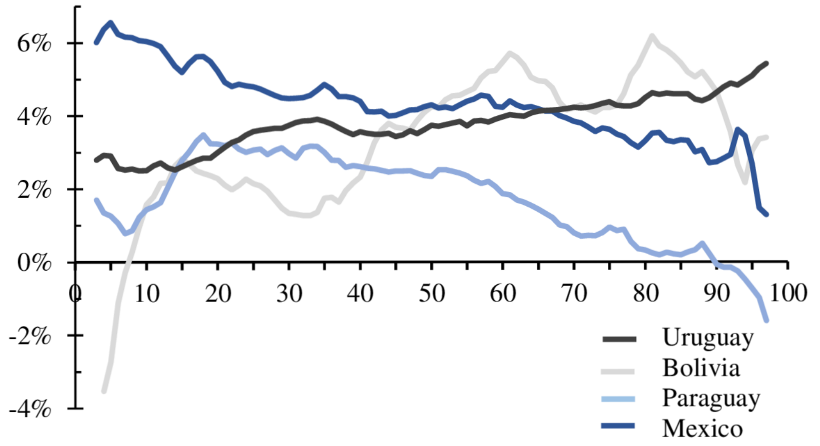
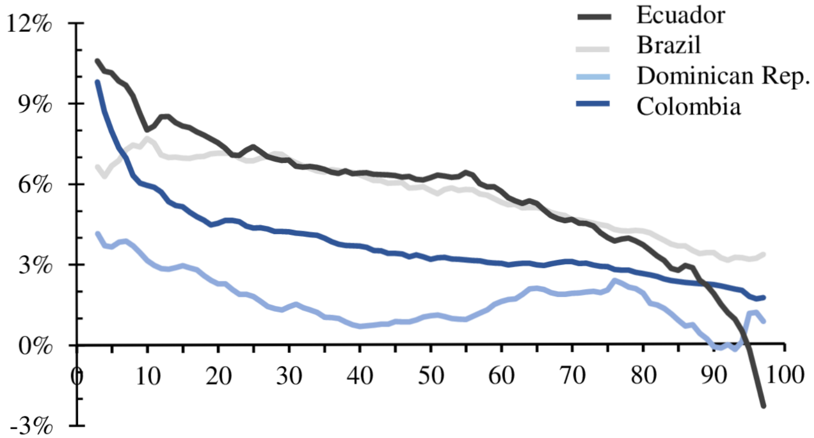
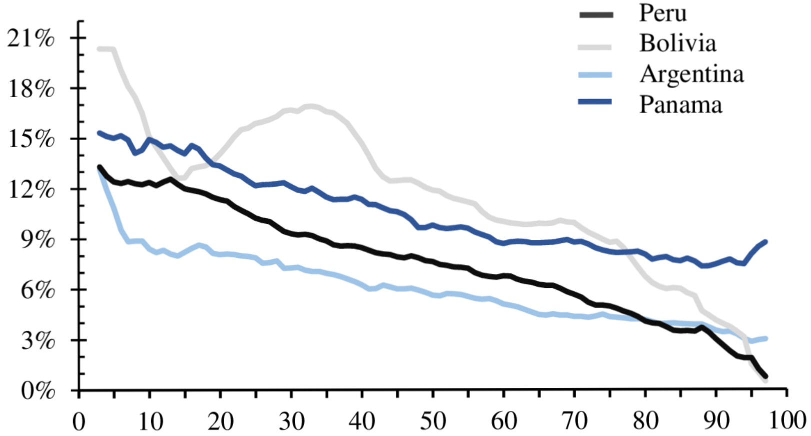


Figure E5. *Growth incidence curves corresponding to sub-period 5.*

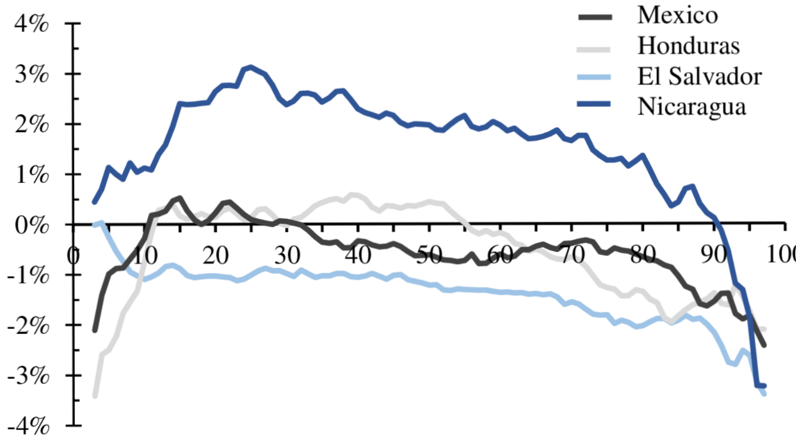
Colombia (2008–2011) and Brazil, Dominican Republic & Colombia (2007–2011)



Peru, Bolivia, Argentina and Panama (2007–2011)



Mexico (2006–2010), Honduras & El Salvador (2007–2011) and Nicaragua (2005–2009)



Chile (2006–2011) and Paraguay, Costa Rica, and Uruguay (2007–2011)

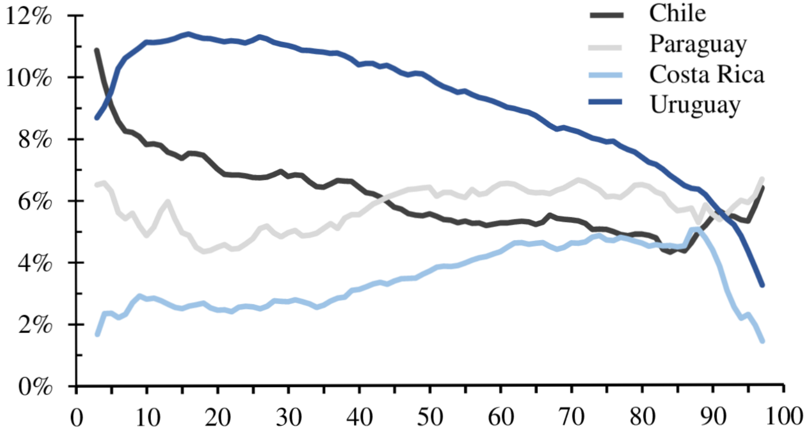
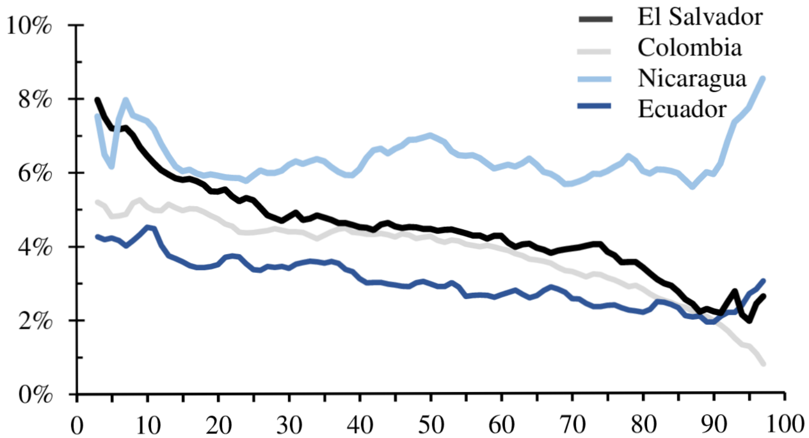
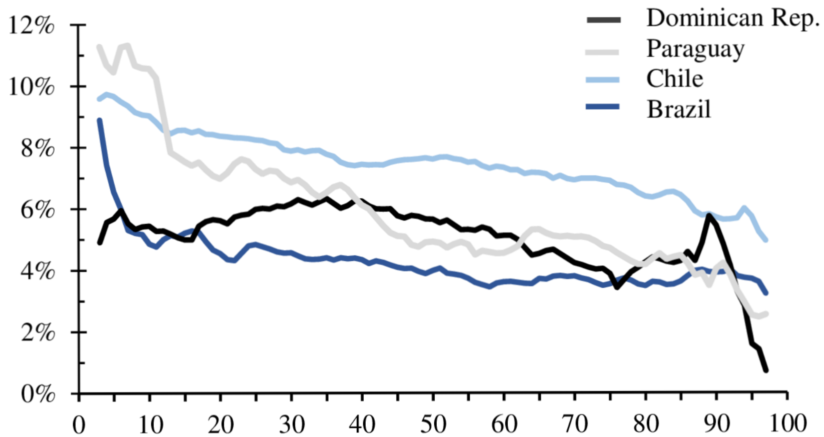


Figure E6. *Growth incidence curves corresponding to sub-period 6*

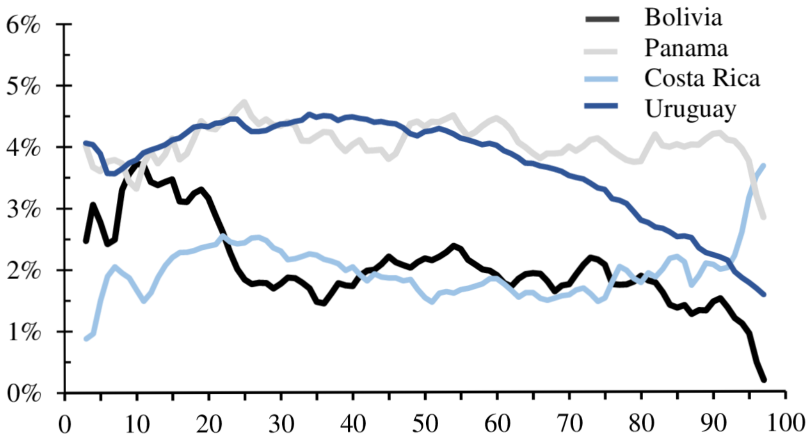
El Salvador, Colombia & Ecuador (2011–2015) and Nicaragua (2009–2014).



Dominican Republic, Paraguay, Chile & Brazil (2011–2015)



Bolivia, Panama, Costa Rica & Uruguay (2011–2015)



Argentina, Honduras, & Peru (2011–2015) and Mexico (2010–2014)

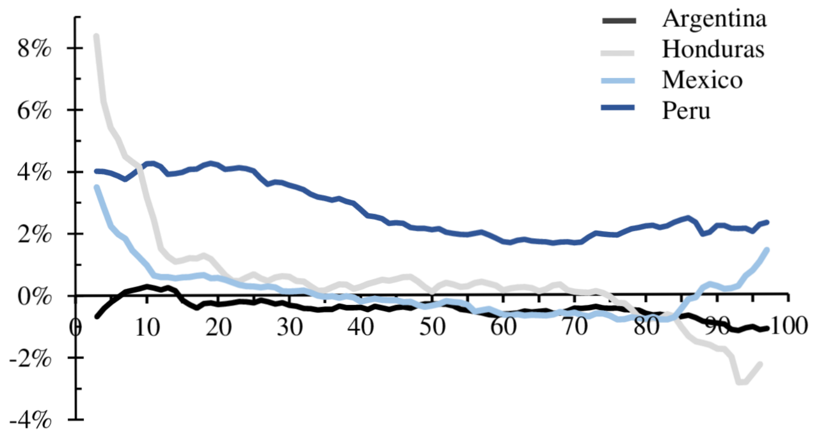
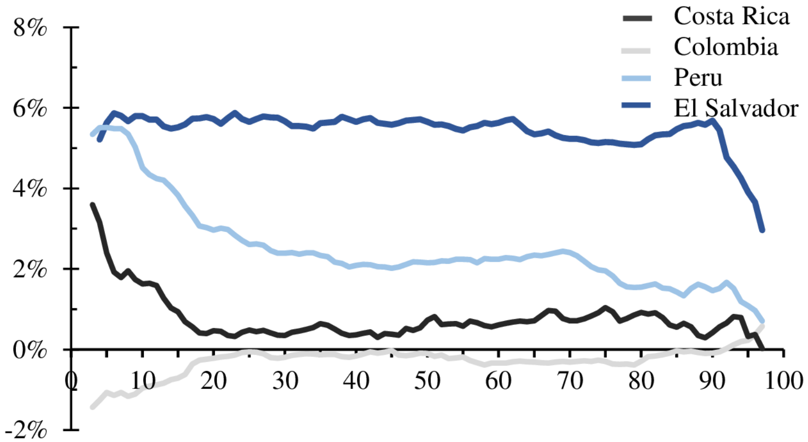
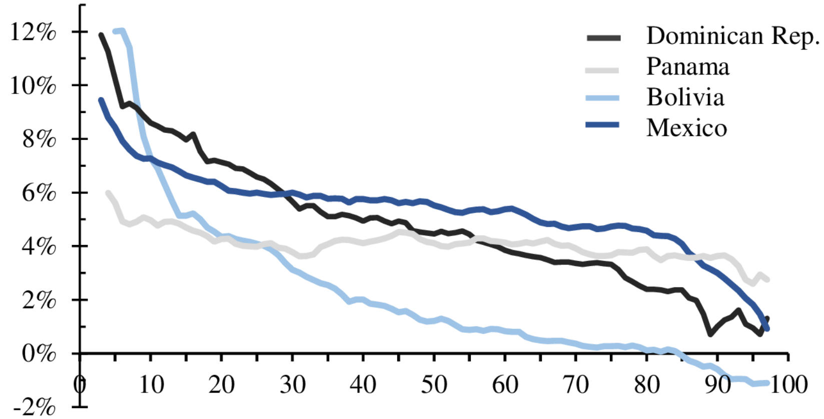


Figure E7. *Growth incidence curves corresponding to sub-period 7*

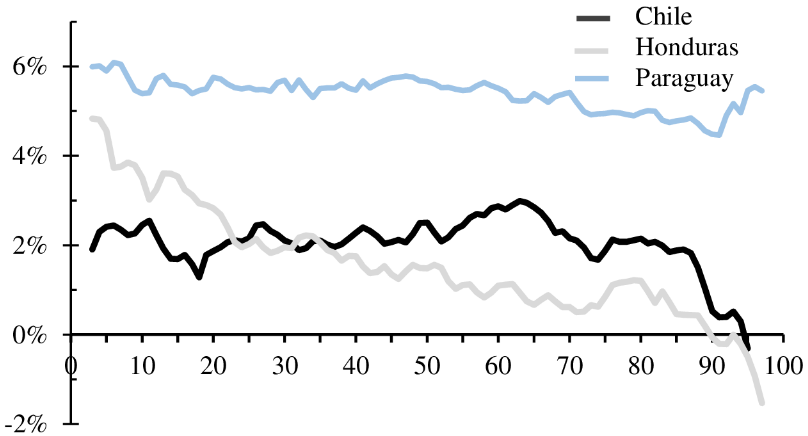
Costa Rica, Colombia, Peru & El Salvador (2015–2019)



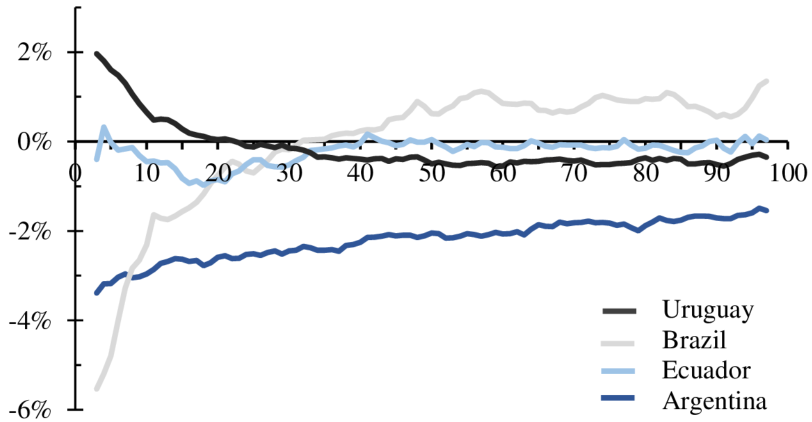
Dominican Republic, Panama, & Bolivia (2015–2019) and Mexico (2014–2018)



Chile (2015–2017) and Honduras & Paraguay (2015–2019)



Uruguay, Brazil, Ecuador & Argentina (2015–2019)



Appendix F.
Stata Outputs

Figure F1. *Pooled OLS output*

Source	SS	df	MS
Model	53.1585937	6	8.85976561
Residual	56.8289662	99	.574029961
Total	109.98756	105	1.04750057

Number of obs	=	106
F(6, 99)	=	15.43
Prob > F	=	0.0000
R-squared	=	0.4833
Adj R-squared	=	0.4520
Root MSE	=	.75765

rppg	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
inc_grw	.9125026	.5865453	1.56	0.123	-.2513305	2.076336
gini_c	-15.82784	2.219855	-7.13	0.000	-20.23251	-11.42316
unmpl_c	-.0628378	.0325428	-1.93	0.056	-.1274098	.0017342
gvexpnd_shr	.0606419	.0211787	2.86	0.005	.0186188	.102665
agrip_grw	-.039167	.2047442	-0.19	0.849	-.4454239	.3670898
trade_c	-.0126325	.0059863	-2.11	0.037	-.0245107	-.0007543
_cons	-.9162709	.281433	-3.26	0.002	-1.474695	-.3578467

Figure F2. *Fixed Effects output*

```
Fixed-effects (within) regression               Number of obs     =        106
Group variable: cntry_ID                        Number of groups  =         16

R-sq:                                           Obs per group:
     within  = 0.4887                                         min =          5
     between = 0.3734                                         avg =        6.6
     overall = 0.4739                                         max =          7

                                                F(6,84)           =      13.38
corr(u_i, Xb)  = -0.0743                        Prob > F          =     0.0000
```

rppg	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
inc_grw	.6962863	.6720846	1.04	0.303	-.6402276	2.0328
gini_c	-15.20216	2.320047	-6.55	0.000	-19.81583	-10.5885
unmpl_c	-.0636844	.0360507	-1.77	0.081	-.1353752	.0080064
gvexpnd_shr	.0837914	.0393062	2.13	0.036	.0056267	.1619561
agrip_grw	.0716466	.2404076	0.30	0.766	-.4064302	.5497234
trade_c	-.012471	.0064148	-1.94	0.055	-.0252276	.0002855
_cons	-1.20115	.5165244	-2.33	0.022	-2.228315	-.1739845
sigma_u	.28080161					
sigma_e	.77023729					
rho	.11731555	(fraction of variance due to u_i)				

F test that all u_i=0: F(15, 84) = 0.79 Prob > F = 0.6893

Figure F3. *Heterokedasticity test for Pooled OLS model*

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of rppg

         chi2(1)      =   228.27
         Prob > chi2  =   0.0000
```

Figure F4. *Alternative Pooled OLS model with robust standard errors.*

```
Linear regression                               Number of obs     =        106
                                                F(6, 99)          =       2.58
                                                Prob > F          =     0.0232
                                                R-squared         =     0.4833
                                                Root MSE          =     .75765
```

rppg	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
inc_grw	.9125026	.6779651	1.35	0.181	-.4327272	2.257732
gini_c	-15.82784	6.81161	-2.32	0.022	-29.34355	-2.312124
unmpl_c	-.0628378	.0485357	-1.29	0.198	-.1591431	.0334675
gvexpnd_shr	.0606419	.0251203	2.41	0.018	.0107977	.1104861
agrip_grw	-.039167	.1210702	-0.32	0.747	-.2793966	.2010626
trade_c	-.0126325	.0069873	-1.81	0.074	-.0264968	.0012318
_cons	-.9162709	.4305863	-2.13	0.036	-1.770648	-.0618942

Figure F5. *GMM (one-step) regression output with robust standard errors.*

```
Dynamic panel-data estimation, one-step system GMM

Group variable: cntry_ID                        Number of obs      =        91
Time variable : year                            Number of groups   =        16
Number of instruments = 12                      Obs per group: min =         4
F(7, 15)      =     16.81                                      avg =      5.69
Prob > F      =     0.000                                      max =         6
```

rppg	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
rppg_lag	.0379296	.0359795	1.05	0.308	-.038759	.1146181
inc_grw	1.013907	.3960281	2.56	0.022	.1697932	1.858021
gini_c	-7.457963	1.941689	-3.84	0.002	-11.59657	-3.319352
unmpl_c	-.0095446	.0247641	-0.39	0.705	-.0623281	.0432388
gvexpnd_shr	.0930252	.0333038	2.79	0.014	.0220398	.1640105
agrip_grw	-.2180746	.121637	-1.79	0.093	-.4773378	.0411886
trade_c	-.0057603	.0039076	-1.47	0.161	-.0140892	.0025685
_cons	-1.145833	.4740167	-2.42	0.029	-2.156175	-.1354901

```
Instruments for first differences equation
  Standard
    D.(gini_c inc_grw unmpl_c gvexpnd_shr agrip_grw trade_c)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/7).rppg collapsed
Instruments for levels equation
  Standard
    _cons

Arellano-Bond test for AR(1) in first differences: z =  -0.59  Pr > z =  0.553
Arellano-Bond test for AR(2) in first differences: z =  -0.22  Pr > z =  0.826

Sargan test of overid. restrictions: chi2(4)    =   5.28  Prob > chi2 =  0.260
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(4)    =   6.94  Prob > chi2 =  0.139
  (Robust, but weakened by many instruments.)
```

Figure F6. *GMM (one-step) regression output including time dummies.*

```
year_1 dropped due to collinearity
year_5 dropped due to collinearity
year_8 dropped due to collinearity
Warning: Number of instruments may be large relative to number of observations.

Dynamic panel-data estimation, one-step system GMM

Group variable: cntry_ID                         Number of obs      =        91
Time variable : year                             Number of groups   =        16
Number of instruments = 17                       Obs per group: min =         4
F(12, 15)     =     89.15                                       avg =      5.69
Prob > F      =     0.000                                       max =         6
```

rppg	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
rppg_lag	.0474856	.057999	0.82	0.426	-.0761363	.1711075
inc_grw	1.267996	.414541	3.06	0.008	.3844226	2.151569
gini_c	-7.816696	1.630932	-4.79	0.000	-11.29295	-4.340446
unmpl_c	-.0091555	.0271483	-0.34	0.741	-.0670207	.0487096
gvexpnd_shr	.0963859	.0302978	3.18	0.006	.0318077	.1609641
agrip_grw	-.1022372	.1106751	-0.92	0.370	-.3381356	.1336612
trade_c	-.0053318	.0038226	-1.39	0.183	-.0134795	.0028159
year_2	.4031033	.3460649	1.16	0.262	-.3345165	1.140723
year_3	.4638079	.1618247	2.87	0.012	.1188867	.808729
year_4	.1126621	.1106631	1.02	0.325	-.1232108	.348535
year_6	-.0450133	.1023447	-0.44	0.666	-.2631557	.1731292
year_7	-.0608551	.110045	-0.55	0.588	-.2954104	.1737002
_cons	-1.371452	.3704234	-3.70	0.002	-2.160991	-.5819134

```
Instruments for first differences equation
  Standard
    D.(gini_c inc_grw unmpl_c gvexpnd_shr agrip_grw trade_c year_1 year_2
    year_3 year_4 year_5 year_6 year_7 year_8)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/7).rppg collapsed
Instruments for levels equation
  Standard
    _cons

Arellano-Bond test for AR(1) in first differences: z =  -0.91  Pr > z =  0.361
Arellano-Bond test for AR(2) in first differences: z =  -0.49  Pr > z =  0.625

Sargan test of overid. restrictions: chi2(4)    =   2.34  Prob > chi2 =  0.674
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(4)    =   2.00  Prob > chi2 =  0.735
  (Robust, but weakened by many instruments.)
```

Figure F7. *Alternative OLS regression using agricultural growth.*

Source	SS	df	MS
Model	53.1443047	6	8.85738412
Residual	56.8432551	99	.574174294
Total	109.98756	105	1.04750057

```
Number of obs   =      106
F(6, 99)        =    15.43
Prob > F        =   0.0000
R-squared       =   0.4832
Adj R-squared   =   0.4519
Root MSE        =   .75774
```

rppg	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
inc_grw	.9220154	.5889556	1.57	0.121	-.2466004	2.090631
gini_c	-15.80008	2.233903	-7.07	0.000	-20.23263	-11.36753
unmpl_c	-.0632683	.0326403	-1.94	0.055	-.1280338	.0014972
gvexpnd_shr	.0598043	.0210882	2.84	0.006	.0179608	.1016479
agri_grw	-.0781282	.7223138	-0.11	0.914	-1.511355	1.355099
trade_c	-.012617	.005987	-2.11	0.038	-.0244965	-.0007376
_cons	-.9020266	.3048907	-2.96	0.004	-1.506996	-.2970572

Figure F8. *Alternative GMM regression using agricultural growth.*

```
Dynamic panel-data estimation, one-step system GMM

Group variable: cntry_ID                       Number of obs      =        91
Time variable : year                           Number of groups   =        16
Number of instruments = 12                     Obs per group: min =         4
F(7, 15)      =      9.50                                     avg =      5.69
Prob > F      =     0.000                                     max =         6
```

rppg	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
rppg_lag	.0119387	.0268396	0.44	0.663	-.0452686	.069146
inc_grw	.9697389	.3705957	2.62	0.019	.1798328	1.759645
gini_c	-6.831759	1.904961	-3.59	0.003	-10.89209	-2.771431
unmpl_c	-.0088931	.0222101	-0.40	0.695	-.0562329	.0384466
gvexpnd_shr	.0907598	.0249461	3.64	0.002	.0375884	.1439313
agri_grw	.6285662	.3478916	1.81	0.091	-.1129471	1.37008
trade_c	-.0050522	.0029962	-1.69	0.112	-.0114384	.001334
_cons	-1.209275	.3654926	-3.31	0.005	-1.988304	-.4302465

```
Instruments for first differences equation
  Standard
    D.(gini_c inc_grw unmpl_c gvexpnd_shr agri_grw trade_c)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/7).rppg collapsed
Instruments for levels equation
  Standard
    _cons

Arellano-Bond test for AR(1) in first differences: z =  -1.05  Pr > z =  0.293
Arellano-Bond test for AR(2) in first differences: z =   0.19  Pr > z =  0.846

Sargan test of overid. restrictions: chi2(4)    =   5.73  Prob > chi2 =  0.220
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(4)    =   8.42  Prob > chi2 =  0.077
  (Robust, but weakened by many instruments.)
```

Figure F9. *Alternative OLS regression using initial agricultural share.*

Source	SS	df	MS			
				Number of obs	=	106
				F(6, 99)	=	15.67
Model	53.5671831	6	8.92786386	Prob > F	=	0.0000
Residual	56.4203767	99	.569902795	R-squared	=	0.4870
				Adj R-squared	=	0.4559
Total	109.98756	105	1.04750057	Root MSE	=	.75492

rppg	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
inc_grw	.9151239	.5841482	1.57	0.120	-.243953	2.074201
gini_c	-15.46978	2.24977	-6.88	0.000	-19.93381	-11.00575
unmpl_c	-.0659738	.032598	-2.02	0.046	-.1306554	-.0012922
gvexpnd_shr	.0574492	.0210957	2.72	0.008	.0155907	.0993077
agri_shr	-.0152366	.0175492	-0.87	0.387	-.0500581	.0195849
trade_c	-.0124898	.0059634	-2.09	0.039	-.0243225	-.0006572
_cons	-.7418178	.3438539	-2.16	0.033	-1.424099	-.0595371

Figure F10. *Alternative GMM regression using initial agricultural share.*

```
Dynamic panel-data estimation, one-step system GMM
------------------------------------------------------------------------------
Group variable: cntry_ID                        Number of obs      =        91
Time variable : year                            Number of groups   =        16
Number of instruments = 12                      Obs per group: min =         4
F(7, 15)      =     10.20                                      avg =      5.69
Prob > F      =     0.000                                      max =         6
------------------------------------------------------------------------------
             |              Robust
        rppg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    rppg_lag |   .0217972   .0367297     0.59   0.562    -.0564904    .1000847
     inc_grw |   .9223804   .3736814     2.47   0.026     .1258974    1.718864
      gini_c |   -7.17355   1.845472    -3.89   0.001    -11.10708    -3.24002
     unmpl_c |   -.019847   .0181501    -1.09   0.291     -.058533     .018839
 gvexpnd_shr |   .0840949   .0287828     2.92   0.011     .0227459    .1454439
    agri_shr |  -.0249227   .0276247    -0.90   0.381    -.0838034     .033958
     trade_c |  -.0059667   .0031643    -1.89   0.079    -.0127113    .0007778
       _cons |  -.8422253   .3912158    -2.15   0.048    -1.676082   -.0083686
------------------------------------------------------------------------------
Instruments for first differences equation
  Standard
    D.(gini_c inc_grw unmpl_c gvexpnd_shr agri_shr trade_c)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/7).rppg collapsed
Instruments for levels equation
  Standard
    _cons
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -0.62  Pr > z =  0.535
Arellano-Bond test for AR(2) in first differences: z =   0.13  Pr > z =  0.899
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(4)    =   6.61  Prob > chi2 =  0.158
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(4)    =   6.67  Prob > chi2 =  0.154
  (Robust, but weakened by many instruments.)
```