Policy Research Working Paper 9038

Poverty Convergence in a Time of Stagnation

A Municipal-Level Perspective from Mexico (1992–2014)

Luis F. Lopez-Calva
Eduardo Ortiz-Juarez
Carlos Rodríguez-Castelán

WORLD BANK GROUP
Poverty and Equity Global Practice
October 2019

Policy Research Working Paper 9038

Abstract

This paper exploits a novel municipal-level data set to explore patterns of convergence in income and poverty in Mexico during 1992–2014. The paper finds that, despite a context of overall stagnant economic growth and poverty reduction, there is evidence of income and poverty convergence at the municipal level. The findings suggest that these convergence processes stem from a combination of considerable positive performance among the poorest municipalities and stagnant and deteriorating performance among richer municipalities. Re distributive programs, such as federal transfers to poor municipalities and cash transfers to poor households, seem to have played an important role in driving these results by bolstering income growth among the poorest municipalities, while also inducing progressive changes in the distribution of income.

This paper is a product of the Poverty and Equity Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at crodriguezc@worldbank.org.

Poverty Convergence in a Time of Stagnation: A Municipal-Level Perspective from Mexico (1992–2014)*

Luis F. Lopez-Calva[†] Eduardo Ortiz-Juarez[‡] Carlos Rodríguez-Castelán[§]

Keywords: Income, poverty, inequality, convergence, growth elasticity, small area estimation

JEL codes: I32, O47, O54, R11

*The authors are grateful to Ted Enamorado for his comments and research assistance. The authors would also like to thank Maria E. Dávalos and Gerardo Esquivel for significant contributions to this work, as well as Jozef Draaisma (peer reviewer), Miguel Székely (peer reviewer), Oscar Calvo-González, Paloma Anos-Casero, Louise Cord, Norbert Fiess, Thania de la Garza Navarrete, Rodrigo García-Verdú, Gonzalo Hernández-Licona, Fernando Blanco, Sandra Martínez-Aguilar, Edgar Medina, Pablo Saavedra, Kinnon Scoot, Gaston Yalonetzky, Robert Zimmerman, officials at CONEVAL and Mexico's Ministry of Social Development, and participants at the EADI Nordic Conference 2017, held in Bergen, Norway, for helpful comments and suggestions. The datasets and codes necessary to replicate the exercises in this paper are available from the authors upon request. The findings, interpretations, and conclusions in this paper are entirely those of the authors. They do not necessarily represent the views of the UNDP, the World Bank, its Executive Directors, or the countries they represent.

[†]United Nations Development Programme; e-mail: luis.lopez-calva@undp.org

[‡]King's College London; e-mail: eduardo.ortiz@kcl.ac.uk

[§]World Bank; e-mail: crodriguezc@worldbank.org

1 Introduction

Despite the government's implementation of an ambitious agenda of economic and social reform, the performance of Mexico has been mediocre in economic growth and poverty reduction since the early 1990s. In 1992–2014, the country's gross domestic product (GDP) expanded at an annual average rate of 2.5 percent. Per capita, this translates into an annual growth rate of only 0.9 percent, making Mexico the second-worst performer in continental Latin America during the period. This mediocre performance was mirrored in income poverty reduction. In 1992, the official poverty headcount ratios for extreme and total poverty were, respectively, 21.4 percent and 53.1 percent. More than 20 years later, in 2014, these ratios remained virtually unchanged, at 20.6 percent and 53.2 percent, respectively.[1]

This poor performance in income growth and the long-run stagnation in poverty rates leave the impression that little has changed in the living standards of the population, especially among the poorest. This is particularly surprising, given that Mexico experienced many changes during this period, including multiple economic crises, the implementation of an ambitious set of structural reforms, and innovations in redistributive social policy. It may be, however, that these aggregate figures are masking trends at the subnational level. To understand clearly how income and poverty are changing, one needs to zoom in to a higher level of spatial disaggregation and unpack how these patterns vary within Mexico.

Specifically, this paper zooms in to explore whether some municipalities have been persistently lagging behind in pockets of poverty (income convergence) and whether poorer, converging municipalities have been able to translate their relative income gains into poverty reduction (poverty convergence). The analysis of convergence in the mean per capita incomes of municipalities follows the framework proposed by Barro and Sala-i Martin (1991). It aims at an understanding of whether poorer municipalities have been capturing the income gains resulting from modest growth and social spending and whether there has been a reduction in regional disparities. The analysis of convergence in poverty headcount ratios applies the poverty convergence decomposition by Ravallion (2012) to assess the effects of initial poverty on both the income growth process and the sensitivity of poverty reduction to income growth.

While several studies have looked at short-term (growth) convergence in income among states in Mexico, this paper contributes by leveraging a unique data set on

[1]All figures on GDP growth rates come from the World Bank's World Development Indicators database. Official income-based poverty rates are from Mexico's National Council for the Evaluation of Social Development Policy (CONEVAL).

municipalities to provide a far more disaggregated look at convergence over a longer period, while also addressing distributional concerns. The data set includes variables on income, poverty, and inequality, spans 22 years (five waves of data over 1992–2014), and covers 2,361 municipalities. To the best of our knowledge, this is the first study that implements Ravallion's (2012) method using municipal-level data.

The rest of the paper is organized as follows. Section 2 reviews the relevant empirical and theoretical literature on convergence, highlighting the scarcity of work exploring within-country poverty convergence at a high level of geographical disaggregation. Section 3 presents the methodology used to construct the dataset, which is a novel exercise applying small area estimation techniques to household surveys and population censuses to compute comparable measures of mean household per capita income, poverty headcount ratios, and the extent of inequality at the municipality level. Sections 4 and 5, respectively, test for convergence in mean per capita incomes and poverty headcount ratios across municipalities. The analysis emphasizes comparisons among subgroups of municipalities that exhibit sizable disparities (for example, urban versus rural, and municipalities located in states along the U.S. border versus the rest) as well as across subperiods to contextualize the various changes Mexico has experienced over the years (that is, economic crises, ups and downs in overall poverty rates, and the expansion of public expenditure). Both analyses explore the role of redistributive programs, such as targeted cash transfers to the poor and fiscal redistribution to subnational governments, in driving these changes. Section 6 digs deeper to explore the role of the initial distribution of poverty and inequality in determining the speed of convergence and decomposes the estimated magnitude of poverty convergence. Section 7 brings together the main messages of each section to conclude. Taken together, the findings suggest that income and poverty convergence have taken place at the municipality level in Mexico during 1992–2014 and that redistribution has played an important role.

2 Literature review and past evidence in Mexico

The theoretical and empirical literature on economic growth offers stylized facts on which the analysis of economic development paths at the municipality level can be anchored. A first widely studied stylized fact stems from the influential works of Baumol (1986) and Barro and Sala-i Martin (1991, 1992, 1995) on the convergence hypothesis, often labeled the catch-up effect or the advantage of backwardness, whereby poorer countries tend to experience more rapid economic growth rates than richer countries, in effect, catching up to the latter.

Two well-known concepts of convergence are used in this paper: sigma convergence (σ-convergence) and beta convergence (β-convergence) (Quah 1993). σ-convergence focuses on the reduction of income dispersion across units of analysis (for example, see Sala-i Martin 1996), and it is commonly estimated using a standard measure of statistical dispersion. β-convergence focuses on the negative relationship between initial levels of income and subsequent growth rates and is commonly estimated using parametric approaches, such as log-linear and nonlinear growth regressions (though non-parametric methods, such as discrete Markov chains, are also common practice). The latter concept distinguishes at least two forms of convergence in the long-run: absolute β-convergence, whereby the incomes of poorer countries converge toward a common steady state, and conditional β-convergence, whereby income convergence, not necessarily toward a common steady state, is conditional on the structural characteristics of economies. A third form, related to conditional β-convergence, is club convergence, whereby conditional convergence may cluster countries around different steady-state equilibriums (Durlauf and Johnson 1995; Quah 1996, 1997; Su 2003). A summary of the theoretical implications and empirical support (or lack thereof) for each of these concepts is presented in Galor (1996).

While most of this literature has focused on the convergence of average income levels, an emerging strand of research has opened the debate on whether country income distributions also converge toward a common invariant state. For example, this research looks at issues such as income inequality convergence (Bénabou 1996; Ravallion 2003; Lin and Huang 2011), and whether income convergence is also accompanied by poverty convergence (Cuaresma et al. 2017; Sala-i Martin 2006; Ravallion 2012). Ravallion (2012) demonstrates that, in standard log-linear growth models with parameters independent of the initial distribution, the existence of income convergence should also reveal the existence of poverty convergence.

This latter implication, that income growth is a necessary condition for poverty reduction, has been widely studied in the literature. Lustig et al. 2016, for example, show how income growth is a main driver of poverty reduction in Latin America. In general, the consensus is that higher growth rates tend to reduce poverty headcounts at a faster pace, particularly if absolute poverty measures are used (Dollar et al. 2016; Dollar and Kraay 2002; Ferreira and Ravallion 2011; Foster and Székely 2008; Fosu 2017; Grimm 2007; Kraay 2006; Ravallion 1995, 2001). This advantage of economic growth and how quickly it reduces poverty, however, usually depend on both the initial income distribution and the changes in distribution experienced because of economic expansion.

This conditionality leads to a second stylized fact: the initial parameters of the income distribution matter both for growth and the efficiency with which growth is able to reduce poverty. According to a well-established theoretical argument, initial conditions dull economic growth and its impact when market failures translate into credit constraints that trigger diminished investments in physical and human capital or, worse, leave investment opportunities entirely unexploited. In particular, if credit rationing combines with investment indivisibilities, this is especially harmful for the poor (Aghion and Bolton 1997; Banerjee and Duflo 2003; Bénabou 1996; Durlauf 1996; Galor and Zeira 1993; Hoff 1996; Ljungqvist 1993; Piketty 1997).

Built on similar arguments, an array of empirical studies on the constraints and determinants of growth has thus tested the role of the initial parameters of the distribution in growth models and confirmed that either higher initial poverty (Ravallion 2012) or higher initial inequality (Alesina and Rodrik 1994; Clarke 1995; Deininger and Squire 1998; Knowles 2005; Persson and Tabellini 1994; Ravallion 1998) are significant constraints to future growth rates. Moreover, some studies have also demonstrated that such unfavorable initial parameters tend to curb the impact that a given growth rate can exert on the proportionate rate of poverty reduction, as revealed by diminished elasticities of poverty to growth (Bourguignon 2003; Lopez and Servén 2006; Ravallion 1997, 2004, 2007, 2012).

Most of the empirical literature on (income) convergence does not explicitly address the influence of the initial distribution of income on subsequent poverty reduction and growth. In Ravallion's (2012) sample of almost 90 countries that have recorded noticeable rates of growth and poverty reduction and in which there are unambiguous signs of income convergence, there is no significant evidence that countries starting out poorer experienced higher relative rates of poverty reduction thereafter. This counterintuitive result is attributed to initial poverty, which, as revealed by a decomposition of the speed of poverty convergence, offsets the advantage of higher growth rates among poorer countries, that is, income convergence and the growth elasticity of poverty reduction.

Taking advantage of a unique panel dataset (1992–2014) on income, poverty, and inequality across municipalities in Mexico, this paper tests most of the above conclusions to provide a more disaggregated, longer-term perspective on the convergence paths and changes in well-being. Previous studies of convergence in Mexico have mainly focused on income growth paths among states, and, while some have found evidence of convergence in the years before the end of the import substitution model, most have consistently reported evidence of divergence after that. For instance, Esquivel (1999) shows that, while the pace of convergence across states was relatively fast over 1940–60, it halted and started to reverse over the next 35 years. This divergence was confirmed by subsequent studies focused on 1985–2000 (Chiquiar 2005; García-Verdú 2005; Rodríguez-Oreggia 2007; Rodríguez-Pose and Sánchez-Reaza 2005). In general, regional divergence during these years was linked to trade liberalization and the entry into force of the North American Free Trade Agreement, which bolstered the emergence of club convergence in the states that had benefited the most from these reforms given their initial endowment of relatively high-skilled labor and better public infrastructure.

Empirical evidence on convergence at a higher level of geographical disaggregation, namely, municipalities, has been scarce in Mexico. This is primarily because of the lack of a sample with robust income information and statistical power at that level. A couple of studies have reported dramatic disparities among municipalities in income and poverty in 2000 (López-Calva et al. 2008; Székely et al. 2007) by applying small area estimation techniques to impute incomes from the main household income survey to the population census. Using this technique and logistic regressions, Mexico's National Council for the Evaluation of Social Development Policy (CONEVAL) has computed rates of and changes in income poverty between 2000 and 2005 and multidimensional poverty between 2010 and 2015 across municipalities. This paper provides the first long-run assessment of regional disparities and paths in income, poverty, and inequality, based on comparable data on municipalities.[2]

3 Mapping income, poverty, and inequality in municipalities

Capturing long-run trends in income, poverty, and inequality among municipalities requires a dataset of intertemporally comparable indicators of well-being that are statistically representative of the population in each municipality. The availability of such a dataset, however, may entail a trade-off between relatively high precision in the measurement of, say, household income and significant geographical detail. One might exploit household surveys designed to capture all sources of income and thus

[2]Two papers have used a preliminary version of this dataset to examine changes across municipalities. Villalobos Barría et al. (2016) have analyzed, through Gaussian mixture modeling, the univariate and joint distribution of human development indicators —income, infant mortality, and years of schooling— and the conformation of development clusters in 1990, 2000, and 2010. Using the same preliminary dataset, Enamorado et al. (2016) study the causal effect of inequality on drug-related homicides and report a sizable decline in inequality in the majority of municipalities over 1990–2010.

retrieve household income with a high degree of precision. However, as with any restricted sample, these surveys are usually representative only nationwide or across provinces or states.

The universal coverage of the population can be approximated through population censuses, which typically provide relevant inputs to measure several dimensions of well-being at high levels of disaggregation (for example, in Mexico, CONEVAL's social backwardness index or the marginalization index of the National Population Council).[3] This greater geographical detail, however, comes at the cost of a lack of robustness in the information on household incomes. Censuses are not designed to collect comprehensive data on income. They provide an incomplete picture of household monetary circumstances, which, at least for the purposes of this analysis, represents a main weakness.

To address the dilemma between precision and geographical detail and, hence, to make the relevant dataset available for empirical analysis, the Elbers et al. (2003) small area estimation technique is used to impute household per capita income from surveys to corresponding households in censuses. This is accomplished by predicting, from an income model in the survey, the parameters and distribution of errors, which are then used to simulate the income distribution in the census dataset from which to compute poverty and inequality indicators.

Two critical steps are necessary to make this model work properly. The first step consists of considering the household survey as a random sample of the total population found in the sample frame of the census. The second step is to identify a set of potential explanatory variables that are common between the survey and the census and that satisfy a conceptual and statistical equality criterion. This means, respectively, that these variables should measure the same phenomenon in both datasets and that the respective distributions of the variables are statistically indistinguishable, that is, the sample mean is statistically equal to the population mean. The variables that satisfy this criterion are then candidate regressors in the modeling of household per capita income in the survey dataset.

[3] These indexes, computed across villages, municipalities, or states, summarize the degree of deprivation in 12 and 9 indicators, respectively, and focus on the dimensions of education, access to basic services in the dwelling, the quality and size of dwellings, health (the social backwardness index), and labor income (the marginalization index). The two indexes are computed through the principal component analysis technique and are then stratified into five groups according to the degree of backwardness or marginalization: very low, low, medium, high, and very high.

Formally, the model takes a generalized least squares form

$$ln\left(y_{hm}\right) = \alpha + \beta X_{hm} + \gamma Z_m + \mu_{hm} \quad (1)$$

to estimate the joint distribution of per capita income y in the household h located in municipality m, conditional on two sets of covariates: X_{hm}, which includes household and individual characteristics, and Z_m, which includes fixed characteristics of the municipality of residence. The parameter α is a household-specific effect; β and γ are the correlation parameters between the corresponding sets of covariates and $ln\left(y_{hm}\right)$; and, $\mu_{hm} = \eta_m + \epsilon_{hm}$ represents an error term, where η_m is the component that is common to all households located in the same municipality (assumed to be homoscedastic and *i.i.d.*), and ϵ_{hm} is the component that is specific to each household (assumed to be heteroscedastic because it depends on the characteristics of the household and the municipality). The estimates of β, γ, and μ_{hm} are then applied to the corresponding sets of covariates X_{hm} and Z_m in the census to simulate, using the bootstrap method, the distribution of household per capita income.

The empirical support of extensive applications has shown this methodology to be robust (Alderman et al. 2002; Bedi et al. 2007). It has become common practice to use the methodology to improve targeting in developing countries facing the dilemma between precision and geographical detail. In Mexico, the small area estimation technique has already been applied to map income-based poverty officially across municipalities, but only in 2000 and 2005.[4] This paper relies on data on five points in time over a 22-year period by pairing available rounds of the Household Income and Expenditure Survey (ENIGH) and censuses collected in or around the same years (1990–92, 2000, 2005, 2010, and 2014–15).[5] At each point in time, the survey is a random sample of the corresponding census sample frame.[6] This allows strict comparability of the distributions of a given variable between both data sources. Even in pairings where gaps exist, that is, 1990–92 and 2014–15, it is possible to identify common sets of covariates X_{hm} that satisfy the equality criterion, mainly because

[4]These exercises were conducted by CONEVAL by simulating income in the population censuses of 2000 and 2005. Though new rounds of census data were available in 2010 and 2015, the estimates of poverty followed a multidimensional approach based on a different methodology. Thus, a longer series of comparable income-based poverty data across municipalities is not officially available.

[5]The census data correspond to the general census of population and housing for the years ending in zero; for 2005, the data are taken from the population and housing count; and, for 2015, they are taken from the intercensal survey. Unless otherwise stated, from here onward, the term census refers indistinguishably to these three data sources.

[6]In 2014–15, both the ENIGH and the intercensal survey represented random samples of the 2010 general census sample frame.

they capture virtually the same context as characteristics of some households change slowly over time.

These X_{hm} sets include characteristics of individuals, households, and dwellings. The set Z_m considers some of these variables to be aggregated at the municipality-level along with data on the coverage and availability of public services and infrastructure.[7] This helps raise the precision of the estimates by minimizing the ratio of the variance of the error η_m relative to the variance of the total error μ_{hm}, that is, the share of the variance of errors that results from unexplained differences across municipalities. The parameters of equation (1) are estimated using the whole sample in each round of the ENIGH. The income distribution is then simulated based on 200 repetitions in the corresponding census dataset, each covering Mexico's total population. The only exception is the census data in 2015, which represent a sample of 5.9 million households; yet, this dataset has sufficient statistical power to provide reliable statistics at the municipality level.

Based on the simulated income distribution, poverty and inequality indicators were computed across municipalities and validated through several tests.[8] The income concept used is household net per capita income, which includes labor income, income from businesses owned by the household, nonlabor income, such as public and private transfers, and an estimate of the imputed rent of owner-occupied dwellings, self-consumption, and in-kind transfers and gifts received. The measurement of poverty was based on the Foster et al. (1984) family of indexes by comparing this income concept with three poverty lines: food poverty, defined as the inability to acquire a basic food basket; capabilities poverty, defined as the inability to cover the value of the food basket, plus expenditures on health and education; and assets poverty, defined as the inability to acquire the latter plus expenditures on clothing, housing, and transportation. The municipalities' inequality levels were computed through an array of well-known indicators such as the Gini coefficient.

This exercise yielded a robust, novel municipality-level dataset with income-based indicators that are comparable both over time and across 2,361 municipalities on which it was possible to compute reliable estimates on each data point over time. These municipalities represent 96 percent of Mexico's current municipalities and cover approximately 98 percent of the country's population. Summary statistics derived from

[7]Some of these variables are derived from the census datasets, while others are taken from administrative records collected in the National System of Municipal Information (SNIM for its acronym in Spanish) and the National Institute of Statistics and Geography (INEGI, for its acronym in Spanish).

[8]A detailed description of the small area estimation methodology used on each data point is available from the authors upon request.

this dataset suggest that mean per capita income in Mexico has virtually stagnated during most of the period under study and exhibited a slight increase only after 2010. Indeed, the annualized growth rate reveals that per capita income expanded by only 0.8 percent in real terms between 1992 and 2014, consistent with the GDP per capita performance described in the introduction. Accordingly, the poverty headcount ratios have not experienced a significant improvement between the initial and final year, though there were important changes in the first five years of the 2000s (see annex, panel a).

In this context of relative stagnation in income growth and overall poverty rates in the long run, the next section focuses on the growth trajectories of mean per capita income of municipalities (constant Mexican pesos at August 2014 prices) with the aim of answering two key initial questions: (1) Have poorer municipalities been persistently lagging in pockets of poverty, or have they captured income gains, thereby catching up to richer municipalities? and (2) What are the trends in income disparities across municipalities?

4 Convergence in the mean per capita income of municipalities

A well-established hypothesis in the economic growth literature is income convergence, whereby incomes tend to grow more quickly in poorer areas than in richer areas. To examine income growth paths across Mexican municipalities, the analysis applies Barro and Sala-i-Martin's (1991) framework on β-convergence and σ-convergence over 1992-2014, with a particular focus on the 2000s. Starting with β-convergence, for each time-span of length τ, the annualized growth rate in mean per capita income (y) in municipality i between the most recent time (t) and the initial year ($t-\tau$) is given by

$$g_i\left(y_{it}\right) = ln\left(y_{it}/y_{it-\tau}\right)/\tau \tag{2}$$

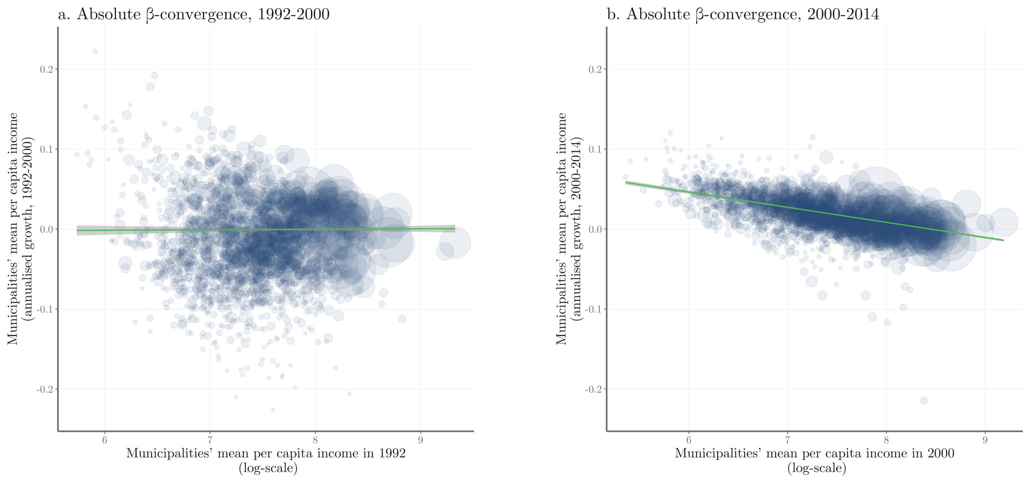
Hence, the empirical specification to analyze the growth process in mean per capita income of municipalities can be written as

$$g_i\left(y_{it}\right) = \alpha + \beta ln\, y_{it-\tau} + \mu_{it} \tag{3}$$

where $ln\, y_{it-\tau}$ is the log initial per capita income; the parameter α is a municipality-specific effect; β is a parameter indicative of the speed of absolute income convergence; and, μ_{it} is a stochastic term.

Estimates of this model, summarized in table 1, panel a, reveal signs of absolute β-convergence in incomes across municipalities in 1992–2014, as shown by a significant coefficient of –0.007, indicating that per capita income grew more quickly in poorer municipalities than in their richer counterparts, at an annual convergence rate of 0.7 percent. A closer look at subperiods, however, shows that the catch-up effect took place during 2000–14 only, with a coefficient of –0.019, whereas, in the 1990s, no evidence of income convergence was found. These opposed results are also illustrated in figure 1. Further exploring the 2000s, the speed of income convergence was greater in the first five years, at an annual rate of 4.3 percent, consistent with the marked reduction in overall poverty headcount ratios from the high levels they had reached after the Tequila Crisis. Income convergence was still evident after 2005, though it occurred at a slower pace, potentially slowed by the various economic shocks that led to recession and nontrivial contractions in the economy.

Figure 1: The mean per capita income of municipalities converged after 2000



Source: World Bank calculations.
Note: The area of symbols is proportional to municipalities' population. The regression line has a slope of 0.001 in panel a, and −0.019 in panel b (significant at the 1 percent level). Mean per capita incomes are in real terms at August 2014 prices.

A breakdown by municipality population size also yields remarkable results. In 1992–2014, the catch-up effect in rural municipalities (defined as those with fewer than 15,000 inhabitants) was at least twice as large as that observed across urban counterparts. Indeed, relative to the latter, the speed of income convergence across

Table 1: Absolute income β-convergence across municipalities, 1992-2014

	(1) 1992-2014	(2) 1992-2000	(3) 2000-2014	(4) 2000-2005	(5) 2005-2010	(6) 2010-2014
a. All municipalities						
$ln\, y_{it-\tau}$	-0.007^{***}	0.001	-0.019^{***}	-0.043^{***}	-0.020^{***}	-0.013^{***}
	(0.001)	(0.003)	(0.001)	(0.003)	(0.003)	(0.003)
Obs.	2,361	2,361	2,361	2,361	2,361	2,361
R^2	0.102	0.000	0.342	0.313	0.076	0.022
b. Urban municipalities						
$ln\, y_{it-\tau}$	-0.008^{***}	-0.003	-0.019^{***}	-0.045^{***}	-0.020^{***}	-0.009^{***}
	(0.001)	(0.004)	(0.001)	(0.003)	(0.004)	(0.004)
Obs.	944	944	1,017	1,017	1,022	1,022
R^2	0.138	0.002	0.334	0.323	0.076	0.012
c. Rural municipalities						
$ln\, y_{it-\tau}$	-0.018^{***}	-0.027^{***}	-0.031^{***}	-0.077^{***}	-0.035^{***}	-0.068^{***}
	(0.001)	(0.004)	(0.002)	(0.003)	(0.004)	(0.008)
Obs.	1,417	1,417	1,344	1,344	1,339	1,339
R^2	0.235	0.050	0.415	0.395	0.062	0.188

Source: World Bank calculations.
Note: The table presents estimates of the parameter β in equation (3), weighted by municipal population at the initial year of each period under study. The dependent variable is the annualized growth rate in the mean per capita income of municipalities. $ln\, y_{it-\tau}$ are municipalities' initial per capita income. All variables are in log-scale and in real per capita terms at August 2014 prices. Urban (rural) municipalities are defined as those with more (fewer) than 15 thousand inhabitants. The intercepts are shown in table 1 in the ancillary file. Robust standard errors are in parentheses
*** $p < .01$, ** $p < .05$, * $p < .1$

rural municipalities was consistently faster and statistically significant in each subperiod (see table 1, panels b and c). While no evidence of convergence across urban municipalities was found in the 1990s, convergence occurred in rural ones at an annual rate of 2.7 percent. Moreover, although the speed of convergence halved in both groups during 2005–10 relative to the previous five years, the pace had recovered across rural municipalities by 2010–14, whereas it slowed even further in urban ones (table 1, panels b and c, columns 4–6).

To examine the conditional income β-convergence hypothesis, whereby paths of mean per capita income growth are conditional on factors such as the initial conditions and structural characteristics of municipalities, the specification in (3) is rewritten as

$$g_i\left(y_{it}\right) = \alpha + \beta ln\, y_{it-\tau} + \gamma X_{it-\tau} + \mu_{it} \tag{4}$$

to allow for the inclusion of a set of municipality-level characteristics $X_{it-\tau}$ that are presumed to exert an influence on mean per capita income growth.

This $X_{it-\tau}$ set includes components of public spending and revenue across municipalities at the initial year of each period under study, which is relevant in light of the reforms in the federal transfer system undertaken in the 1990s. In particular, the 1998 reform that introduced Ramo 33, which aimed at redistributing additional fiscal revenues to subnational governments for social development, has allowed municipalities to benefit from larger volumes of federal transfers. For example, average per capita unconditional (participaciones federales) and conditional (Ramo 33) federal transfers, respectively, increased twofold and threefold in real terms in 2000–14 (see annex, panel b).

Making equation (4) conditional on, for instance, total per capita public expenditure in the initial year reveals that the speed of convergence over 1992–2014 jumped from the 0.7 percent found in the absolute setting to 1.2 percent and that the pace of conditional income convergence was, again, particularly rapid in the first five years of the 2000s. Although there was no evidence of absolute income convergence in the 1990s, conditional convergence did record a rate of 1.6 percent in these years, and it was significant at the 1 percent level (table 2, panel a).[9] Table 2, panels b and c show, respectively, the estimates in urban and rural municipalities, with two particular results. First, income convergence occurred, again, at a more rapid pace in rural municipalities than in urban ones in all periods under study. Second, and consistent with the whole sample, there are signs of conditional convergence in urban municipalities in the 1990s, at an annual rate of 2 percent.

The conditional model shifts the convergence rates upward in most cases relative to the absolute model. The only exception is 2005–10 when the magnitude of income convergence remained virtually unchanged. A plausible explanation is that the coefficient of initial per capita public spending was negative during those years when the economy was hit by various adverse shocks. The expectation, confirmed in the remaining cases, is that the point estimate of the variable is positive and significant,

[9] The focus is on total public spending only because no sizable differences in the rates of convergence appear if particular components of public spending or revenues are used instead, and this reduces the sample significantly because no disaggregated public finance data are available for all municipalities (see tables 2–11 and 17–26 in the ancillary file). Moreover, to exploit the panel dataset of municipalities and control for time-invariant factors, conditional convergence is estimated using fixed effects models, which consistently confirm convergence, as in the standard ordinary least squares model. Random effects specifications also produce coefficients with the same signs. As extra robustness checks, 5-year and 10-year averages are used for the public spending variables and generalized method of moments (GMM) techniques. The results are again consistent; that is, poor municipalities converge at a faster rate when compared to rich municipalities.

Table 2: Tests of β-convergence conditional on total public spending, 1992-2014

	(1) **1992-2014**	**(2)** **1992-2000**	**(3)** **2000-2014**	**(4)** **2000-2005**	**(5)** **2005-2010**	**(6)** **2010-2014**
			a. All municipalities			
$ln\, y_{it-\tau}$	-0.012^{***}	-0.016^{***}	-0.020^{***}	-0.047^{***}	-0.020^{***}	-0.015^{***}
	(0.001)	(0.005)	(0.001)	(0.003)	(0.004)	(0.003)
Public spending	0.003^{***}	0.012^{***}	0.004^{***}	0.008^{**}	-0.008^{*}	0.024^{***}
	(0.001)	(0.004)	(0.001)	(0.003)	(0.004)	(0.005)
Obs.	2,234	2,234	2,193	2,193	2,116	2,045
R^2	0.166	0.056	0.342	0.318	0.089	0.061
			b. Urban municipalities			
$ln\, y_{it-\tau}$	-0.013^{***}	-0.020^{***}	-0.021^{***}	-0.049^{***}	-0.020^{***}	-0.014^{***}
	(0.002)	(0.006)	(0.002)	(0.003)	(0.004)	(0.004)
Public spending	0.003^{**}	0.012^{***}	0.006^{***}	0.011^{***}	-0.006	0.028^{***}
	(0.001)	(0.005)	(0.002)	(0.004)	(0.005)	(0.006)
Obs.	923	923	971	971	985	937
R^2	0.216	0.067	0.345	0.333	0.086	0.066
			c. Rural municipalities			
$ln\, y_{it-\tau}$	-0.020^{***}	-0.044^{***}	-0.031^{***}	-0.083^{***}	-0.035^{***}	-0.077^{***}
	(0.001)	(0.005)	(0.002)	(0.003)	(0.005)	(0.009)
Public spending	0.002^{***}	0.016^{***}	0.001	0.009^{***}	-0.013^{***}	0.012^{**}
	(0.001)	(0.002)	(0.001)	(0.003)	(0.004)	(0.005)
Obs.	1,311	1,311	1,222	1,222	1,131	1,108
R^2	0.253	0.112	0.417	0.405	0.095	0.220

Source: World Bank calculations.
Note: The table presents estimates of parameters β and γ in equation (4), weighted by municipal population at the initial year of each period under study. The dependent variable is the annualized growth rate in the mean per capita income of municipalities over the period. $ln\, y_{it-\tau}$ and public spending are for the initial year and are in log-scale and in real per capita terms at August 2014 prices. Urban (rural) municipalities are defined as those with more (fewer) than 15,000 inhabitants. The intercepts are shown in tables 2–11 in the ancillary file. Robust standard errors are in parentheses.
*** $p < .01$, ** $p < .05$, * $p < .1$

meaning that the initial level of public spending exerts a positive influence on income growth through, for instance, the allocation of resources to public investment or transfers and subsidies. If the model in (4) controls for the latter components instead of total public spending, it can be verified that both public investment and transfers and subsidies exhibit a negative and significant sign during 2005–10 (see tables 2–11 in the ancillary file). Hence, it seems that the initial level of per capita public spending in 2005 was not sufficient to promote income growth through those channels in an environment of economic and fiscal contraction toward the end of the 2000s and thereby accelerate the pace of convergence.

In a variation of model (4), a control was also run for the annualized growth rate in the number of beneficiary families in Prospera, Mexico's flagship conditional cash transfer (CCT) program, to capture the influence of the program's expansion on the speed of convergence since its launch as Progresa in 1997. By 2000, the program was benefiting around 2.4 million families living in extreme poverty; five years later, the number reached 4.9 million, which is equivalent to an annual growth rate of 20 percent. While the expansion continued after 2005, this was at a significantly lower rate, 2.4 percent annually, reaching 5.7 million and 6.0 million families in 2010 and 2014, respectively.

Table 3 summarizes the estimates of this conditional model. It suggests that, in general, the speed of income convergence rose relative to the corresponding coefficients shown in table 2. The point estimate for the CCT variable exhibits a positive and significant effect in both 2000–14 and 2000–05, but it is particularly high in the latter period, coinciding with the dramatic expansion in CCT coverage. This expansion seems to have boosted the rate of convergence in the first years of the decade through the rise in per capita income in municipalities with the poorest populations (column 2). After 2005, the sign of the variable became negative, and the variable had no apparent influence on the pace of income convergence, suggesting that the subsequent growth in CCT coverage was too small to exert a substantial effect on the mean per capita income of municipalities.

A noticeable finding throughout all previous specifications is that the income convergence process continued after 2010. Though it occurred at a slower pace than in the previous two five-year periods in terms of the whole sample, the pace was particularly high across rural, poorer municipalities in 2010–14. What explains this result given that, as suggested before, the expansion in CCT coverage should not have had much effect in the last part of the period under study? More and better federal transfers allocated to municipalities may hold the answer. A recent redistributive assessment of the Social Infrastructure Contributions Fund (FAIS, for its acronym in Spanish), which is a crucial component of Ramo 33, suggests that the identification of priority attention zones within the country improved the targeting and implementation of federal transfers for municipal social infrastructure and that this had a positive, though modest effect both on the level and growth of household incomes across all municipalities in 2000–14 (Rodríguez-Castelán et al., 2017). The study highlights that such transfers were crucial to improving a number of socioeconomic indicators within municipalities, in particular in 2010–14, which may reflect better targeting on less well advantaged groups.

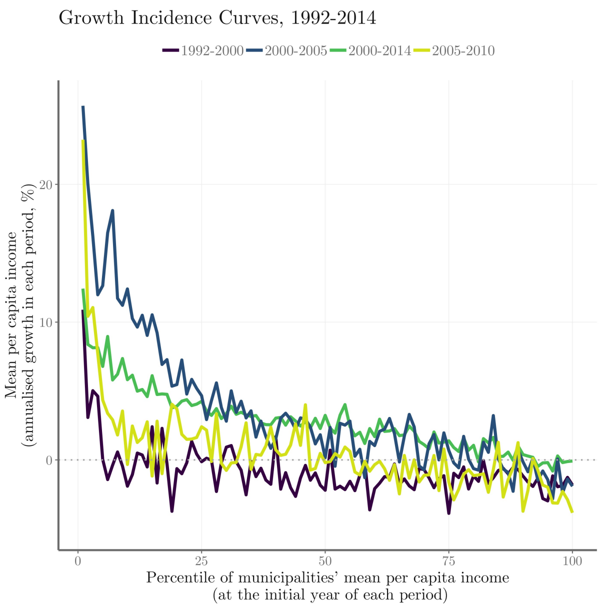
Table 3: Tests of β-convergence conditional on public spending and CCT data, 2000–14

	(1) **2000-2014**	**(2)** **2000-2005**	**(3)** **2005-2010**	**(4)** **2010-2014**
		a. All municipalities		
$ln\, y_{it-\tau}$	−0.025*** (0.002)	−0.059*** (0.004)	−0.026*** (0.003)	−0.015*** (0.004)
Public spending	0.003** (0.001)	0.006** (0.003)	−0.010*** (0.003)	0.025*** (0.005)
Annual growth in CCT coverage	0.035*** (0.010)	0.067*** (0.014)	−0.023 (0.026)	−0.055** (0.024)
Obs.	1,957	1,957	2,106	2,035
R^2	0.367	0.348	0.182	0.065
		b. Urban municipalities		
$ln\, y_{it-\tau}$	−0.025*** (0.002)	−0.060*** (0.005)	−0.027*** (0.003)	−0.014*** (0.004)
Public spending	0.004*** (0.001)	0.008** (0.003)	−0.009** (0.004)	0.029*** (0.006)
Annual growth in CCT coverage	0.033*** (0.010)	0.066*** (0.015)	−0.023 (0.027)	−0.055** (0.025)
Obs.	878	878	975	927
R^2	0.369	0.364	0.197	0.072
		c. Rural municipalities		
$ln\, y_{it-\tau}$	−0.033*** (0.002)	−0.095*** (0.004)	−0.035*** (0.005)	−0.076*** (0.009)
Public spending	0.000 (0.001)	0.010*** (0.003)	−0.013*** (0.004)	0.008 (0.006)
Annual growth in CCT coverage	0.011 (0.013)	0.058*** (0.011)	−0.072 (0.044)	−0.110* (0.057)
Obs.	1,079	1,079	1,131	1,108
R^2	0.434	0.426	0.098	0.230

Source: World Bank calculations.
Note: The table presents estimates of parameters β and γ in equation (4), weighted by municipal population at the initial year of each period under study. The dependent variable is the annualized growth rate in the mean per capita income of municipalities over the period. $ln\, y_{it-\tau}$ and public spending are for the initial year and are in log-scale and in real per capita terms in August 2014 prices. The growth rate in CCT coverage is the annualized growth rate in the number of beneficiary families in each municipality over the period. Urban (rural) municipalities are defined as those with more (fewer) than 15,000 inhabitants. The intercepts are shown in tables 3–6 and 8–11 in the ancillary file. Robust standard errors are in parentheses.
*** $p < .01$, ** $p < .05$, * $p < .1$

A critical aspect of all previous results is that the income convergence process took place in a context of overall low growth in mean per capita income, which averaged 0.8 percent over 1992–2014.[10]. A closer look at the data reveals a relatively higher growth rate in this period among the poorest municipalities (for instance, 2.5 percent annually among the poorest 10 percent), whereas it was negative among the richest ones (for example, –0.6 percent annually among the top 10 percent). Indeed, nonanonymous growth incidence curves for some revealing periods (figure 2) show that, over 1992–2000, the bottom 10 percent of municipalities experienced positive income growth, averaging 2 percent annually, while the rest observed negative rates, –1.1 percent among the remaining 90 percent and –1.9 percent among the top 10 percent.

Figure 2: Poorer municipalities experienced higher growth in income than richer ones



Source: World Bank calculations.

The story in 2000–14 was, in general, more optimistic. During these years, the vast majority of municipalities experienced positive growth, though there were again

[10]The documented process of income convergence across municipalities over 1992-2014 can coexist with patterns of regional divergence after the entry into force of the North American Free Trade Agreement, as reported by the literature focusing on growth at the level of states (World-Bank 2018). There are at least two explanations for this coexistence. The first source of the discrepancy is that state-level analyses typically use state's GDP, a metric that, while measuring the value of production, often fails to reflect average living standards as measured by microdata, as in this paper. A second source is the unit of analysis. While results from state-level studies tend to be biased by the weight exerted by large urban agglomerations concentrating a number of municipalities, in municipality-level analysis that issue can be naturally avoided.

those at the bottom who exhibited relatively higher rates. This performance was mainly driven by the high rates achieved during the first five years of the decade, which benefited a larger share of municipalities at the bottom. Mean per capita income among the poorest half expanded by 6.8 percent annually, while, among the upper half, it increased only by an annual rate of 0.4 percent and reduced by 1.3 percent among the top 10 percent. In 2005–10, the economic slowdown took a toll on the income performance of municipalities, with growth rates averaging 0.6 percent annually and, with the exception of the poorest 10 percent of municipalities, the rest experienced an average rate of –0.8 percent.

Thus, the observed process of income convergence stems from a combination of positive and relatively high growth in mean per capita income among the first decile of municipalities and stagnant and negative growth among those located at the middle and top of the distribution, respectively. To explore this process, the analysis focused on two additional groups of municipalities characterized by dissimilar levels of development and exposure to economic shocks: those located in states along the U.S. border, which are more economically well integrated with the United States and exhibit higher levels of mean per capita income, and the rest, hereafter referred to as non–US border municipalities.

The estimates of model (4) across both groups, conditional on per capita public spending, show that the speed of income convergence was evident throughout all periods and consistently higher in municipalities of the former group (table 4, panels b and c). A careful look at how income growth performed in each group reveals some clues to understanding the result. For instance, over 1992–2000, income convergence in non–U.S. border municipalities resulted, again, from relatively high growth rates among the poorest municipalities and negative rates among the rest. By contrast, the speed of convergence across those in border states stems from an inverted-U-shaped growth pattern. That is, while mean per capita income among both the poorest and richest 20 percent contracted, the contraction occurred at a lower annual rate in the former, –0.2 and –0.7 percent, respectively. Remarkably, the bulk of municipalities in the middle of the distribution experienced positive growth rates. It seems, then, that, while the Tequila Crisis had adverse nationwide effects, some relatively poorer municipalities in states along the U.S. border may have slightly benefited from the devaluation of the currency and the entry into force of the North American Free Trade Agreement, thus catching up with their richer counterparts, and relatively more quickly than in the rest of the country.[11]

Table 4: Tests of β-convergence conditional on total public spending, 1992–2014

	(1) **1992-2014**	**(2)** **1992-2000**	**(3)** **2000-2014**	**(4)** **2000-2005**	**(5)** **2005-2010**	**(6)** **2010-2014**
			a. All municipalities			
$ln\, y_{it-\tau}$	-0.012***	-0.016***	-0.020***	-0.047***	-0.020***	-0.015***
	(0.001)	(0.005)	(0.001)	(0.003)	(0.004)	(0.003)
Obs.	2,234	2,234	2,193	2,193	2,116	2,045
R^2	0.166	0.056	0.342	0.318	0.089	0.061
			b. Municipalities in states along the U.S. border			
$ln\, y_{it-\tau}$	-0.017***	-0.028***	-0.022***	-0.051***	-0.060***	-0.044**
	(0.004)	(0.010)	(0.004)	(0.012)	(0.009)	(0.017)
Obs.	267	267	262	262	267	266
R^2	0.250	0.113	0.226	0.256	0.198	0.055
			c. Municipalities in non-U.S. border states			
$ln\, y_{it-\tau}$	-0.011***	-0.020***	-0.019***	-0.044***	-0.014***	-0.017***
	(0.001)	(0.006)	(0.001)	(0.003)	(0.004)	(0.003)
Obs.	1,967	1,967	1,931	1,931	1,849	1,779
R^2	0.154	0.052	0.307	0.274	0.056	0.089

Source: World Bank calculations.
Note: The table presents estimates of the parameter β in equation (4), weighted by municipal population at the initial year of each period under study. The dependent variable is the annualized growth rate in the mean per capita income of municipalities over the period. $ln\, y_{it-\tau}$ and public spending are for the initial year and are in log-scale and in real per capita terms at August 2014 prices. The coefficients for per capita public spending and the intercept are shown in tables 2–6 and 12–16 in the ancillary file. Robust standard errors are in parentheses.
*** $p < .01$, ** $p < .05$, * $p < .1$

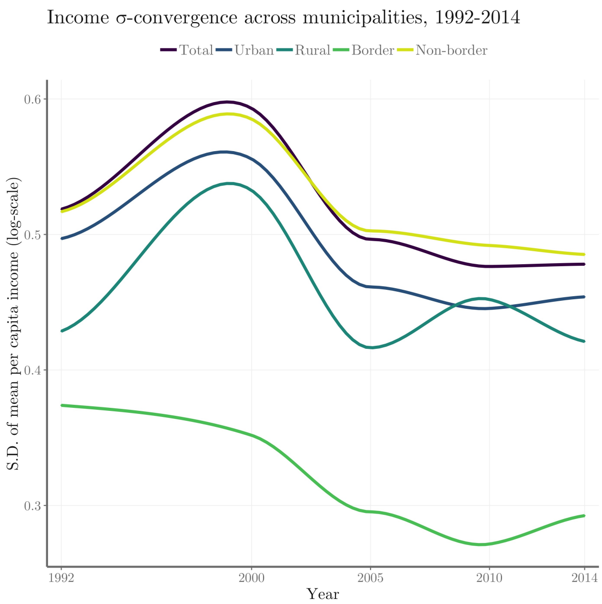
The difference in the speed of convergence between non–U.S. border municipalities (1.4 percent) and municipalities in border states (6.0 percent) over 2005–10 may also be explained by the following growth patterns. Income growth averaged almost 8 percent annually among the poorest 10 percent of municipalities in both groups, while it decreased among the top 10 percent. The difference lies in the magnitude of this loss: it averaged –1.6 percent annually in non–U.S. border municipalities, whereas it was –5.4 percent annually in border states. In this case, then, it seems that the United States–originated housing bubble, which unleashed the global financial crisis, had a strong regional bias, with disproportionate effects on those municipalities most

[11] As reference, growth in mean per capita income over 1992–2000 was positive in municipalities located in border states, with an annual rate of 0.3 percent, whereas it was negative among non–U.S. border municipalities: –0.9 percent.

integrated with the United States.[12] Similar growth patterns may also explain the difference in the speed of income convergence between the groups over 2010–14.

A salient outcome of the documented process of income β-convergence within the country is that it was quite effective in reducing regional disparities, in particular after 2000, which is consistent with empirical evidence of an overall decline of income inequality in the following years (Esquivel et al. 2010), and also confirmed by the analysis with our data, as shown later. Figure 3 shows the evolution of the standard deviation of logged mean per capita income across municipalities, or σ-convergence. Starting with the whole sample, after regional disparities increased sharply in the 1990s, they experienced a steep decline during the first five years of the 2000s and continued declining moderately up to 2010. Regional disparities remained relatively unchanged after that; yet, it is significant that, relative to 1992, income dispersion was almost 8 percent lower by 2014.

Figure 3: Regional disparities narrowed sharply over the 2000s



Source: World Bank calculations.

Similar results in terms of trends and orders of magnitude are evident across both urban and non–U.S. border municipalities, with declines in income dispersion of 8.6 percent and 6.1 percent, respectively, in 1992–2014. Two additional results are worth noting. First, income disparities in rural municipalities deteriorated slightly after the

[12]Indeed, growth rates in mean per capita income in municipalities located in states along the U.S. border averaged –0.1 percent annually, whereas their non–U.S. border counterparts recorded an annual average rate of 0.8 percent.

sharp decline in the first half of the 2000s, and, although the differences narrowed again after 2010, the level recorded in 2014 was virtually the same as the one in 1992. Second, the relatively high β-convergence coefficients across municipalities in border states seem to have reduced income dispersion along the U.S. border at a rate of 22 percent in 1992–2014.

5 Testing for poverty convergence

Have poorer, converging municipalities been able to translate their relative income gains into poverty reduction? If per capita income follows a log-normal distribution, then any change in the poverty headcount ratio is determined, in a magnitude η, by two components: one that is attributable to changes in income and one that is attributable to changes in the distribution of income. The relationship between each component and changes in poverty is illustrated in figure 4 over 1992–2014. As expected, those municipalities that experienced relatively higher rates of poverty reduction, according to the food poverty line, were those that experienced higher growth rates in mean per capita income (panel a), but also experienced progressive changes in the distribution of income (panel b), because such changes imply transferring resources from richer to poorer populations, thus stimulating poverty reduction.[13]

Focusing on the first component, for now, let

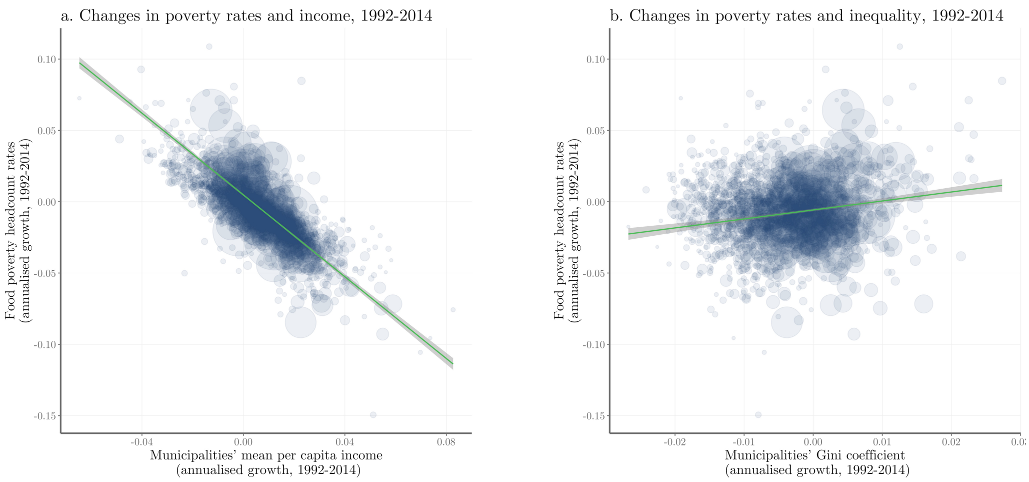
$$g_i\left(P_{it}\right) = \delta + \eta g_i\left(y_{it}\right) + \nu_{it} \tag{5}$$

be the partial elasticity of poverty to growth in the mean per capita income of municipalities, representing the percent change in the poverty headcount ratio as a result of a 1 percent increase in income, holding the income distribution constant. $g_i\left(P_{it}\right)$ is the annualized change in poverty rates, calculated as in (2); η is the elasticity parameter, with the expectation that $\eta < 0$; δ is a municipality-specific effect; and, ν_{it} is a stochastic term.[14]

[13]The bulk of the following analysis focuses on extreme poverty as measured by the food poverty line. This is deliberate because the narrative is consistent, and conclusions hold when using higher thresholds such as the capabilities and assets poverty lines.

[14]Similarly, $g_i\left(P_{it}\right) = \delta + \eta g_i\left(G_{it}\right) + \nu_{it}$ can represent the partial inequality elasticity of poverty or the percent change in the poverty headcount ratio as a result of a 1 percent increase in inequality, holding per capita income constant, with the expectation that $\eta > 0$, and with $g_i\left(G_{it}\right)$ as the annualized rate of change in inequality. The growth and inequality elasticity parameters can be denoted as η^y and η^G, respectively, and hence, under log normality, changes in poverty rates can be expressed as $g_i\left(P_{it}\right) \approx \eta^y g_i\left(y_{it}\right) + \eta^G g_i\left(G_{it}\right)$.

Figure 4: Changes in food poverty rates, inequality, and per capita income, 1992–2014



Source: World Bank calculations.
Note: The area of the symbols is proportional to the total population of the municipalities. The regression line has a slope of -1.42 in panel a and 0.63 in panel b (both significant at the 1 percent level).

Estimates of (5) confirm that higher growth rates in income tend to reduce poverty. In 1992–2014, for instance, a 1 percent growth rate in the mean per capita income of municipalities would lead to a 1.4 percent decline in the food poverty headcount ratio (table 5, panel a). The results also suggest that food poverty is more responsive to growth among both urban municipalities and those located in states along the U.S. border relative to their corresponding counterparts (panels b–e).

According to the data, such counterparts consistently exhibit higher food poverty rates over time: around 30 percent higher in rural municipalities than in urban ones, and twice the size in non–U.S. border municipalities than in those located in border states. Thus, food poverty tends to be more responsive to growth in municipalities where poverty rates are relatively lower, which fits well-known evidence that, under log normality, holding the income distribution constant, the growth elasticity will decrease in absolute value as the poverty rate rises (Bourguignon, 2003). In other words, poverty itself seems to act as a barrier to poverty reduction.[15]

Regardless of the context-specific magnitude of the growth elasticity parameter, the fact that growth in the mean per capita income of municipalities tends to reduce food poverty rates, plus the previous evidence of income convergence, imply that those municipalities with relatively high initial poverty headcount rates ($lnP_{it-\tau}$)

[15]These elasticities, in general, are also more responsive to growth, the lower the value of the poverty line. For instance, relative to the food poverty line, the elasticity almost invariably contracts by half in absolute value in the case of the assets poverty line (see table 33 in the ancillary file).

Table 5: Growth elasticities of food poverty reduction across municipalities, 1992–2014

	(1) 1992-2014	(2) 1992-2000	(3) 2000-2014	(4) 2000-2005	(5) 2005-2010	(6) 2010-2014
a. All municipalities						
$g_i(y_{it})$	−1.425***	−1.291***	−1.671***	−1.504***	−1.472***	−1.736***
	(0.089)	(0.072)	(0.083)	(0.114)	(0.082)	(0.077)
Obs.	2,361	2,361	2,361	2,361	2,361	2,361
R^2	0.535	0.411	0.517	0.432	0.427	0.549
b. Urban municipalities						
$g_i(y_{it})$	−1.513***	−1.348***	−1.736***	−1.620***	−1.457***	−1.751***
	(0.109)	(0.091)	(0.092)	(0.133)	(0.102)	(0.094)
Obs.	944	944	1,017	1,017	1,022	1,022
R^2	0.540	0.391	0.511	0.456	0.400	0.521
c. Rural municipalities						
$g_i(y_{it})$	−1.142***	−1.018***	−1.210***	−0.942***	−1.482***	−1.680***
	(0.041)	(0.052)	(0.150)	(0.060)	(0.067)	(0.111)
Obs.	1,417	1,417	1,344	1,344	1,339	1,339
R^2	0.599	0.488	0.580	0.312	0.540	0.686
d. Municipalities in states along the U.S. border						
$g_i(y_{it})$	−1.878***	−1.112**	−1.837***	−1.276***	−1.551***	−1.904***
	(0.308)	(0.531)	(0.166)	(0.371)	(0.255)	(0.175)
Obs.	267	267	267	267	267	267
R^2	0.501	0.127	0.600	0.201	0.339	0.660
e. Municipalities in non-U.S. border states						
$g_i(y_{it})$	−1.298***	−1.263***	−1.434***	−1.436***	−1.324***	−1.698***
	(0.065)	(0.077)	(0.095)	(0.143)	(0.074)	(0.092)
Obs.	2,094	2,094	2,094	2,094	2,094	2,094
R^2	0.587	0.464	0.453	0.435	0.450	0.516

Source: World Bank calculations.
Note: The table presents estimates of the parameter η in equation (5), weighted by municipal population at the initial year of each period under study. The dependent variable is the annualized growth in the food poverty headcount ratios of municipalities over the period. $g_i(y_{it})$ are the annualized changes in mean per capita income at the municipal level over the period at August 2014 prices. Urban (rural) municipalities are defined as those with more (fewer) than 15,000 inhabitants. The intercepts are shown in table 32 in the ancillary file. Robust standard errors are in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

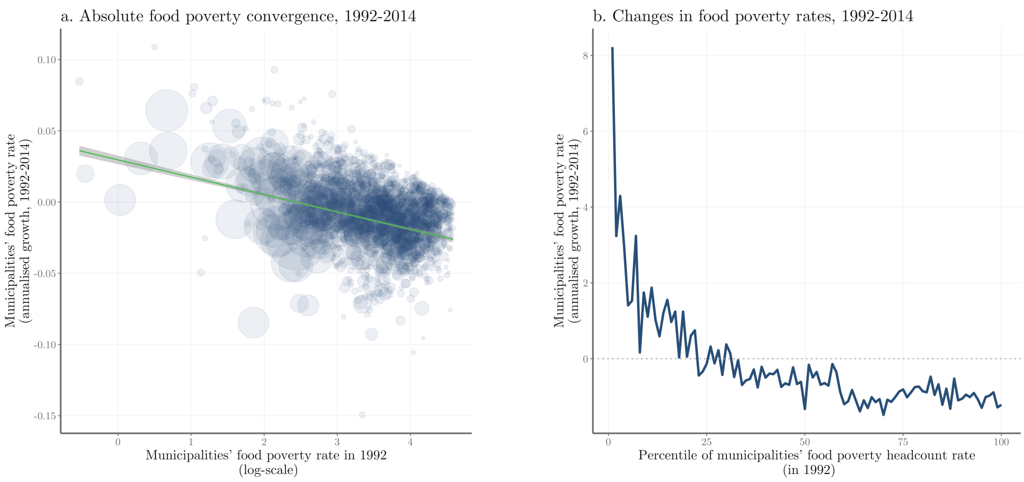
should have experienced higher subsequent rates of poverty reduction over the period under study. To test this, let

$$g_i(P_{it}) = \alpha + \beta ln\, P_{it-\tau} + \mu_{it} \tag{6}$$

be the empirical specification for the annualized proportionate change in poverty rates, or poverty convergence, where β is the speed of poverty convergence parameter.

Indeed, estimates of (6) suggest that poorer municipalities reduced their headcount ratios at a faster pace than richer and poverty increasing counterparts over 1992–2014. In fact, food poverty rates among the 20 percent of municipalities with the lowest incidence in 1992 recorded nontrivial increases by 2014 (figure 5). A closer look at subperiods reveals a positive sign of the poverty convergence parameter in the 1990s, indicating that poorer municipalities became poorer after the Tequila Crisis or, at least, that their poverty rates stagnated. Conversely, sizable signs of poverty convergence are found after 2000, in particular during 2000–05 (table 6, panel a). The breakdown by population size in panels b and c reveals that both urban and rural municipalities experienced poverty convergence, though poverty convergence in the latter occurred even in the 1990s and, in general, at a faster pace than in the former.

Figure 5: Convergence in food poverty rates, 1992–2014



Source: World Bank calculations.
Note: The area of the symbols in panel a is proportional to the total population of the municipalities. The regression line has a slope of –0.012 in panel a (significant at the 1 percent level).

Sizable poverty convergence in the 1990s also occurred across municipalities located in states along the U.S. border, whereas the opposite sign was found across non–U.S. border municipalities. After 2000, though convergence unambiguously occurred in both groups, those in border states exhibited a considerably higher coefficient during 2005–10 (table 6, panels d and e). The evidence presented in Section 4 above helps explain these results: poorer municipalities in border states were able to converge relatively more quickly in the 1990s and late-2000s because mean per capita

Table 6: Tests of food poverty convergence across municipalities, 1992–2014

	(1) 1992-2014	(2) 1992-2000	(3) 2000-2014	(4) 2000-2005	(5) 2005-2010	(6) 2010-2014
a. All municipalities						
$lnP_{it-\tau}$	−0.012***	0.014**	−0.031***	−0.055***	−0.038***	−0.048***
	(0.002)	(0.006)	(0.002)	(0.006)	(0.005)	(0.006)
Obs.	2,361	2,361	2,361	2,361	2,361	2,361
R^2	0.206	0.025	0.565	0.333	0.175	0.164
b. Urban municipalities						
$lnP_{it-\tau}$	−0.013***	0.014**	−0.031***	−0.057***	−0.038***	−0.044***
	(0.002)	(0.007)	(0.002)	(0.007)	(0.006)	(0.006)
Obs.	944	944	1,017	1,017	1,022	1,022
R^2	0.229	0.024	0.575	0.353	0.193	0.142
c. Rural municipalities						
$lnP_{it-\tau}$	−0.017***	−0.032***	−0.033***	−0.077***	−0.031***	−0.114***
	(0.001)	(0.007)	(0.006)	(0.015)	(0.007)	(0.009)
Obs.	1,417	1,417	1,344	1,344	1,339	1,339
R^2	0.192	0.064	0.375	0.276	0.031	0.426
d. Municipalities in states along the U.S. border						
$lnP_{it-\tau}$	−0.023***	−0.044***	−0.027***	−0.058***	−0.097***	−0.038*
	(0.004)	(0.008)	(0.004)	(0.011)	(0.013)	(0.023)
Obs.	267	267	267	267	267	267
R^2	0.375	0.185	0.281	0.194	0.392	0.031
e. Municipalities in non-U.S. border states						
$lnP_{it-\tau}$	−0.009***	0.019**	−0.028***	−0.053***	−0.020***	−0.055***
	(0.002)	(0.008)	(0.003)	(0.010)	(0.003)	(0.006)
Obs.	2,094	2,094	2,094	2,094	2,094	2,094
R^2	0.114	0.041	0.507	0.282	0.067	0.243

Source: World Bank calculations.
Note: The table presents estimates of the parameter β in equation (6), weighted by municipal population at the initial year of each period under study. The dependent variable is the annualized growth in the food poverty headcount ratios of municipalities over the period. $lnP_{it-\tau}$ are municipalities' initial poverty headcount ratio. All variables are in log-scale. Urban (rural) municipalities are defined as those with more (fewer) than 15,000 inhabitants. The intercepts are shown in table 34 in the ancillary file. Robust standard errors are in parentheses.
*** $p < .01$, ** $p < .05$, * $p < .1$

incomes in their richer counterparts were disproportionately affected by the economic contractions that characterized these years.

6 Initial distribution and the speed of poverty convergence

While poorer municipalities experienced poverty convergence for most of the period 1992-2014, little is known about the influence of the parameters of the initial distribution of income in shaping the speed of poverty convergence. Focusing on initial poverty, the analysis builds on Ravallion's (2012) decomposition of poverty convergence elasticity to explore how the initial poverty headcount ratios of municipalities might affect their advantage, given their poorer start, through two channels: the growth rates in mean per capita income and the impact of that growth on poverty reduction, as revealed by the partial elasticity of poverty to mean per capita income.

Starting with the first channel, the analysis estimates three augmented versions of the income β-convergence model in (4). In the first version, the annualized growth rates in mean per capita income depend on the initial per capita income of the municipalities, plus their initial food poverty headcount ratios:

$$g_i\left(y_{it}\right) = \alpha + \beta ln\, y_{it-\tau} + \gamma lnP_{it-\tau} + \mu_{it} \tag{7}$$

Estimates of the parameter γ reveal some adverse effects of initial poverty on income growth at any given initial mean, although the coefficient is sizable (–0.022) and significant at the 1 percent level only in the 1990s (table 7, panel a). An opposing result is shown in column 4, where the food poverty headcount ratio in 2000 exerted a positive effect (0.007) on growth in the subsequent five years. While this effect is small and significant only at the 10 percent level, it coincided with the more rapid expansion of CCTs across the poorest households located in the most marginalized municipalities.[16]

As initial poverty rates are not independent from other parameters of the distribution, the analysis added, as a third regressor in the second version of the model, the initial inequality in municipalities, measured by the Gini coefficient ($lnG_{it-\tau}$). The results now reveal a positive and significant, yet moderate effect of initial poverty rates on income growth during both 1992–2014 and 1992–2000 and a more sizable effect during 2000–05 (see table 7, panel b), which supports the plausible argument that initially poorer municipalities experienced higher subsequent growth in the mean per capita

[16]The coefficient over 2000–05 even increases for higher values of the poverty line: 0.014 and 0.041 in the case of, respectively, the capabilities and assets poverty lines. In both cases, the effects are statistically significant at the 1 percent level (see table 37 in the ancillary file).

Table 7: Growth in mean per capita income conditional on initial parameters, 1992–2014

	(1) 1992-2014	(2) 1992-2000	(3) 2000-2014	(4) 2000-2005	(5) 2005-2010	(6) 2010-2014
	a. Conditional on initial poverty					
$ln\, y_{it-\tau}$	−0.009***	−0.033***	−0.022***	−0.032***	−0.036***	−0.003
	(0.003)	(0.008)	(0.003)	(0.007)	(0.008)	(0.010)
$lnP_{it-\tau}$	−0.001	−0.022***	−0.002	0.007*	−0.010*	0.006
	(0.002)	(0.005)	(0.002)	(0.004)	(0.005)	(0.006)
Obs.	2,361	2,361	2,361	2,361	2,361	2,361
R^2	0.103	0.039	0.344	0.318	0.084	0.024
	b. Conditional on initial poverty and inequality					
$ln\, y_{it-\tau}$	0.005	0.014*	−0.014***	−0.000	−0.022**	0.003
	(0.003)	(0.008)	(0.004)	(0.008)	(0.010)	(0.013)
$lnP_{it-\tau}$	0.008***	0.009**	0.002	0.021***	−0.002	0.009
	(0.002)	(0.005)	(0.002)	(0.004)	(0.007)	(0.008)
$lnG_{it-\tau}$	−0.045***	−0.155***	−0.031***	−0.130***	−0.058***	−0.016
	(0.005)	(0.015)	(0.011)	(0.026)	(0.017)	(0.024)
Obs.	2,361	2,361	2,361	2,361	2,361	2,361
R^2	0.222	0.170	0.363	0.379	0.098	0.025
	c. Conditional on initial poverty and inequality and extra controls					
$ln\, y_{it-\tau}$	–	–	−0.003	−0.004	−0.021**	0.003
	–	–	(0.004)	(0.010)	(0.009)	(0.014)
$lnP_{it-\tau}$	–	–	0.016***	0.035***	0.007	0.015
	–	–	(0.003)	(0.007)	(0.006)	(0.010)
$lnG_{it-\tau}$	–	–	−0.038***	−0.112***	−0.054***	−0.031
	–	–	(0.006)	(0.016)	(0.014)	(0.025)
Public sector payroll	–	–	0.007***	0.011***	0.007***	0.012***
	–	–	(0.001)	(0.003)	(0.003)	(0.004)
Public investment	–	–	−0.000	0.000	−0.003*	−0.000
	–	–	(0.000)	(0.001)	(0.002)	(0.003)
Public transfers/subsidies	–	–	−0.001	0.000	−0.008***	0.007**
	–	–	(0.001)	(0.002)	(0.001)	(0.003)
Growth in CCT coverage	–	–	0.033***	0.059***	−0.019	−0.062**
	–	–	(0.011)	(0.015)	(0.025)	(0.025)
Obs.	–	–	1,793	1,793	1,910	2000
R^2	–	–	0.440	0.403	0.234	0.075

Source: World Bank calculations.
Note: The table presents the estimates of equation (7) and extensions, weighted by municipal population at the initial year of each period under study. The dependent variable is the annualized growth rate in the mean per capita income of municipalities over the period. $ln\, y_{it-\tau}$, $lnP_{it-\tau}$, $lnG_{it-\tau}$, and all public expenditure variables are for the initial year and are in log-scale. All monetary variables are in real per capita terms at August 2014 prices. The growth rate in CCT coverage is the annualized growth rate in the number of beneficiary families in each municipality over the period. The empty cells in panel c indicate that models conditional on CCT data were not estimated because the data are available only from 2000 onward. The intercepts are shown in tables 37–40 in the ancillary file. Robust standard errors are in parentheses.
*** $p < .01$, ** $p < .05$, * $p < .1$

income as a result of the expansion in CCTs among the poorest. In the rest of the subperiods, the coefficients are statistically indistinguishable from zero.

To investigate these results further, the analysis tested the previous augmented model by adding extra controls for concepts of either public spending or revenues and with and without CCT data. Invariably, the story holds under different specifications: the positive and significant effects of initial food poverty headcount ratios on income growth are found over 2000–14, in particular during the expansion of CCT coverage in 2000–05.[17] One such specification is shown in table 7, panel c, in which the point estimates for the annualized growth rate in the number of beneficiary families exhibit positive and significant effects in the first years of the program's expansion, consistent with the findings in the conditional income β-convergence model above.

The second channel, that is, the growth elasticity of poverty reduction, can be analyzed through a variation of equation (5) by regressing $g_i(P_{it})$ on the growth rate in mean per capita income interacted with the initial poverty headcount ratios. This adjusted rate is given by the growth rate in municipality's mean per capita income, multiplied by 1 minus the municipality's initial poverty headcount ratio ($P_{it-\tau}$), which penalizes more the sensitivity of food poverty to subsequent growth rates in municipalities starting out relatively poorer. The poverty-adjusted growth elasticity of poverty reduction is then defined as follows:

$$g_i(P_{it}) = \eta(1 - P_{it-\tau})\, g_i(y_{it}) + \nu_{it} \tag{8}$$

The estimates for the whole sample of municipalities are shown in table 8 (panel a). Notice that they increased in absolute value in all periods relative to the ordinary elasticities in table 5. To illustrate the implications of the poverty-adjusted elasticity, consider, for instance, the value of –1.983 in 1992–2014. If a municipality's initial food poverty rate is 10 percent and the municipality experiences a 4 percent annual growth rate in mean per capita income, then that municipality would expect an annual poverty reduction of 7.1 percent. If, instead, initial poverty stands at 70.0 percent, and the annual income growth rate is again 4 percent, then the municipality would expect a poverty reduction of only 2.4 percent annually. Then, as in the previous section, poverty tends to be less responsive to growth, or the elasticity declines in absolute value, the higher the initial poverty rate.

However, the estimates reveal that poverty-adjusted elasticities are consistently higher in absolute value in poorer municipalities than in richer counterparts. For instance, at

[17] The various specifications of this augmented model are shown in tables 37–44 of the ancillary file.

an initial food poverty rate of 63 percent or more, at or above one standard deviation above the mean, a 1 percent increase in growth during 1992–2014 would lead to an annual decline in the poverty rate of almost 3.4 percent, whereas, in municipalities with initial food poverty at 20.0 percent or less, at or below one standard deviation below the mean, the elasticity is roughly −2 (table 8, panels b and c, column 1).

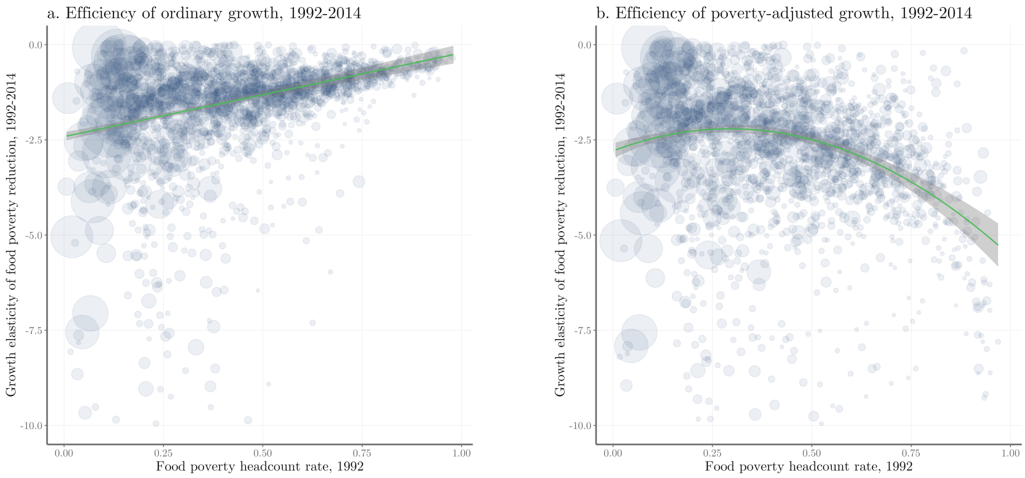
Table 8: Poverty-adjusted growth elasticities, 1992–2014

	(1) 1992-2014	**(2) 1992-2000**	**(3) 2000-2014**	**(4) 2000-2005**	**(5) 2005-2010**	**(6) 2010-2014**
			a. All municipalities			
$(1-P_{it-\tau})\,g_i\,(y_{it})$	−1.983***	−1.885***	−2.288***	−2.280***	−1.874***	−1.990***
	(0.151)	(0.135)	(0.163)	(0.195)	(0.118)	(0.116)
Obs.	2,361	2,361	2,361	2,361	2,361	2,361
R^2	0.499	0.421	0.453	0.489	0.432	0.451
	b. Municipalities with relatively low initial food poverty rates					
$(1-P_{it-\tau})\,g_i\,(y_{it})$	−1.984***	−1.756***	−1.870***	−2.247***	−1.337***	−2.182***
	(0.233)	(0.233)	(0.167)	(0.249)	(0.170)	(0.155)
Obs.	426	426	436	436	383	440
R^2	0.486	0.293	0.365	0.423	0.277	0.601
	c. Municipalities with relatively high initial food poverty rates					
$(1-P_{it-\tau})\,g_i\,(y_{it})$	−3.387***	−2.863***	−2.872***	−3.911***	−2.444***	−3.082***
	(0.124)	(0.242)	(0.142)	(0.264)	(0.106)	(0.095)
Obs.	433	433	458	458	425	457
R^2	0.882	0.785	0.596	0.621	0.828	0.881

Source: World Bank calculations.
Note: The table presents estimates of the parameter η in equation (8), weighted by municipal population at the initial year of each period under study. The dependent variable is the annualized growth in the food poverty headcount ratios of municipalities over the period. $(1-P_{it-\tau})\,g_i\,(y_{it})$ are the annualized changes in mean per capita income at the municipal level over the period at August 2014 prices, adjusted by municipalities' initial food poverty headcount ratio. Municipalities with low (high) initial food poverty rates are those with headcount ratios one standard deviation below (above) the mean headcount ratios for the whole sample. The intercepts are shown in table 45 in the ancillary file. Robust standard errors are in parentheses.
*** $p < .01$, ** $p < .05$, * $p < .1$

Hence, contrary to the linear relationship by which the ordinary growth elasticity of poverty reduction falls in absolute value as poverty rates rise, it can be readily verified that the poverty-adjusted growth elasticity follows a concave relationship with poverty (figure 6). In other words, those municipalities with very high levels of food poverty in 1992 experienced sufficiently higher subsequent growth in mean per capita income to achieve substantial rates of poverty reduction by 2014, which unambiguously occurred (see figure 5, panel b), at least as substantial as in contexts of low poverty and relatively high income growth. A salient result is observed during the first five years of the 2000s. Coinciding with the expansion of the CCT program, a 1 percent increase in the poverty-adjusted growth rate would lead to a 3.9 percent reduction in food poverty headcount ratios among the poorest municipalities, while the corresponding poverty reduction among less poor counterparts would be only 2.2 percent (see table 8, panels b and c, column 4).

Figure 6: Efficiency of growth in reducing food poverty, by initial poverty rates, 1992–2014



Source: World Bank calculations.
Note: The area of the symbols is proportional to the total population of municipalities. For visibility purposes, the elasticities in both panels are capped at −10.

To understand how the extent of poverty convergence was shaped by the initial food poverty rates of municipalities, the analysis exploited all previous evidence computed for each channel to apply Ravallion's (2012) decomposition of poverty convergence elasticity. This decomposition results from the derivative of equations (7) and (8) as

$$\frac{\partial g_i\left(P_{it}\right)}{\partial lnP_{it-\tau}} = \eta\beta\left(1-P_{it-\tau}\right)\left[\frac{\partial lnP_{it-\tau}}{\partial lny_{it-\tau}}\right]^{-1} + \eta\gamma\left(1-P_{it-\tau}\right) - \eta g_i\left(y_{it}\right)P_{it-\tau} \qquad (9)$$

where $\frac{\partial g_i(P_{it})}{\partial lnP_{it-\tau}}$ is the speed of food poverty convergence, equivalent to the parameter β in (6); the first element at the right-hand side of the equation is the mean convergence effect; the second element, $\eta\gamma\left(1-P_{it-\tau}\right)$, is the effect of initial poverty; and the third element, $\eta g_i\left(y_{it}\right)P_{it-\tau}$, represents the poverty elasticity effect. Based on the estimates of η in table 8; the parameters β and γ in table 7; the ordinary elasticities of municipalities' initial food poverty with respect to their initial mean per capita income $\left(\frac{\partial lnP_{it-\tau}}{\partial lny_{it-\tau}}\right)$[18]; and, the sample means of $P_{it-\tau}$ and $g_i\left(y_{it}\right)$, the computation of (9) yields virtually the same food poverty convergence rates calculated above (see table 6, panel a).

For instance, the poverty convergence rate calculated based on (9) is -0.011 during 1992–2014, which is very close to the coefficient of -0.012 computed based on equation (6) for the same period. The decomposition of that rate reveals that the convergence effect accounted for -0.007 and that poverty was actually responsive to growth, with a poverty elasticity effect of -0.005. By contrast, the initial poverty rates of municipalities exerted an adverse, yet moderate effect of 0.001. In the 1990s only, unsurprisingly, a convergence effect of -0.024 was more than offset by both the initial poverty effect (0.024) and the poverty elasticity (0.015) effect, thus confirming the significant poverty divergence of 0.014 found in those years. Meanwhile, in 2000–14, both convergence and poverty elasticity effects explain in similar magnitudes (-0.016 and -0.020, respectively) the totality of the speed of poverty convergence (-0.034), with only a slightly adverse effect of initial poverty, at 0.002. These results confirm that the process of income convergence and the efficiency of growth in reducing poverty effectively translated into poverty convergence during 1992–2014 in general, but particularly after 2000.

Focusing on the first five years of the 2000s, probably the most revealing period under study, the decomposition offers a remarkable result: the three effects moved in the same favorable direction. The convergence rate of -0.055 was mostly explained, again in similar magnitudes, by the convergence effect (-0.024) and the poverty elasticity effect (-0.022). But, saliently, the initial poverty rates of municipalities also contributed an effect of -0.009, equivalent to 16 percent of the speed of poverty convergence. This result supports the evidence in tables 7 and 8 for this period, which suggest plausibly that starting out (very) poor in 2000 was associated with high growth rates in mean per capita income in the next five years. In a context of disappointing economic growth, such high rates could have been the result of the explosive expansion of cash transfers among the extreme poor and of social spending in general, potentially having the double effect of bolstering per capita incomes enough to have reduced food poverty, while fostering progressive changes in the distribution, which, in turn, may promote poverty reduction (see figure 4, panel b).

To shed some light on the latter issue, the analysis also explored the role of inequality. Initial inequality in municipalities tends to exert sizable and significant adverse effects

[18] The computation of these elasticities through ordinary least squares yields -1.505 in 1992, -1.662 in 2000, -1.664 in 2005, and -1.553 in 2010.

on subsequent growth rates in mean per capita income (see table 7). This is consistent with a large body of empirical literature on growth. Moreover, the data also reveal that initial inequality tends to curb the impact that growth in mean per capita income has on food poverty reduction, thus aligning with cross-country empirical evidence that wide inequality causes the poor to accrue a smaller share of the gains from growth in income. For instance, in those municipalities with a Gini coefficient at or below one standard deviation below the mean in 1992 (equivalent to 0.37 or less), a 1 percent growth in mean per capita income over 1992–2014 would lead to a decline in food poverty of roughly 2 percent annually. In contrast, in those municipalities with an initial Gini of 0.48 or more, at or above one standard deviation above the mean, the poverty reduction would occur at 1.07 percent a year (table 9, panel a, column 1).

This tendency of food poverty to be less responsive to growth in more unequal municipalities is confirmed in all subperiods, and it generally holds when growth rates in mean per capita income are adjusted by initial poverty (table 9, panel b) or even by initial inequality (table 9, panel c) as

$$g_i\left(P_{it}\right) = \eta\left(1 - G_{it-\tau}\right) g_i\left(y_{it}\right) + \nu_{it} \tag{10}$$

which yields a distribution-corrected growth elasticity of poverty, as proposed by Ravallion (1997), where $G_{it-\tau}$ is the initial Gini coefficient.

A closer examination of the data, however, suggests that the relationship between initial inequality and the efficiency of growth in reducing poverty in a country with dramatic regional disparities is far from linear. The nonlinearity is confirmed in figure 7. Even when growth elasticities are computed using the ordinary growth rate, there is a dim indication that food poverty rates over 1992–2014 were more responsive to growth in some highly unequal municipalities than in low-inequality counterparts (figure 7, panel a). This indication becomes clearer after penalizing more the income growth rates in municipalities with relatively higher Gini coefficients in 1992 (figure 7, panel b). Sizable changes in mean per capita income and (hence) in food poverty rates thus occurred not only among the poorest municipalities, as documented above, but also among municipalities with relatively high initial inequality.

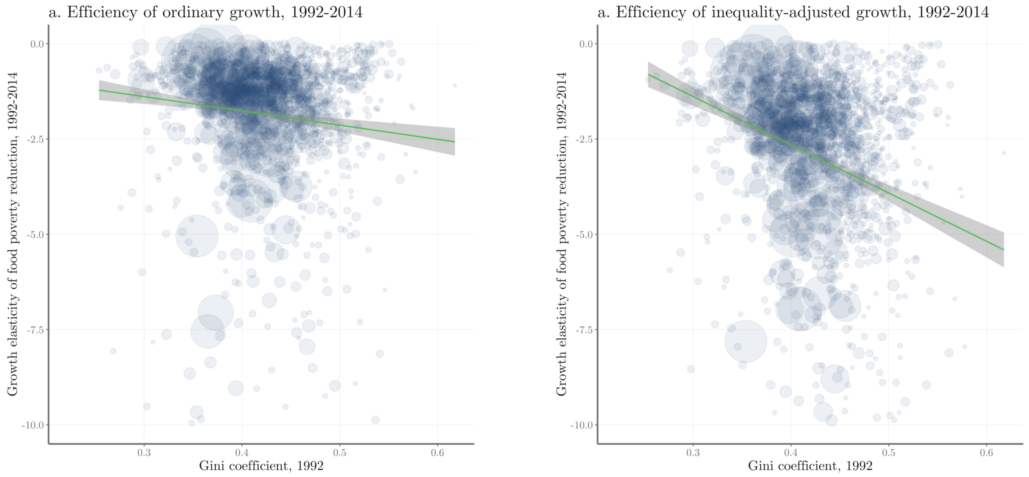
Indeed, the distribution of municipalities according to their Gini coefficient in 1992 reveals that poverty reduction tended to be slightly higher among the top 40 percent more unequal municipalities (figure 8, panel a). Inequality among the latter also declined markedly over 1992–2014, which suggests that the magnitude of food poverty

Table 9: Growth elasticities of poverty in low and high inequality contexts, 1992–2014

	(1) 1992-2014	(2) 1992-2000	(3) 2000-2014	(4) 2000-2005	(5) 2005-2010	(6) 2010-2014
a. Ordinary growth elasticities						
Municipalities with relatively low initial inequality						
$g_i(y_{it})$	-2.015^{***}	-1.569^{***}	-1.779^{***}	-1.738^{***}	-1.673^{***}	-2.261^{***}
	(0.143)	(0.158)	(0.273)	(0.417)	(0.096)	(0.292)
Obs.	370	370	313	313	371	336
R^2	0.734	0.414	0.693	0.400	0.541	0.659
Municipalities with relatively high initial inequality						
$g_i(y_{it})$	-1.069^{***}	-0.924^{***}	-1.241^{***}	-1.184^{***}	-1.662^{***}	-1.613^{***}
	(0.050)	(0.073)	(0.239)	(0.273)	(0.214)	(0.141)
Obs.	364	364	344	344	342	364
R^2	0.769	0.508	0.359	0.329	0.496	0.584
b. Poverty-adjusted growth elasticities						
Municipalities with relatively low initial inequality						
$(1-P_{it-\tau})\, g_i(y_{it})$	-2.588^{***}	-2.357^{***}	-1.561^{***}	-3.904^{***}	-3.019^{***}	-2.561^{***}
	(0.191)	(0.335)	(0.879)	(1.265)	(0.190)	(0.397)
Obs.	370	370	313	313	371	336
R^2	0.636	0.434	0.305	0.264	0.584	0.533
Municipalities with relatively high initial inequality						
$(1-P_{it-\tau})\, g_i(y_{it})$	-1.676^{***}	-1.468^{***}	-1.829^{***}	-1.875^{***}	-2.611^{***}	-2.045^{***}
	(0.062)	(0.104)	(0.420)	(0.352)	(0.339)	(0.253)
Obs.	364	364	344	344	342	364
R^2	0.785	0.497	0.400	0.396	0.525	0.519
c. Distribution-corrected growth elasticities						
Municipalities with relatively low initial inequality						
$(1-G_{it-\tau})\, g_i(y_{it})$	-3.042^{***}	-2.336^{***}	-2.383^{***}	-2.418^{***}	-2.403^{***}	-3.149^{***}
	(0.221)	(0.249)	(0.375)	(0.590)	(0.137)	(0.415)
Obs.	370	370	313	313	371	336
R^2	0.717	0.401	0.678	0.395	0.542	0.656
Municipalities with relatively high initial inequality						
$(1-G_{it-\tau})\, g_i(y_{it})$	-2.191^{***}	-1.905^{***}	-2.362^{***}	-2.301^{***}	-3.051^{***}	-2.709^{***}
	(0.106)	(0.154)	(0.452)	(0.518)	(0.385)	(0.236)
Obs.	364	364	344	344	342	364
R^2	0.769	0.515	0.367	0.339	0.479	0.579

Source: World Bank calculations.
Note: The table presents estimates of the parameter η in equations (5), (8) and (10), weighted by municipal population at the initial year of each period under study. The dependent variable is the annualized growth in the food poverty headcount ratios of municipalities over the period. The growth rates in mean per capita income are the annualized changes at the municipal level over the period at August 2014 prices. Municipalities with low (high) initial inequality are those with Gini coefficients at or below (at or above) one standard deviation below (above) the mean Gini coefficient for the whole sample. The intercepts are shown in table 48 in the ancillary file. Robust standard errors are in parentheses.
*** $p < .01$, ** $p < .05$, * $p < .1$

Figure 7: Efficiency of growth in reducing food poverty, by initial inequality levels; 1992–2014



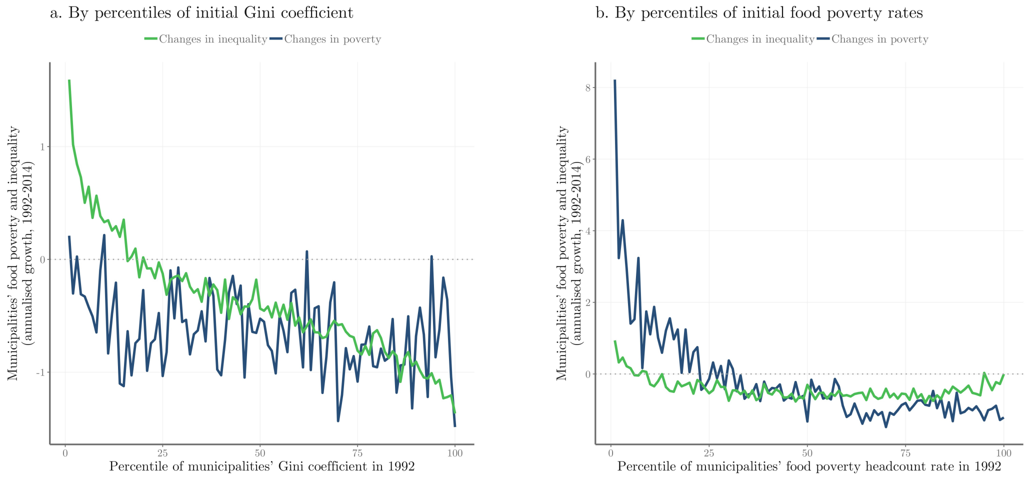
Source: World Bank calculations.
Note: The areas of the symbols are proportional to the total population of the municipalities. For visibility purposes, the elasticities in both panels are capped at -10.

reduction observed among poorer municipalities was not the result of income gains only, but also of progressive changes. It also suggests a plausible process of inequality convergence across municipalities, which is confirmed by a coefficient of -0.04 during 1992–2014 (significant at the 1 percent level) that results from the standard model for the annualized proportionate change in inequality, as in equations (3) or (6).[19] In addition, it can be confirmed that, in the majority of the initially poorest municipalities where subsequent food poverty reduction took place, the latter was accompanied by a decline in the Gini coefficient (figure 8, panel b).

These results seem to suggest that, in general, inequality in the country declined over the period under study, which is confirmed by a population-weighted average reduction of -0.8 Gini points during 1992–2014. This reduction, however, was far from generalized across municipalities. About 71 percent of all municipalities, which account for almost half of the country's population, experienced a decline in inequality above the national average, reaching -5.3 Gini points, and slightly more than 4 percent of municipalities also improved their inequality level, though at a lower rate than the national figure, reaching only -0.4 Gini points. The remaining 25 percent of municipalities, which are home to the other half of the country's population, experienced a deterioration in inequality of around 3.4 Gini points, on average. Despite the

[19]The magnitude and significance of the inequality convergence parameter are robust to the specification that regress the annualized absolute difference in inequality levels on the initial Gini coefficient, as in Bénabou (1996).

Figure 8: Annualized rates of change in food poverty and inequality, 1992–2014



Source: World Bank calculations.

last result, which is basically a reflection of the rebound of inequality in the country after 2010, this highlights that the vast majority of municipalities experienced, in general, progressive changes in their income distribution and that this occurred over most of the last quarter century: the population-weighted national average shows a decline of -1.2 and -4.1 Gini points in the 1990s and in the first decade of the 2000s, respectively.

7 Summing up

Between 1992 and 2014, Mexico experienced relative stagnation in both economic growth and poverty reduction. These aggregate numbers leave the impression that little has changed in the living standards of the population. This paper explores how taking a more disaggregated approach to measuring changes in living standards can help to better unpack this picture. By analyzing income per capita convergence and poverty convergence at the municipality-level over different subperiods, this paper finds that key changes in living standards have indeed taken place. In particular, the analysis reveals the following three main findings related to income convergence, poverty convergence, and the role of the initial distribution of income.

First, in terms of income convergence, this paper finds that mean per capita income grew consistently more quickly in the poorest municipalities than in richer counterparts. This confirms that, in general, convergence occurred in a sizable and significant magnitude; however, the speed of income convergence was more rapid after 2000 and heterogeneous between urban and rural municipalities and between those located in the north of the country and the rest. Second, in terms of poverty convergence, this paper finds that growth in mean per capita income among poorer, converging municipalities was relatively efficient in reducing poverty headcount ratios. This suggests that the process of income convergence effectively translated into an unambiguous process of poverty convergence. Third, in terms of the role of the initial distribution of income in determining convergence processes, this paper finds that the growth of income among the poorest in a context of stagnant or disappointing overall economic growth promoted sizable reductions in food poverty rates, whereas declining inequality —and inequality convergence— eventually made growth rates more efficient in reducing subsequent poverty rates in the less advantaged municipalities.

From a policy perspective, redistributive programs such as the accelerated expansion of cash transfers and the improved federal allocations to municipalities, in particular, had a positive impact on both income convergence and poverty convergence. Apparently, increasing transfers had the double effect of bolstering sufficiently high growth rates in income among the poorest, while fostering progressive changes in the distribution of income. While these results are good news from an egalitarian perspective, it is noticeable that the convergence processes partially took place because richer municipalities were losing ground or standing still at best. While this gives less cause for celebration, all subnational changes analyzed in this paper highlight, in general, that the poorest regions in Mexico have been able to achieve development gains even in the face of nontrivial economic crises that could have seriously undermined equity within the country.

References

Aghion, P. and P. Bolton (1997). A Theory of Trickle-Down Growth and Development. *The Review of Economic Studies 64*(2), 151–172.

Alderman, H., M. Babita, G. Demombynes, N. Makhatha, and B. Özler (2002). How Low Can You Go? Combining Census and Survey Data for Mapping Poverty in South Africa. *Journal of African Economies 11*(2), 169–200.

Alesina, A. and D. Rodrik (1994). Distributive Politics and Economic Growth. *The Quarterly Journal of Economics 109*(2), 465–490.

Banerjee, A. V. and E. Duflo (2003). Inequality and Growth: What Can the Data Say? *Journal of Economic Growth 8*(3), 267–299.

Barro, R. J. and X. Sala-i Martin (1991). Convergence across States and Regions. *Brookings Papers on Economic Activity 22*(1), 107–182.

Barro, R. J. and X. Sala-i Martin (1992). Convergence. *Journal of Political Economy 100*(2), 223–251.

Barro, R. J. and X. Sala-i Martin (1995). *Economic Growth*. Cambridge, MA: The MIT Press.

Baumol, W. J. (1986). Productivity Growth, Convergence, and Welfare: What the Long-Run Data Show. *The American Economic Review 76*(5), 1072–1085.

Bedi, T., A. Coudouel, and K. Simler (2007). *More than a Pretty Picture: Using Poverty Maps to Design Better Policies and Interventions*. Washington DC: World Bank Publications.

Bénabou, R. (1996). Inequality and Growth. In B. S. Bernanke and J. J. Rotemberg (Eds.), *NBER Macroeconomics Annual 1996*, Volume 11. London: The MIT Press.

Bourguignon, F. (2003). The Growth Elasticity of Poverty Reduction: Explaining Heterogeneity Across Countries and Time Periods. In T. S. Eicher and S. J. Turnovsky (Eds.), *Inequality and Growth, Theory and Policy Implications*. Cambridge, MA: The MIT Press.

Chiquiar, D. (2005). Why Mexico's Regional Income Convergence Broke Down. *Journal of Development Economics 77*(1), 257–275.

Clarke, G. R. G. (1995). More Evidence on Income Distribution and Growth. *Journal of Development Economics 47*(2), 403–427.

Cuaresma, J. C., S. Klasen, and K. M. Wacker (2017). Is There Poverty Convergence? Discussion paper 1711, Gutenberg School of Management and Economics, Mainz.

Deininger, K. and L. Squire (1998). New Ways of Looking at Old Issues: Inequality and Growth. *Journal of Development Economics 57*(2), 259–287.

Dollar, D., T. Kleineberg, and A. Kraay (2016). Growth Still is Good for the Poor. *European Economic Review 81*, 68–85.

Dollar, D. and A. Kraay (2002). Growth is Good for the Poor. *Journal of Economic Growth 7*(3), 195–225.

Durlauf, S. N. (1996). A Theory of Persistent Income Inequality. *Journal of Economic Growth 1*(1), 75–93.

Durlauf, S. N. and P. A. Johnson (1995). Multiple Regimes and Cross-country Growth Behaviour. *Journal of Applied Econometrics 10*(4), 365–384.

Elbers, C., J. O. Lanjouw, and P. Lanjouw (2003). Micro-Level Estimation of Poverty and Inequality. *Econometrica 71*(1), 355–364.

Enamorado, T., L. F. López-Calva, C. Rodríguez-Castelán, and H. Winkler (2016). Income Inequality and Violent Crime: Evidence from Mexico's Drug War. *Journal of Development Economics 120*, 128–143.

Esquivel, G. (1999). Convergencia Regional en México, 1940-1995. *El Trimestre Económico 66*(264(4)), 725–761.

Esquivel, G., N. Lustig, and J. Scott (2010). Mexico: A Decade of Falling Inequality: Market Forces or State Action? In L. F. López-Calva and N. Lustig (Eds.), *Declining Inequality in Latin America: A Decade of Progress?*, A Decade of Progress?, pp. 175–217. Brookings Institution Press.

Ferreira, F. H. G. and M. Ravallion (2011). Poverty and Inequality: The Global Context. In B. Nolan, W. Salverda, and T. M. Smeeding (Eds.), *The Oxford Handbook of Economic Inequality*. Oxford: Oxford University Press.

Foster, J., J. Greer, and E. Thorbecke (1984). A Class of Decomposable Poverty Measures. *Econometrica 52*(3), 761–766.

Foster, J. E. and M. Székely (2008). Is Economic Growth Good for the Poor? Tracking Low Incomes Using General Means. *International Economic Review 49*(4), 1143–1172.

Fosu, A. K. (2017). Growth, Inequality, and Poverty Reduction in Developing Countries: Recent Global Evidence. *Research in Economics 71*(2), 306–336.

Galor, O. (1996). Convergence? Inferences from Theoretical Models. *The Economic Journal 106*(437), 1056–1069.

Galor, O. and J. Zeira (1993). Income Distribution and Macroeconomics. *The Review of Economic Studies 60*(1), 35–52.

García-Verdú, R. (2005). Income, Mortality, and Literacy Distribution Dynamics Across States in Mexico: 1940-2000. *Cuadernos de Economía 42*(125), 165–192.

Grimm, M. (2007). Removing the Anonymity Axiom in Assessing Pro-poor Growth. *The Journal of Economic Inequality 5*(2), 179–197.

Hoff, K. (1996). Market Failures and the Distribution of Wealth: A Perspective from the Economics of Information. *Politics & Society 24*(4), 411–432.

Knowles, S. (2005). Inequality and Economic Growth: The Empirical Relationship Reconsidered in the Light of Comparable Data. *The Journal of Development Studies 41*(1), 135–159.

Kraay, A. (2006). When is Growth Pro-poor? Evidence from a Panel of Countries. *Journal of Development Economics 80*(1), 198–227.

Lin, P.-C. and H.-C. R. Huang (2011). Inequality Convergence in a Panel of States. *The Journal of Economic Inequality 9*(2), 195–206.

Ljungqvist, L. (1993). Economic Underdevelopment: The Case of a Missing Market for Human Capital. *Journal of Development Economics 40*(2), 219–239.

Lopez, J. H. and L. Servén (2006). A Normal Relationship? Poverty, Growth, and Inequality. Policy Research Working Paper 3814, World Bank, Washington, D.C.

López-Calva, L. F., Á. Meléndez, E. G. Rascón, L. Rodríguez-Chamussy, and M. Székely (2008). El ingreso de los hogares en el mapa de México. *El Trimestre Económico LXXV (4)*(300), 843–896.

Lustig, N., L. F. López-Calva, and E. Ortiz-Juarez (2016). Deconstructing the Decline in Inequality in Latin America. In K. Basu and J. Stiglitz (Eds.), *Inequality and Growth: Patterns and Policy. Volume II: Regions and Regularities.* New York: Palgrave Macmillan.

Persson, T. and G. Tabellini (1994). Is Inequality Harmful for Growth? *The American Economic Review 84*(3), 600–621.

Piketty, T. (1997). The Dynamics of the Wealth Distribution and the Interest Rate with Credit Rationing. *The Review of Economic Studies 64*(2), 173–189.

Quah, D. T. (1993). Galton's Fallacy and Tests of the Convergence Hypothesis. *The Scandinavian Journal of Economics 95*(4), 427–443.

Quah, D. T. (1996). Convergence Empirics across Economies with (Some) Capital Mobility. *Journal of Economic Growth 1*(1), 95–124.

Quah, D. T. (1997). Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs. *Journal of Economic Growth 2*(1), 27–59.

Ravallion, M. (1995). Growth and Poverty: Evidence for Developing Countries in the 1980s. *Economics Letters 48*(3-4), 411–417.

Ravallion, M. (1997). Can High-inequality Developing Countries Escape Absolute Poverty? *Economics Letters 56*(1), 51–57.

Ravallion, M. (1998). Does Aggregation Hide the Harmful Effects of Inequality on Growth? *Economics Letters 61*(1), 73–77.

Ravallion, M. (2001). Growth, Inequality and Poverty: Looking Beyond Averages. *World Development 29*(11), 1803–1815.

Ravallion, M. (2003). Inequality Convergence. *Economics Letters 80*(3), 351–356.

Ravallion, M. (2004). *Pro-Poor Growth: A Primer.* Policy Research Working Paper, World Bank. Washington, DC.

Ravallion, M. (2007). Inequality IS Bad for the Poor. In J. Micklewright and S. P. Jenkins (Eds.), *Inequality and Poverty Re-Examined.* Oxford: Oxford University Press.

Ravallion, M. (2012). Why Don't We See Poverty Convergence? *American Economic Review 102*(1), 504–523.

Rodríguez-Castelán, C., K. Cadena, and L. Moreno (2017). Evaluacion de largo plazo de los impactos distributivos del Fondo de Infraestructura Social Municipal (FISM). Technical Report, Banco Mundial, Washington, DC.

Rodríguez-Oreggia, E. (2007). Winners and Losers of Regional Growth in Mexico and their Dynamics. *Investigación Económica LXVI*(259), 43–62.

Rodríguez-Pose, A. and J. Sánchez-Reaza (2005). Economic Polarization Through Trade: Trade Liberalization and Regional Growth in Mexico. In R. Kanbur and A. J. Venables (Eds.), *Spatial Inequality and Development*. New York: Oxford University Press.

Sala-i Martin, X. (1996). Regional Cohesion: Evidence and Theories of Regional Growth and Convergence. *European Economic Review 40*(6), 1325–1352.

Sala-i Martin, X. (2006). The World Distribution of Income: Falling Poverty and... Convergence, Period. *The Quarterly Journal of Economics 121*(2), 351–397.

Su, J.-J. (2003). Convergence Clubs among 15 OECD Countries. *Applied Economics Letters 10*(2), 113–118.

Székely, M., L. F. López-Calva, Á. Meléndez Martínez, E. G. Rascón, and L. Rodríguez-Chamussy (2007). Poniendo a la pobreza de ingresos y a la desigualdad en el mapa de México. *Economía Mexicana. Nueva Época XVI*(2), 239–303.

Villalobos Barría, C., S. Klasen, and S. Vollmer (2016). The Distribution Dynamics of Human Development in Mexico 1990–2010. *Review of Income and Wealth 62*(S1), S47–S67.

World-Bank (2018). Mexico. Systematic Country Diagnostic. Report 132634-MX, World Bank, Washington, D.C.

Annex: Summary statistics of the income, poverty and inequality dataset

	1992		2000		2005		2010		2014	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
	a. Descriptive statistics of the income, poverty, and inequality dataset									
Simple averages across municipalities										
Real per capita income (MXN$ August 2014)	1,738.0	842.7	1,578.3	932.2	1,699.3	902.4	1,663.5	881.0	1,966.9	967.4
Gini coefficient	0.426	0.055	0.385	0.062	0.379	0.053	0.341	0.045	0.384	0.039
Poverty headcount (% of population)										
Food poverty	41.6	21.4	44.5	25.4	37.7	22.0	38.7	23.7	35.6	19.5
Capabilities poverty	49.6	21.4	52.3	24.9	46.0	22.4	47.5	24.0	44.0	20.1
Assets poverty	68.6	17.9	70.7	20.2	67.0	19.3	69.7	20.1	65.4	18.1
Population-weighted averages of municipality figures										
Real per capita income (MXN$ August 2014)	2,765.2	1,424.6	2,870.8	1,492.9	2,966.1	1,295.8	2,755.6	1,215.5	3,245.6	1,452.1
Poverty headcount (% of population)										
Food poverty	25.9	19.3	24.1	21.7	19.7	17.4	20.8	17.7	20.9	15.6
Capabilities poverty	33.6	20.4	31.5	23.0	26.7	18.8	28.9	18.9	28.3	17.0
Assets poverty	55.7	19.4	53.3	21.7	49.1	18.6	54.1	18.3	50.6	17.7
Average population by municipality	34,016	100,736	40,525	120,304	42,839	127,807	45,817	131,249	49,742	141,243
	b. Summary statistics on municipalities' public spending and revenues									
Simple averages across municipalities										
Public spending (per capita, MXN$ August 2014)	80.3	103.2	158.3	124.3	254.1	160.0	343.6	199.7	418.8	308.6
Public sector payroll	25.0	50.3	41.6	41.4	76.4	69.0	91.4	80.4	105.1	92.0
Transfers and subsidies	7.2	14.1	21.9	23.8	25.2	22.5	34.5	45.1	25.5	32.9
Public investment	21.4	30.6	40.2	48.2	76.0	52.4	123.8	93.3	162.8	185.0
Public debt	5.8	10.6	7.0	18.3	11.5	15.3	15.5	18.6	14.0	19.0
Public revenues (per capita, MXN$ August 2014)	80.3	103.2	157.9	124.5	254.0	160.4	344.1	200.3	419.3	309.7
Taxes	8.1	16.9	5.4	11.5	9.4	17.8	10.8	19.4	12.8	24.1
Unconditional federal transfers (*participaciones*)	53.8	76.4	95.8	86.5	126.1	122.1	145.5	131.2	163.5	164.1
Conditional federal transfers (*Ramo 33*)	–	17.5	59.2	50.0	88.4	44.5	140.7	85.2	202.1	175.2
Average CCT beneficiary families by municipality	–	–	1,156	1,607	2,077	2,815	2,413	3,439	2,527	3,915
Number of municipalities covered in the dataset		2,361		2,361		2,361		2,361		2,361
Total population covered in the analysis		80,310,818		95,678,853		101,144,021		108,174,343		117,439,680
Total population in the country		81,249,645		97,483,412		103,263,388		112,336,538		119,530,753
Total CCT beneficiary families in the country		–		2,437,297		4,892,284		5,682,617		5,965,275

Source: World Bank calculations based on ENIGH and census datasets; World Bank calculations based on the public finance dataset of the National Institute of Statistics and Geography (INEGI) and on administrative records of the flagship CCT program —introduced as *Progresa* in 1997 and rebranded as *Oportunidades* in 2002 and more recently as Prospera.