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ABSTRACT

Within-Country Poverty Convergence: Evidence from Mexico*

Trends in aggregate growth and poverty reduction hide a multiplicity of development processes at the local level. The analysis reported in this paper exploits a unique panel dataset of poverty maps covering almost 2,400 municipalities in Mexico and spanning 22 years, first, to test hypothesis that there is within-country income convergence. Second, through a decomposition of the poverty convergence elasticity, the analysis investigates whether this convergence, if it exists, has translated into poverty convergence. In a context of overall stagnant economic growth and poverty reduction since 1990, the analysis finds evidence of both income and poverty convergence among municipalities. As a cause of these, the results point to a combination of positive performance among the poorest municipalities and stagnant or deteriorating performance among more well off municipalities. Redistributive programs such as cash transfers to poor households 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.

JEL Classification: I32, O47, O54, R11

Keywords: income, inequality, convergence, poverty convergence elasticity, small area estimation

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1 Introduction

Despite the implementation of an ambitious agenda of structural reforms and innovations in redistributive social policy since the early 1990s, Mexico has exhibited long-run stagnation in poverty rates and mediocre performance in economic growth. This is surprising at first sight and leaves the impression that little has changed in the living standards of the population, especially among the poorest. It may be, however, that aggregate statistics are masking subnational trends.

To understand how income and poverty are changing, one needs to zoom in to a higher level of spatial disaggregation and unpack how the patterns vary within the country. Specifically, this paper zooms in to explore whether some municipalities have been persistently lagging within pockets of poverty (income convergence), whether poorer, converging municipalities have been able to translate relative income gains into poverty reduction (poverty convergence), and whether the initial parameters of the distribution have a role in shaping the patterns of convergence.

The analysis of convergence relies on the mean per capita incomes of municipalities and follows the framework proposed by Barro and Sala-i Martin (1991). It aims at an understanding of whether poorer municipalities have been capturing 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 elasticity decomposition of Ravallion (2012) to assess the effects of initial poverty on both the income growth process and the sensitivity of poverty reduction to income growth.

The analysis has produced three main findings. First, it confirms that sizable, significant municipal-level income convergence occurred, although the speed of the convergence was heterogeneous depending on geographical location. Second, it finds that the growth in mean per capita income among poorer, converging municipalities was relatively efficient in reducing poverty headcount ratios, suggesting that a process of poverty convergence unambiguously occurred. Third, it shows that growth in income among the poorest in a context of disappointing overall economic growth promoted large reductions in extreme poverty rates, whereas declining inequality and inequality convergence eventually made growth rates more efficient in reducing subsequent poverty rates in less advantaged municipalities.

While several subnational studies have looked at growth convergence among states or provinces (see Barro and Sala-i Martin 1992; Chiquiar 2005; Sala-i Martin 1996; Weeks and Yao 2003), empirical evidence at a higher level of geographical disaggregation has been scarce (an exception being Higgins et al. 2006). This paper contributes by leveraging a unique five-wave panel dataset on municipalities to provide a far more highly disaggregated look at convergence over a long period, spanning 22 years, while also addressing distributional concerns. This appears to be the first study that implements a poverty convergence elasticity decomposition using municipal-level data. In doing so, it provides insights for granular policy intervention by showing the areas and the components associated with lagging convergence. It also provides a framework for similar analyses in developing countries.

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 small area estimation methodology used to construct the municipal-level dataset. 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, as well as across subperiods that have witnessed various changes, including economic crises, ups and downs in overall poverty rates, and the expansion of public expenditure. 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.

2 Literature review

The theoretical and empirical literature on economic growth offers stylized facts upon which the analysis of economic development paths among municipalities can be anchored. A first widely studied stylized fact stems from the influential works of Barro and Sala-i Martin (1991, 1992, 1995) and Baumol (1986) 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 (see Sala-i Martin 1996), usually through 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 log-linear and nonlinear parametric approaches (though nonparametric 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.[1] A summary of the theoretical implications of 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 incomes, an emerging strand of research has opened the debate on whether income distribution also converges toward a common invariant state. For example, this paper looks at issues such as income inequality convergence (Bénabou 1996; Lin and Huang 2011; Ravallion 2003), and whether income convergence is also accompanied by poverty convergence (Cuaresma et al. 2017; Ravallion 2012; Sala-i Martin 2006). 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.

The latter implication, that income growth is a necessary condition for poverty reduction, has been widely studied in the literature. Lustig et al. 2016, for instance, 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 be associated with reductions in poverty headcounts at a more rapid pace, particularly if measures of absolute poverty 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 usually depends, however, 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 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 if market failures translate into credit constraints that trigger diminished investments in physical and human capital or, worse, leave investment opportunities entirely unexploited. In particular, the combination of credit rationing and investment indivisibilities is especially harmful for

[1] A third form, related to conditional β-convergence, is club convergence, whereby conditional convergence may cluster in countries around different steady-state equilibriums (Durlauf and Johnson 1995; Quah 1996, 1997; Su 2003).

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 have tested the role of the initial parameters of distribution in growth models and confirmed that either greater initial poverty (Ravallion 2012) or greater initial inequality (Alesina and Rodrik 1994; Clarke 1995; Deininger and Squire 1998; Knowles 2005; Persson and Tabellini 1994; Ravallion 1998) represent significant constraints to future growth rates. 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 highly 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 since then. For instance, Esquivel (1999) shows that, while the pace of convergence across states was relatively rapid in 1940–60, convergence halted and started to reverse over the next 35 years. This divergence has been 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 the incomes derived from the main household income survey into population census data. Using this technique and logistic regressions, Mexico's National Council for the Evaluation of Social Development Policy 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 income, poverty, and inequality pathways based on comparable data on municipalities.

3 Mapping income, poverty, and inequality

Capturing long-run trends in income, poverty, and inequality among municipalities requires a dataset of intertemporally comparable welfare measures 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 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. Greater geographical detail, on the other hand, can be achieved through population censuses, although this comes at the cost of a lack of robustness in the information on household incomes. Because censuses are not designed to collect comprehensive data on income, they provide an incomplete picture of household monetary circumstances, and, at least for the purposes of this paper, this represents a main weakness.

To address the trade-off between precision and geographical detail, this paper exploits the small area estimation technique proposed by Elbers et al. (2003) to impute household per capita income from available rounds of the Household Income and Expenditure Survey to corresponding households in censuses collected in or around the same years (1990–92, 2000, 2005, 2010, and 2014–15).[2] 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 and thereby compute poverty and inequality indicators.

Formally, the model takes a generalized least squares form, as follows:

$$ln\,(y_{hm}) = \alpha + \beta X_{hm} + \gamma Z_m + \mu_{hm} \tag{1}$$

The equation is used 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 characteristics of individuals, households, and dwellings, and Z_m, which comprises the fixed characteristics of the relevant municipality, including the coverage and availability of public services and infrastructure. This latter set helps raise the precision of the estimates by minimizing the share of the variance of errors that results from unexplained differences across municipalities.

The parameter α is a household-specific effect; β and γ are the correlation parameters between the corresponding sets of covariates and $ln\,(y_{hm})$; and $\mu_{hm} = \eta_m + \epsilon_{hm}$ represents an error term, wherein η_m is the component that is common to all households located in the same municipality (assumed to be homoscedastic, independent, and identically distributed), 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 whole census dataset to simulate, using the bootstrap method and with 200 repetitions, the distribution of household per capita income.

Two critical sequential requirements must be fulfilled to make this model work properly. First, at each point in time, the survey should be a random sample of the corresponding census sample frame.[3] Second, the set of covariates X_{hm} that are common between the two data sources should satisfy a conceptual and statistical equality criterion. This means, respectively, that these variables should measure the

[2] For years ending in zero, the census data correspond to the general census of the population and of housing; for 2005, the data are taken from the population and housing count; and, for 2015, they are taken from the intercensal survey, which is based on a sample of 5.9 million households that is representative at the municipal level. Unless otherwise stated, from here onward, the term census refers indistinguishably to these three data sources.

[3] In 2014–15, both the Household Income and Expenditure Survey and the intercensal survey represented random samples of the 2010 general census sample frame.

same phenomenon and that their respective distributions are statistically indistinguishable.[4]

Based on the simulated income distributions, poverty and inequality indicators were computed across municipalities. The measurement of poverty was based on the Foster et al. (1984) family of indexes by comparing simulated income with the official extreme (food) poverty line, defined as the inability to acquire a basic food basket.[5] Municipality inequality levels were computed using the Gini coefficient. This exercise yielded a novel municipality-level dataset with income-based indicators that are comparable both over time and across 2,361 municipalities and 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 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 overall growth performance of gross domestic product per capita at slightly less than 1 percent reported elsewhere.[6] Accordingly, poverty headcount ratios did not experience significant improvement between the initial and final years, though there were important changes during the first five years of the 2000s (see annex, panel a).

4 Convergence in mean per capita income

This section focuses on the growth trajectories of mean per capita income in municipalities —in constant Mexican pesos at August 2014 prices— with the aim of answering two key questions given the context of relative stagnation in income growth and in overall poverty rates: (1) Have poorer municipalities persistently lagged within pockets of poverty, or have they captured income gains, thereby catching up with more

[4]Even in survey-census pairings where gaps exist, for instance 1990–92 and 2014–15, it is possible to identify common covariates X_{hm} that satisfy the equality criterion both because the survey is a random sample of the census sample frame and because such covariates capture virtually the same context given that some characteristics of households and individuals change only slowly over time.

[5]The income concept used corresponds to 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.

[6]See, for instance, WEO (World Economic Outlook Database), International Monetary Fund; WDI (World Development Indicators), World Bank.

well off municipalities? and (2) What are the trends in income disparities across municipalities?

According to a well-established hypothesis about income convergence in the economic growth literature, incomes tend to grow more quickly in poorer areas than in richer areas. To examine income growth trends across Mexican municipalities, the analysis applies the framework of Barro and Sala-i Martin (1991) on β-convergence and σ-convergence over 1992–2014, with a particular focus on the 2000s. In the case of 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 as follows:

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

Hence, the empirical specification for the analysis of the growth process in mean per capita income among municipalities can be written as follows:

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

where $ln\, y_{it-\tau}$ is the log initial per capita income; the parameter α s 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 more well off municipalities, at an annual convergence rate of 0.7 percent. A closer look at subperiods shows, however, 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). The speed of income convergence was greater during the first five years of the 2000s, 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 was occurring at a slower pace, potentially slowed by the various economic shocks that had led to recession and nontrivial contractions in the economy.

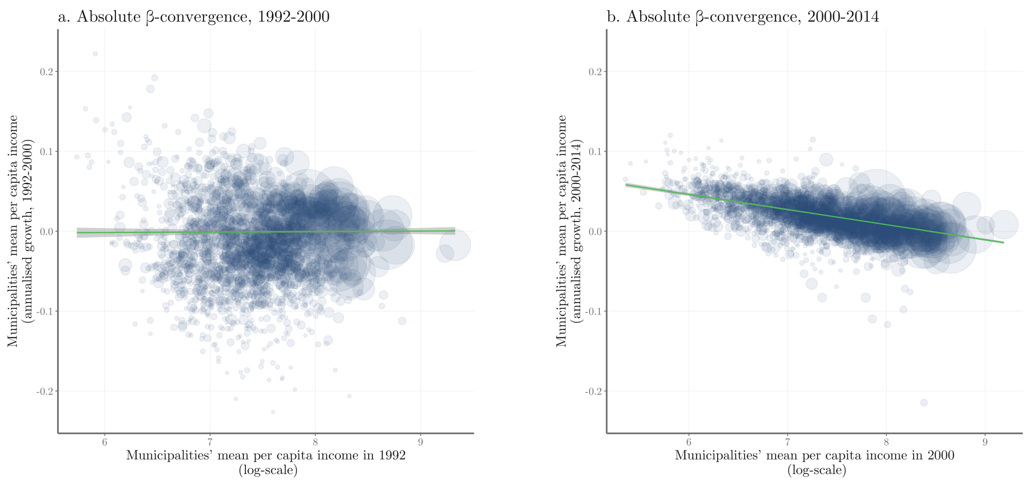
A breakdown by the population of municipalities also yields remarkable results. In 1992–2014, the catch-up effect in rural municipalities (those with fewer than 15,000 inhabitants) was at least twice as large as the effect observed across urban munic-

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

	(1)	(2)	(3)	(4)	(5)	(6)
	1992-2014	1992-2000	2000-2014	2000-2005	2005-2010	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: Authors' calculations.
Note: The table presents estimates of the parameter β in equation (3), weighted by the 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 the initial per capita incomes of municipalities. 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 15,000 inhabitants. The intercepts are shown in table 1 in the ancillary file. Robust standard errors are in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

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



Source: Authors' calculations.
Note: The area of symbols is proportional to the populations of the municipalities. 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.

ipalities. Indeed, income convergence across rural municipalities was consistently more rapid 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 municipalities at an annual rate of 2.7 percent. Moreover, although the speed of convergence declined by half 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 municipalities (see 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 the structural characteristics of municipalities, the specification in equation (3) is rewritten as follows:

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

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 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 was significant at the 1 percent level (table 2, panel a).[7] Table 2, panels b and c, show,

[7]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

respectively, the estimates in urban and rural municipalities, with two particular results. First, income convergence occurred at a more rapid pace in rural municipalities than in urban municipalities 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.

Table 2: β-convergence tests conditional on 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: Authors' calculations.
Note: The table presents estimates of parameters β and γ in equation (4), weighted by the 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.
*** $p < .01$, ** $p < .05$, * $p < .1$

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 techniques. The results are consistent, that is, poor municipalities converge at a more rapid rate relative to rich municipalities.

The conditional model shifts the convergence rates upward relative to the absolute model in most cases. 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 these years, when the economy was prey to various adverse shocks. The expectation, confirmed in the remaining cases, is that the point estimate of the variable is positive and significant, 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 equation (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 these channels in an environment of economic and fiscal contraction toward the end of the 2000s and therefore did not accelerate the pace of convergence.

In a variation of the model illustrated in equation (4), the annualized growth rate in the number of beneficiary households in Prospera, Mexico's flagship conditional cash transfer (CCT) program, was included to capture the influence of the program's expansion on the speed of convergence since the launch of Progresa, the antecedent of Prospera, in 1997. By 2000, the program was benefiting around 2.4 million households living in extreme poverty; five years later, the number had reached 4.9 million, equivalent to an annual growth rate of 20 percent. While the expansion continued after 2005, this was at a much lower rate, 2.4 percent annually, reaching 5.7 million and 6.0 million households 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.

Table 3: β-convergence tests 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***	-0.059***	-0.026***	-0.015***
	(0.002)	(0.004)	(0.003)	(0.004)
Public spending	0.003**	0.006**	-0.010***	0.025***
	(0.001)	(0.003)	(0.003)	(0.005)
Annual growth in CCT coverage	0.035***	0.067***	-0.023	-0.055**
	(0.010)	(0.014)	(0.026)	(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***	-0.060***	-0.027***	-0.014***
	(0.002)	(0.005)	(0.003)	(0.004)
Public spending	0.004***	0.008**	-0.009**	0.029***
	(0.001)	(0.003)	(0.004)	(0.006)
Annual growth in CCT coverage	0.033***	0.066***	-0.023	-0.055**
	(0.010)	(0.015)	(0.027)	(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***	-0.095***	-0.035***	-0.076***
	(0.002)	(0.004)	(0.005)	(0.009)
Public spending	0.000	0.010***	-0.013***	0.008
	(0.001)	(0.003)	(0.004)	(0.006)
Annual growth in CCT coverage	0.011	0.058***	-0.072	-0.110*
	(0.013)	(0.011)	(0.044)	(0.057)
Obs.	1,079	1,079	1,131	1,108
R^2	0.434	0.426	0.098	0.230

Source: Authors' calculations.
Note: The table presents estimates of parameters β and γ in equation (4), weighted by the 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 households 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.
*** $p < .01$, ** $p < .05$, * $p < .1$

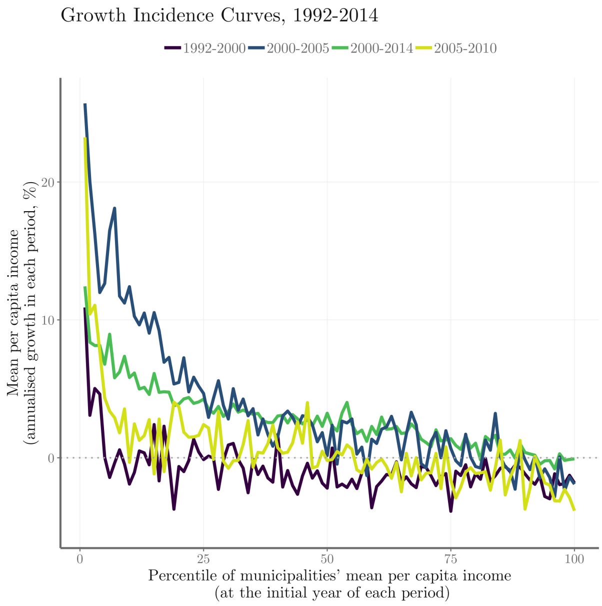
A noticeable finding throughout all previous specifications is that the income convergence process continued after 2010. Though it occurred at a slower pace than in the previous two five-year periods in terms of the whole sample, the pace was particularly high across poorer rural municipalities in 2010–14. What explains this result, given that 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, 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 on both 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 advantaged groups.

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.[8] A closer look at the data reveals a relatively higher growth rate among the poorest municipalities during this period (for instance, 2.5 percent annually among the poorest 10 percent), whereas it was negative among the richest municipalities (for example, –0.6 percent annually among the top 10 percent). Indeed, nonanonymous growth incidence curves on 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.

The story in 2000–14 was, in general, more optimistic. During these years, the vast majority of municipalities experienced positive growth, though there were some at the bottom that 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 fell by 1.3 percent among the top 10 percent. In 2005–10, the economic slowdown took a toll on the income

[8] 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 (Chiquiar 2005; Esquivel 1999; García-Verdú 2005; Rodríguez-Oreggia 2007; Rodríguez-Pose and Sánchez-Reaza 2005; 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 the state gross domestic product, 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 the results of state-level studies tend to be biased by the weight exerted by large urban agglomerations concentrating a number of municipalities, this issue can be naturally avoided in municipality-level analyses.

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



Source: Authors' calculations.

performance of municipalities; growth rates averaged 0.6 percent annually and, with the exception of the poorest 10 percent, municipalities 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 incomes among the first decile of municipalities and stagnant growth and negative growth among municipalities in 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: municipalities located in Mexican 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–U.S. 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 in the first group (table 4, panels b and c). A careful look at the income growth performance of each group reveals some clues to aid in understanding the results. For instance, over 1992–2000, income convergence in non–U.S. border municipalities derived from relatively high growth rates among the poorest municipalities and negative rates among the rest. By contrast, the speed of convergence across municipalities 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 percent and –0.7 percent, respectively. 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 benefited slightly 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.[9]

Table 4: β-convergence tests conditional on 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: Authors' calculations.
Note: The table presents estimates of the parameter β in equation (4), weighted by the 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.
*** $p < .01$, ** $p < .05$, * $p < .1$

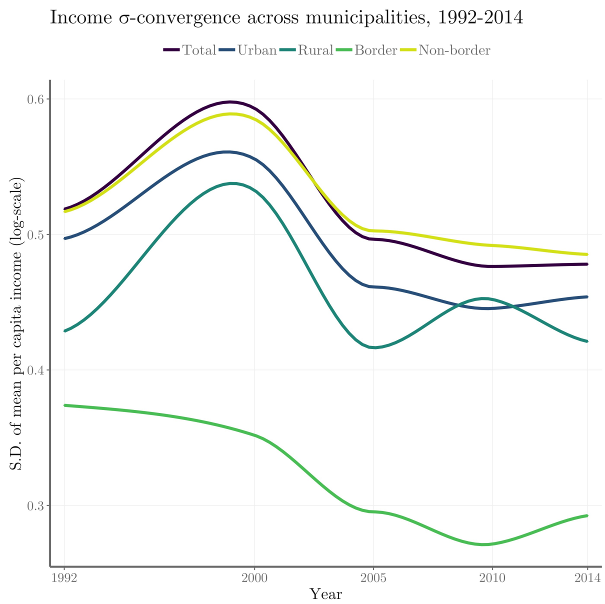
The difference in the speed of convergence between non–U.S. border municipalities (1.4 percent) and municipalities in border states (6.0 percent) over 2005–10 may also be explained by the following growth patterns. Income growth averaged almost 8 percent annually among the poorest 10 percent of municipalities in both groups,

[9] As a 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.

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 highly integrated with the United States.[10] 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 in income inequality in the following years (Esquivel et al. 2010). This is also confirmed by the analysis with study data hereafter. Figure 3 shows the trends in 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: Authors' calculations.

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

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 noticing. First, income disparities in rural municipalities deteriorated slightly after the 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 level recorded in 1992. Second, the relatively high β-convergence coefficients across municipalities in border states seem to signal a reduction in 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 extreme poverty reduction 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 resource transfers from richer to poorer populations, thus stimulating poverty reduction.

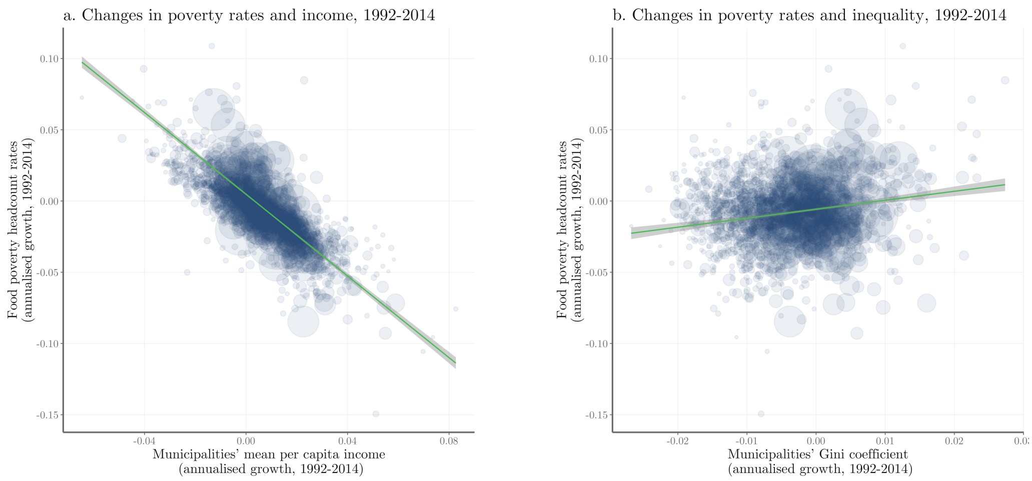
Focusing on the first component for now, let

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

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 equation (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.[11]

[11] 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 extreme poverty rates, inequality, and per capita income, 1992–2014



Source: Authors' 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 equation (5) confirm that higher growth rates in income tend to be associated with reductions in poverty. In 1992–2014, for instance, a 1 percent growth rate in the mean per capita income of municipalities led to a 1.4 percent decline in the extreme poverty headcount ratio (table 5, panel a). The results also suggest that extreme poverty is more responsive to growth among both urban municipalities and municipalities in states along the U.S. border relative to their corresponding counterparts (panels b–e). According to the data, such counterparts consistently exhibit higher extreme poverty rates over time: around 30 percent higher in rural municipalities than in urban municipalities, and twice the size in non–U.S. border municipalities than in municipalities in border states. Thus, extreme 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.[12]

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

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

Table 5: Growth elasticities of extreme poverty reduction, 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: Authors' calculations.
Note: The table presents estimates of the parameter η in equation (5), weighted by the municipal population at the initial year of each period under study. The dependent variable is the annualized growth in the extreme 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.
*** $p < .01$, ** $p < .05$, * $p < .1$

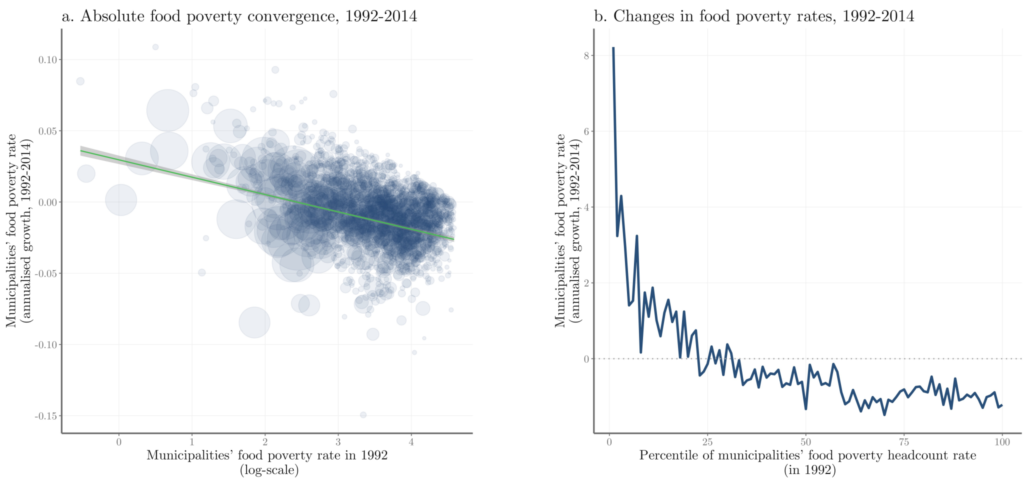
extreme poverty rates, plus the evidence on income convergence, imply that those municipalities with relatively high initial poverty headcount rates ($lnP_{it-\tau}$) should have experienced higher subsequent rates of poverty reduction over the period under study. To test this, let

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

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 equation (6) suggest that poorer municipalities reduced their headcount ratios at a more rapid pace than richer and poverty increasing counterparts over 1992–2014. In fact, extreme poverty rates among the 20 percent of municipalities with the lowest incidence in 1992 had recorded nontrivial increases by 2014 (figure 5). A closer look at subperiods reveals the 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 more rapid pace than in the former.

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



Source: Authors' 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, municipalities in border states exhibited a considerably higher coefficient during 2005–10 (table 6, panels d and e). The evidence presented in section 4 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 incomes in their richer counterparts were disproportionately affected by the economic contractions that characterized these years.

Table 6: Tests of extreme poverty convergence, 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: Authors' calculations.
Note: The table presents estimates of the parameter β in equation (6), weighted by the municipal population at the initial year of each period under study. The dependent variable is the annualized growth in the extreme poverty headcount ratios of municipalities over the period. $lnP_{it-\tau}$ are the initial poverty headcount ratios of municipalities. 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.
*** $p < .01$, ** $p < .05$, * $p < .1$

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 the decomposition of poverty convergence elasticity of Ravallion (2012) to explore how the initial poverty headcount ratios of municipalities might affect the advantage of municipalities, 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.

On the first channel, the analysis estimates three augmented versions of the income β-convergence model in equation (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 extreme poverty headcount ratios, as follows:

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

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 extreme 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.[13] Because initial poverty rates are not independent of other parameters of the distribution, a third regressor —the initial inequality in municipalities as measured by the Gini coefficient ($lnG_{it-\tau}$)— was added to the analysis in the second version of the model. The results now reveal a positive and significant, though 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 mean per capita 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, the analysis tested the previous augmented model by adding extra controls for concepts of either public spending or revenue and with and without CCT data. Invariably, the story holds under different specifications: the positive and significant effects of the initial extreme poverty headcount ratios on income growth are found over 2000–14, in particular during the expansion of CCT

[13]The coefficient over 2000–05 even increased at 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: Mean per capita income growth 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: Authors' calculations.
Note: The table presents the estimates of equation (7) and extensions, weighted by the 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 households 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.
*** $p < .01$, ** $p < .05$, * $p < .1$

coverage in 2000–05.[14] 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 households 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 the mean per capita incomes of municipalities, multiplied by 1 minus the municipality's initial poverty headcount ratio $(P_{it-\tau})$, which tends to penalize more substantially the sensitivity of extreme 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 the initial extreme poverty rate of a municipality is 10 percent and the municipality experiences a 4 percent annual growth rate in mean per capita income, then the 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 4.0 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 municipalities. For instance, at an initial extreme 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 extreme 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).

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

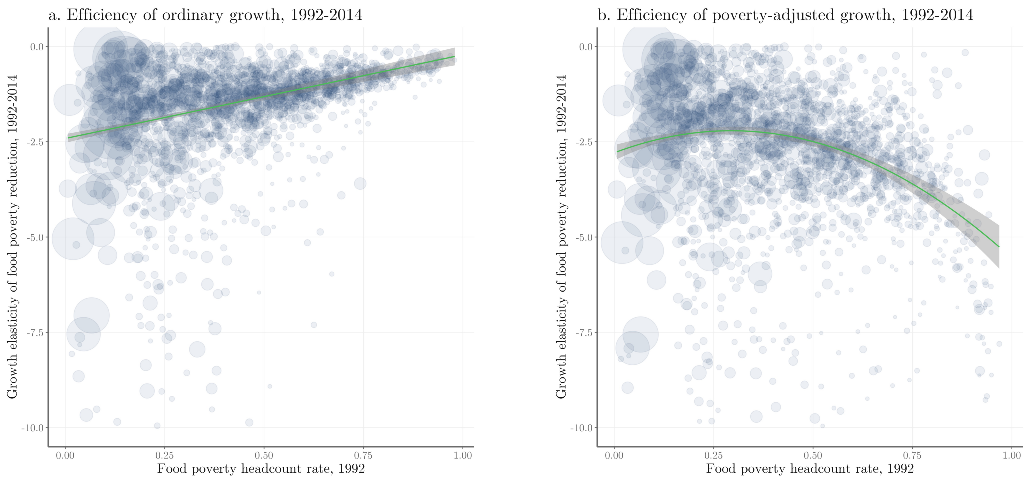
Table 8: Poverty-adjusted growth elasticities, 1992–2014

	(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 extreme 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 extreme 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: Authors' calculations.
Note: The table presents estimates of the parameter η in equation (8), weighted by the municipal population at the initial year of each period under study. The dependent variable is the annualized growth in the extreme 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 and adjusted by the initial extreme poverty headcount ratios of municipalities. Municipalities with low (high) initial extreme 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 poverty-adjusted growth elasticity follows a concave relationship with poverty (figure 6). In other words, those municipalities with high levels of extreme 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 extreme 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 extreme (food) poverty, by initial poverty rates, 1992–2014



Source: Authors' 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 extreme poverty rates of municipalities, the analysis exploited all previous evidence computed for each channel to apply the decomposition of poverty convergence elasticity of Ravallion (2012). This decomposition results from the derivative of equations (7) and (8) as follows:

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

where $\frac{\partial g_i(P_{it})}{\partial lnP_{it-\tau}}$ is the speed of extreme poverty convergence, equivalent to the parameter β in equation (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 extreme poverty with respect to their initial mean per capita income $\left(\frac{\partial lnP_{it-\tau}}{\partial lny_{it-\tau}}\right)$[15]; and, the sample means of $P_{it-\tau}$ and $g_i\left(y_{it}\right)$, the computation of equation (9) yields virtually the same extreme poverty convergence rates calculated above (see table 6, panel a).

For instance, the poverty convergence rate calculated based on equation (9) is −0.011 during 1992–2014, which is close to the coefficient of −0.012 computed based on

[15] 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.

equation (6) for the same period. The decomposition of the 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, at 0.001. In the 1990s only, a convergence effect of −0.024 was more than offset by both the initial poverty effect (0.024) and the poverty elasticity effect (0.015), 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, in similar magnitudes, by the convergence effect (−0.024) and the poverty elasticity effect (−0.022). But 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 sufficiently to have reduced extreme poverty, while fostering progressive changes in the distribution, which, in turn, may promote poverty reduction (see figure 4, panel b).

To shed 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 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 extreme 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 extreme 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 extreme poverty to be less responsive to growth in more unequal municipalities is confirmed in all subperiods, and it generally holds if 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 follows:

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

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 suggests, however, 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 if growth elasticities are computed using the ordinary growth rate, there is an indication that extreme 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 extreme poverty rates thus occurred not only among the poorest municipalities, as documented above, but also among municipalities with relatively high initial inequality.

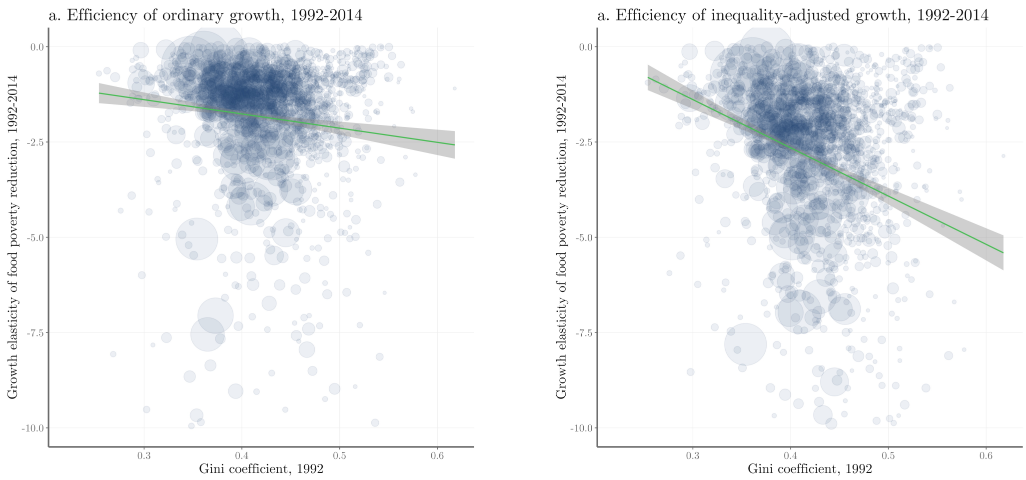
Indeed, the distribution of municipalities according to their Gini coefficient in 1992 reveals that poverty reduction tended to be slightly greater among the top 40 percent more unequal municipalities (figure 8, panel a). Inequality among the latter also declined markedly over 1992–2014, which suggests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

Table 9: Growth elasticities of poverty, 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: Authors' calculations.
Note: The table presents estimates of the parameter η in equations (5), (8) and (10), weighted by the municipal population at the initial year of each period under study. The dependent variable is the annualized growth in the extreme 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.
*** $p < .01$, ** $p < .05$, * $p < .1$

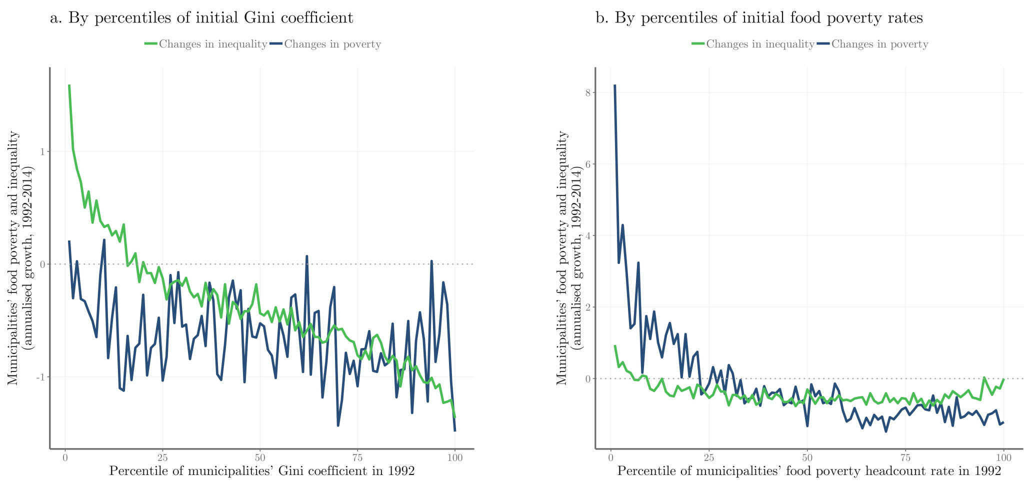
Figure 7: Efficiency of growth in reducing extreme (food) poverty, by initial inequality levels, 1992–2014



Source: Authors' 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.

(3) or (6).[16] In addition, it can be confirmed that, in the majority of the initially poorest municipalities where extreme poverty reduction subsequently took place, the latter was accompanied by a decline in the Gini coefficient (figure 8, panel b).

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



Source: Authors' calculations.

[16]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).

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 latter 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 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. The 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 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, the analysis finds that mean per capita income grew consistently more quickly in the poorest municipalities than in richer municipalities. This confirms that, in general, convergence occurred at a sizable, significant magnitude; however, the speed of income convergence was more rapid after 2000 and heterogeneous between urban and rural municipalities and between municipalities located in the north of the country and the rest. Second, in terms of poverty convergence, the analysis 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, the analysis finds that the growth of income among the poorest in a context of stagnant or disappointing overall economic growth promoted sizable reductions in extreme 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 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.

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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: Authors' calculations calculations based on ENIGH and census datasets, 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. *Notes*: Capabilities poverty is defined as the inability to cover the value of the food basket, plus expenditures on health and education, while assets poverty is defined as the inability to acquire the latter plus expenditures on clothing, housing, and transportation.