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Economic growth and income distribution in Mexico: A cointegration exercise

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ABSTRACT

The empirical evidence on the relationship between income inequality and economic growth is widely recognized and, now, there are rich databases for carry on panel-data type of analyses. However, time series studies for specific countries may be more attractive and yield revealing results. For this reason, we study hereafter the long-run relationship between economic growth and income inequality in the case of Mexico. To this end, a time series of data for the Gini coefficients from Solt (2011) is used over the period 1968–2010, within a cointegration exercise. Being related to a single country, our results are suffering less from problems of heterogeneity, endogeneity, and measurement errors, which are commonly encountered in cross-country growth regressions. We first investigate (and confirm) that the two series of per capita GDP and Gini index are cointegrated. Five different methodologies are implemented in our analysis, so that the robustness of cointegration results is guaranteed. We consistently also find that the relationship between those variables is negative. Moreover, results show the per capita GDP to be weakly exogenous. According to tests for Granger causality, unidirectional causality runs from per capita GDP to the Gini index.

1. Introduction

1.1. The literature and the justification for a single-country regression model

The relationship between growth and inequality has been extensively debated in the literature, older and more recent, in a variety of ways (one can check the introduction by Gobbin and Rayp (2008), and read a good recent survey in Shin (2012)). Still, no final undisputed conclusions have been reached on a number of issues.

In classical models, economic growth depends mainly on the rate at which nations accumulate productive resources, and is linked to the aggregate savings rate. In such vision, distributional considerations matter for growth only if households' propensity to save varies with income and/or wealth. If the rich save at a higher rate (a view proposed by e.g. Nicholas Kaldor), distributionally unequal societies would be able to build up their productive capacity (and speed up their growth) faster than *more equal* ones. Inequality would foster growth because output growth requires capital accumulation and, for example, new industries typically require larger investments. Thus, a higher concentration of income/wealth supports a higher capital accumulation rate and, in the example, would stimulate growth through the development of more capital-intensive industries. (More recently, Forbes (2000) and Arjona et al. (2001) seem to return to this view, though via distinct arguments.)

On the other hand, in a well-known article, Kuznets (1955) found the famous inverted U pattern between per capita income and inequality on the basis of a cross-country analysis. According to the author's original interpretation, the foremost driving force would be the structural change occurring as labor shifted from a poor and less productive traditional sector to a more productive and differentiated modern one. Arguments supporting a positive and a negative relationship (the two arms of the U-Shape relationship) have both been offered. (Bénabou (1996) and Aghion et al. (1999) provide excellent surveys of various contributions to this debate.)

Frank (2009) has investigated the long-run relationship between (a measure of) inequality and growth performance in the United States, to conclude that there is a significant positive relationship between them. Using panel data for twelve developed economies, Andrews et al. (2011) find that, since 1960, higher inequality would be associated with higher growth. On the other hand, Davis' (2007) model generates a relationship between growth and income inequality that is negative across countries and positive within countries over time. Recently, in Shin's

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(2012) stochastic optimal growth model made up of heterogeneous agents, a positive and a negative relationship turn up to be both possible, depending on the stage of development of the economy.

Other contributions (Alesina and Rodrik, 1994; Perotti, 1994, 1996; Persson and Tabellini, 1994) have argued that a higher inequality at the beginning of a long-term period is linked to poorer growth performance, relationship being therefore negative. This view too has been challenged: while a negative relationship seems to hold for developing countries, there appears to be no clear relation at all for richer ones. Herzer and Vollmer (forthcoming) summarize all previous empirical literature in a long run analysis of 46 countries over the period 1970–1995, and a negative relationship appears to emerge.

However, despite the wealth of accumulated evidence, most empirical literature relies on standard cross-country and panel regressions and thus suffers from the limitations of such an approach. The same Herzer and Vollmer (forthcoming) summarize a number of criticisms of such models, in particular pointing out that a cross-country analysis implicitly assumes a common economic structure. The homogeneous panel estimators being used produce inconsistent and potentially misleading estimates of the average parameter values of models when slope coefficients differ across cross-section units (see Pesaran and Smith (1995)).[*]

Cointegration analysis applied to a single country does not suffer from such criticisms. Gobbin and Rayp (2008) apply Johansen's cointegration methodology to the analysis of the income inequality and economic growth relationship in Belgium, the US and Finland. Finding in each case quite different results, leads them to conclude that: "A country-specific estimation approach is needed since 'one-size-fits-all' does not apply in the field of growth empirics." (*ibidem*, p. 892).

Accordingly, our paper focuses on the experience of a single country, Mexico, so that we do not encounter data comparability problems (see e.g. Knowles (2005)), while avoiding the other problems in cross section and panel data studies. It tackles the issue of the inequality-growth nexus by using a bivariate cointegrated vector autoregressive (VAR) approach, so that none of the common problems arise of parameter heterogeneity, omitted variable bias and endogeneity.

1.2. The Mexican economy: a short overview

Hereafter, we consider Mexico, an economy with alternating performance that can be briefly sketched out as follows. The country grew at an average annual rate of over 6.5% between 1960 and 1980, resulting in significant improvements in per capita GDP and living standards. Between 1980 and 1987, however, average real GDP growth dropped to less than 1% and productivity growth fell to negative figures. The economic reforms of the latter part of the 1980s helped the country to recover from the 1982 debt crisis, with GDP growth rate averaging 3.8% between 1990 and 1994 (Faal, 2005). In 1995, soon after the Tequila crisis of the previous year, GDP levels declined by 6.2% but the economy still managed to grow at 5%–6% in the ensuing three years, to drop again from 6.2% in 2000 down to −0.2% in 2001. However, improved economic conditions in the United States after 2001 helped to recover soon. Mexico's GDP grew at a 3% average annual rate between 2001 and 2007, but it slowed down to 1.5% in 2008 and then contracted at a sharp −6.5% in 2009. E.g., 2006 Mexican GDP growth rate was 4.8% but one year later it had decreased to 3.3%.[†] The unemployment rate went from 3.7% in 2006 up to 5.5% in 2009. Labor productivity growth remained low throughout: its average annual growth rate was a modest 1% between 2001 and 2007, in 2008 it fell by 2.1%. Per capita GDP, which in 2008 was 31% relative to the United States, is the lowest in the OECD (see OECD Report on the Mexican economy, 2010).

Mexico is also a country of great contrasts, where levels of poverty and deficits in the social indicators are higher than one might expect at its level of development. The issue of (the levels and evolution of) poverty and inequality is closely related with the shortcomings of certain external shocks and with the process of structural reform initiated in the eighties. In particular, there are two components of the latter that may have very significantly affected economic and social differentiation. One of them is the trade liberalization which began in the mid-eighties and culminated with the signing of the NAFTA treaty, then launched in 1994. The other is the land reform bill that authorizes the privatization of *ejidos* (i.e. areas of communal land of which community members individually possess and farm parcels[‡]).

Thus, income inequality in Mexico rose sharply between 1984 and 1994 with the Gini coefficient going from 49.1 up to 54.9 (Bouillon et al., 1999) and, the Lorenz curves showing no crossings, such increase is unambiguous (Lustig and Szekely, 1997). Bouillon et al. (1999) attempt to identify which factors lie behind this rise. Results of their exercise show that the widening gap in the "returns" to education explains about fifty percent of the observed increase, while the "returns" to regional location account to around 24%, in the South alone for a 15%.[§]

To compare with our exercise hereafter, it is worth recalling the Ortega-Díaz (2006) analysis relying on dynamic panel data analysis, with both urban personal income for grouped data and household income from national surveys. They find that inequality and growth are positively related. However, with a periodization, two relationships emerge: 1) a negative influence of inequality on growth during a period of restrictive trade policies, and 2) a positive relationship with trade openness. Compared to Ortega-Diaz, our paper uses a different methodology, cointegration. With this approach, we come up with a robust result about the existence of a cointegrating relationship between inequality and economic growth.

Henceforth, we look at such long-run relationship over the 1968–2010 history of Mexico. Economic growth is measured by per capita GDP and inequality by the Gini coefficient (also known as the Gini index or Gini ratio). Solt (2011) has recently provided annually-based time series of Gini coefficients for several countries. Therefore, no one has the 30-odd observations needed to carry out our type of analysis.

Section 2 of the paper describes the database and the specification of the model. Then, Section 3 presents our empirical results for the cointegrating equations with various approaches, while Section 4 reports a test for Granger causality. Section 5 concludes.

2. Data and model specification

2.1. Data set

Annual per capita GDP is, of course, gross domestic product divided by midyear population (data are in constant 2000 U.S. dollars), where GDP is calculated without deductions for depreciation of fabricated

[*] Moreover, still according to the authors, the approach suffers of

i) an endogeneity problem and the use of instrumental variables may lead to spurious results;

ii) Cross country and panel studies use the growth rate of income as dependent variable: however, this tends to be roughly constant over time, while inequality indicators show large and persistent movements over time. The empirical implication is that there cannot be a long-run relationship between the growth rate of income and the index of inequality over time;

iii) In order to eliminate business cycle effects, cross-country analysis uses time-averaged data but this can induce a spurious contemporaneous correlation between them (see Ericsson et al., 2001). Moreover, Banerjee and Duflo (2003) maintain that cross-country data is deficient due to differences in cultural structure, technology level, and financial institutions. As regard to measurement errors, they are largely related to the variable measuring income distribution inequality while being less or not at all applicable to other variables (Barro, 2000).

[†] EIU, Country Reports: Mexico, various years.

[‡] More details in Lustig and Szekely (1997).

[§] They use a micro-simulation decomposition methodology and a reduced-form household income regression model.

assets or for depletion and degradation of natural resources. Source is the World Bank database from the World Development Indicators (WDI).

For income inequality data we use the Standardized World Income Inequality Database, Version 3.1, by Frederick Solt (2011), of the Southern Illinois University. From such database we use the variable list called *GINI_NET*, which is an estimate of Gini index of inequality in equivalized (square root scale) household disposable income, using Luxembourg Income Study data as the standard.

The analysis starts with a visual inspection of data series in order to identify whether there is any abnormal movement in the variables.

Fig. 1 clearly shows that the two time series exhibit distinct trends: while per capita GDP is growing, the Gini index is decreasing over time.

2.2. Model specification

Our aim is first to ascertain the existence of a long-run relationship between Mexico's income inequality and economic growth for a specific sample period and we do this by using cointegrating techniques. All tests are designed to find the stationary linear combinations of vector time series (for instance the vectors GINI(GDP)), and a number of cointegrating factors are determined. From the econometric point of view, we estimate a simple specification for the relation GINI–GDP. In order to check for robustness of the estimated coefficients, cointegrating equations are estimated with alternative methods. That is:

1 Johansen's maximum likelihood (JML) and VECM. As is known, cointegration means that a linear combination of different order 1-integrated variables I(1) is stationary (I(0)), and it implies the existence of an empirical long-run relationship between those variables. Error correction models (VECM) incorporate these aspects by mapping the I(1) variables into the I(0)-space. In this way, it is possible to draw valid statistical inference, while preserving theoretical interpretability. With Johansen's approach (Johansen, 1988), the null hypothesis of no cointegration may be tested against different alternatives implying two or more cointegrating vectors.

2 Fully modified ordinary least square (FMOLS), canonical cointegration regression (CCR), and dynamic ordinary least squares (DOLS). These are single equation methods while JML is a vector. For instance, FMOLS modifies least squares to account for “serial correlation effects” and for the “endogeneity” in the regressors resulting from the existence of a cointegrating relationship. In the same vein, CCR and DOLS estimators deal with the problem of second-order asymptotic bias arising from serial correlation and endogeneity, and together with FMOLS they are asymptotically equivalent and efficient.

Of course, if all such alternative methods yield similar results, confidence in their estimates increases.

Let $y_t = (y_{1t}, y_{2t})$ be a bivariate vector for the natural logarithms of per capita GDP (PCGDP) and of Gini index. The generating mechanism for y_t is the cointegrated system in its triangular form:

$$y_t = \beta' y_{2t} + u_{1t}, \tag{1}$$

$$\Delta y_{2t} = u_{2t}, \tag{2}$$

where $u_t = (u_{1t}, u_{2t})$ is, generally, strictly stationary with zero mean and finite covariance matrix Φ. The benchmark case can be defined by u_t being IIDN(0, Φ) and Φ block-diagonal; in this case, Δy_{2t} is strictly exogenous and the OLS estimator of β is efficient. But if Φ is not block-diagonal and/or the u_t process is weakly dependent, the OLS is not efficient.

Then, the following two cointegrating equations are estimated:

$$\begin{aligned} \mathrm{LnPCGDP}_t &= \alpha_1 + \beta_1 \mathrm{LnGINI}_t +{}^t u_{1t} \\ \mathrm{LnGINI}_t &= \alpha_2 + \beta_2 \mathrm{LnPCGDP}_t + u_{2t}. \end{aligned} \tag{3}$$

Our strategy is the following. As a first step, using conventional tests we will examine whether the time series under investigation can be characterized as integrated processes of order 1, *I*(1). Next step, Johansen's (1995) multivariate cointegration technique is employed to determine whether variables share a common stochastic trend. In the third step, estimates of the cointegrating relations are obtained by applying Johansen's system estimator, and then an Error Correction Model is estimated. Moreover, to make sure to obtain robust results, various estimators are used. In fact, to this end, our paper applies the fully modified ordinary least squares (OLS) estimator of Phillips and Hansen (1990, 1995), the canonical cointegrating regression (CCR) of Park (1992), and the dynamic OLS estimator of Stock and Watson (1993). As is known, these single-equation estimators are asymptotically equivalent to Johansen's maximum likelihood estimator in the case where variables are *I*(1) and there is a single cointegrating vector. Although the Engle and Granger (1987) technique yields consistent but inefficient long-run parameters, the latter are also reported hereafter. Moreover, parameter instability in the cointegrating relationship is tested using methods discussed in Hansen (1992).

The last step tests for Granger causality in a cointegrated bivariate system applying the approach suggested by Lütkepohl and Reimers (1992).

3. Results

The first cointegration step is to study the stationarity of the series by unit root tests. We have applied the Augmented Dickey–Fuller (ADF) test, Philips–Perron, and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) battery of unit root tests, since the ADF-tests are known to have low

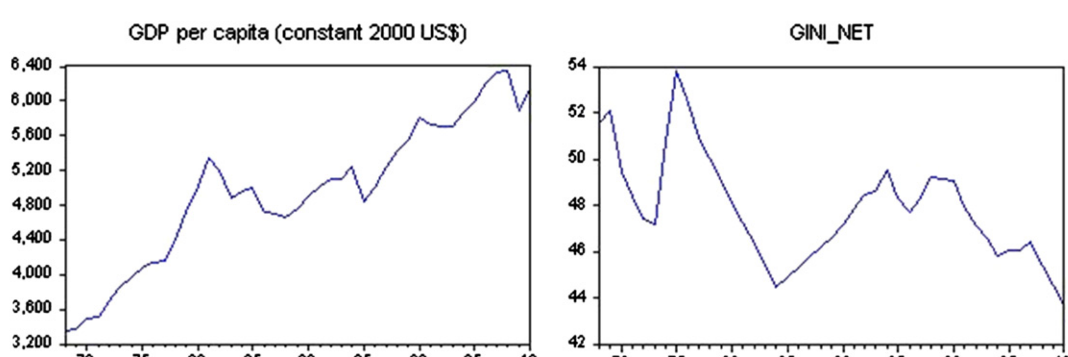

Fig. 1. Per capita GDP (constant 2000 US$) and Gini index.

Table 1
Unit root test results: logs of PCGDP and GINI index (in levels and differences).

Test	ADF				KPSS				Philips–Perron			
	t-Statistic	p-Value	t-Statistic	p-Value	LM-Stat	CV 5%	LM-Stat	CV 5%	t-Statistic	p-Value	t-Statistic	p-Value
Variable	LnPCGDP		LnGini		LnPCGDP		LnGini		LnPCGDP		LnGini	
Trend & intercept	−2.593	0.285	−3.182	0.102	0.125	0.146	0.090	0.146	−2.137	0.511	−1.773433	0.6997
Intercept	−1.857	0.349	−2.716	0.080	0.746	0.463[a]	0.398	0.463	−1.824	0.364	−1.749936	0.3995
None	2.608	0.997	−0.884	0.327					2.608	0.997	−0.944915	0.3019
Variable	ΔLnPCGDP		ΔLnGini		ΔLnPCGDP		ΔLnGini		ΔLnPCGDP		ΔLnGini	
Trend & intercept	−5.328	0.0005[b]	−4.045	0.0147[a]	0.069	0.146	0.068	0.146	−5.316	0.0005[b]	−3.791098	0.0272[a]
Intercept	−5.222	0.0001[b]	−4.098	0.0026[b]	0.202	0.463	0.069	0.463	−5.229	0.0001[b]	−3.853658	0.0051[b]
None	−4.617	0.0000[b]	−4.027	0.0002[b]					−4.613	0.0000[b]	−3.892837	0.0003[b]

Source: Own elaboration.
[a] Null hypothesis rejected at 5%.
[b] Null hypothesis rejected at 1%.

power for highly persistent series. The null hypothesis of KPSS test is stationarity, complementing the ADF and Philips–Perron test.

Table 1 shows unit root tests for the Mexican per capita GDP and GINI index in levels and differences. (Variables are expressed in logarithmic form.)

According to the tests, Mexican PCGDP and GINI index taken in logs are integrated processes of first order $I(1)$. Hence, as mentioned before, to study the cointegrating relationship, we have applied five methodologies.

3.1. Johansen cointegration test

We have first applied the methodology proposed by Johansen (1988, 1995), Juselius (2006) and Harris (1995), which requires estimating a Vector Error Correction (VEC) model. The VEC is a VAR with the long run relationship showing how variables come back to the equilibrium after suffering a shock.

In order to obtain the optimal VEC model, the lag is selected automatically using Akaike's Information Criterion (AIC). Estimates of the autoregressive parameters with minimum AIC are calculated, suggesting a lag length of three (see Table 2).

To detect the existence of a cointegrating relation, the Johansen maximum likelihood method provides both trace and maximum eigenvalue statistics. Notice, in Table 3, that the test detects the existence of one cointegrating vector.

Incorrect signs can be produced if exogeneity is not studied (see McCallum, 1984). Thus, to apply inference techniques we must test for weak exogeneity. I.e. under weak exogeneity (WE) statistically efficient estimation and inference can be achieved by considering only the conditional model and not taking the rest of the system into account. (In other words, there is no loss of information by abstracting from the marginal model.) Thus, if LnPCGDP is weakly exogenous, we are allowed to carry out optimal inference with respect to the set of parameters of the long run equation. This means that we can take the parameters of the long run equation without the necessity of modeling the endogenous dynamic of LnPCGDP. Such dynamic is related with the corresponding speed adjusted coefficient α in the VEC model: when it is equal to zero, the endogenous dynamic of LnPCGDP can be ignored and the variable can be considered as exogenous.[**] The $Chi^2(1)$ statistic of 3.707 and the p-value of 0.054 indicate that we can indeed consider LnPCGDP as a weakly exogenous variable. Therefore, the estimated equation is:

$$LnGINI_t = \alpha + \beta LnPCGDP_t + u_t.$$

So, Eq. (1), the estimated relationship including weakly exogeneity, is given by:

$$\underset{[12.025]}{LnGINI = 5.199} \underset{[-3.121]}{-0.158} \ LnPCGDP \tag{4}$$

Eq. (4) confirms that the relationship between Mexican LnPCGDP and the LnGINI index is negative. Estimation in terms of elasticity indicates that an increment of 1% in the per capita GDP produces a decrease of 0.158% in the GINI index.

3.2. Engle–Ganger cointegration test

The residual-based Engle–Granger cointegration test has also been used, the test aiming at determining whether single-equation estimates of the equilibrium error are stationary (Engle and Granger, 1987). The following cointegrating equation was estimated:

$$\underset{[18.086]}{LnGINI = 5.211} \underset{[-4.668]}{-0.158} \ LnPCGDP \tag{5}$$

Table 4 shows the ADF test for the residuals of the two equations (in system (3) above). The null hypothesis of no cointegration is rejected when considering an ADF model with trend and intercept. The MacKinnon critical values are also considered.

Although the ordinary least squares (OLS) estimator is consistent in the presence of a serial correlation in the error term and/or a correlation between the regressors and cointegration errors, the OLS estimator is known to contain the so-called second-order bias (see Kiviet and Phillips, 1993). In the literature, there are three typical estimators that deal with such a problem: i) the fully modified OLS estimator proposed by Phillips and Hansen (1990), ii) Park's (1992) canonical cointegrating regression estimator, and iii) the dynamic OLS (DOLS) estimator of Phillips and Loretan (1991), Saikkonen (1992), and Stock and Watson (1993). These three estimators are known to be asymptotically equivalent and efficient (see Hayakawa and Kurozumi, 2008).

Table 2
Optimal Lags according to AIC criteria.

Lag	AIC
1	−8.578
2	−8.881
3	−8.921
4	−8.737

Source: Own elaboration.

[**] Specifically, as outlined by Harris (1995), a variable is deemed to be weakly exogenous if its speed of adjustment coefficient is not statistically different from zero. Were weak exogeneity be observed in one of the series, this would imply that the cointegrating relationship remains external to the equation.

Table 3
Johansen Cointegration Test (Trace tests).

Trace test				
Hypothesis	Eigenvalue	Statistic	C.V.: 0.05	Prob.[b]
None[a]	0.317	22.152	20.262	0.027
At most 1	0.170	7.288	9.165	0.112

Source: Own elaboration.
[a] Denotes rejection of the hypothesis at the 0.05 level.
[b] MacKinnon et al. (1999) p-values.

Table 5
Cointegration Test — Hansen parameter instability.

Series: LNGDP–LNGINI. Null hypothesis: Series are cointegrated				
Lc statistic	Stochastic trends (m)	Deterministic trends (k)	Excluded trends (p2)	Prob.[a]
0.156361	1	0	0	>0.2

Source: Own elaboration.
[a] Hansen (1992) Lc(m2 = 1, k = 0) p-values, where m2 = m-p2 is the number of stochastic trends in the asymptotic distribution.

3.3. Fully modified ordinary least squares

The FM-OLS regression is designed to provide efficient estimates of cointegrating regressions. The method modifies least squares to account for serial correlation effects and for the endogeneity in the regressor that results from the existence of a cointegrating relationship (Eqs. (1)–(2)).

Eq. (6) gives the estimated relationship (through system (3)) using the FM-OLS with constant and without trend (results do not change when considering a trend):

$$\underset{[12.8451]}{LnGINI = 4.8355} - \underset{[-2.5426]}{0.1155}\ LnPCGDP. \tag{6}$$

Eq. (6) confirms a negative relationship between Mexico's PCGDP and the GINI index.

Notice that the suggestion from the data, i.e. series plot with stochastic movements (Fig. 1) may indicate a situation of cointegration with structural change, and when this happens usual tests do not support the case for cointegration.

Hansen's (1992) test for structural change is a form of testing model specification, with at the same time important consequences in terms of economic analysis. Next Table 5 reports the results from this test with the null of cointegration against the alternative hypothesis of no cointegration.

Results show that the null hypothesis (of cointegration) cannot be rejected. Note that, Hansen's Lc statistic being significant at the 20%, the parameters are stable, in turn implies that variables are cointegrated. This same procedure of Hansen Instability cointegration test has been used in all the following cointegrating regressions, and results do not change.

3.4. Canonical cointegration regression

The CCR estimator is based on a transformation of the variables in the cointegrating regression, removing the second-order bias of the OLS estimator in the general case mentioned in (1) and (2). In our context, the OLS estimator is asymptotically equivalent to the ML estimator: the reason is that the transformation of the variables eliminates asymptotically the endogeneity caused by the long-run correlation of y_t. In addition, the CCR estimator shows that the transformation of the variables eradicates the asymptotic bias due to the possible cross correlation between u_{1t} and u_{2t} (see Montalvo, 1995).

Then, the estimated relationship (through system (3)) using CCR with either constant trend or without trend (results do not change, in fact), is given by:

$$\underset{[14.6844]}{LnGINI = 4.9943} - \underset{[-3.3429]}{0.13411}\ LnPCGDP. \tag{7}$$

Once again, Eq. (7) also confirms the negative relationship between the Mexican PCGDP and the GINI index seen before, with an increment of 1% in the PCGDP reducing inequality by 0.13411%, a comparable result.

Table 4
Engle–Granger cointegration test on residuals.

Test	ADF	
	t-Statistic	p-Value
Variable	Residual LnPCGDP(LnGINI)	
Trend & intercept	−3.305	0.0797[a]
Intercept	−2.321	0.1704
None	−2.341	0.0203[b]
Variable	Residual LnGINI(LnPCGDP)	
Trend & intercept	−3.326	0.0764[a]
Intercept	−3.373	0.0178[b]
None	−3.431	0.0011[c]

Source: own calculations. The significant model is highlighted.
[a] Rejection of no-cointegration at 10%.
[b] Rejection of no-cointegration at 5%.
[c] Rejection of no-cointegration at 1%.

3.5. Dynamic ordinary least squares

DOLS by Stock and Watson (1993) estimate β by running the regression

$$y_{1t} = \beta' y_{2t} + d(L)\Delta y_{2t} + v_t,$$

where L is a lag operator and d(L) is the lag operator polynomial 1-L. The leads and lags of Δy_{2t} eliminate asymptotically any possible bias due to endogeneity or serial correlation. DOLS estimation results are

$$\underset{[9.3212]}{LnGINI = 5.1086} - \underset{[-2.3069]}{0.1480}\ LnPCGDP. \tag{8}$$

Once again a negative relationship, with an increment of 1% in per capita GDP associated with a reduction of the country's Gini index by 0.14%.

4. Granger causality and impulse response functions

4.1. Causality direction between per capita GDP and GINI index

A first attempt to get an insight about the direction of causality can be the weakly exogeneity test. However, exogeneity does not mean causality. However, if two series are individually $I(1)$ and cointegrated, a causal relationship will exist in at least one direction (Engle and Granger, 1987). Furthermore, the Granger representation theorem demonstrates how to model cointegrated $I(1)$ series in the form of a VAR model. In particular, the VAR can be built either in terms of levels of the data (the $I(1)$ variables) or in terms of their first differences ($I(0)$ variables) with the addition of an error correction term (ECM) to capture short-run dynamics.

Toda and Yamamoto (1995) suggest testing Granger–causality by applying a VAR model with an extra lag. This procedure is advisable when variables are $I(1)$, however this method could be inefficient with small samples and there may be a loss of power due to over-specifying the lag length. Lütkepohl (2005) remarks that there are in fact cases where the extra lag is not necessary to obtain asymptotic

Chi-square distribution of the Wald test for Granger-causality. For example, for bivariate processes with $I(1)$ variables and cointegration rank 1, no extra lag is needed. In fact, Lütkepohl and Reimers (1992) show that Wald tests for Granger causality in cointegrated bivariate VARs (this is the case in the present work) are asymptotically distributed as Chi-square. Dolado and Lütkepohl (1996) Monte Carlo simulation with a VAR system of two $I(1)$ variables and small samples (T = 50, 100, 200), shows that, when there is cointegration, the standard Wald test yields better results than a modified test estimating extra coefficients.

Thus, the Toda and Yamamoto procedure is not always needed. Since we have one cointegration relationship in a bivariate model with $I(1)$ variables, we can follow Lütkepohl and Reimers' (1992) suggestion. Results of the VAR Granger causality based on the Wald test are reported in the next Table 6.

From the upper panel, we can reject the null of no-causality from LnPCGDP to LnGINI, at the 10% significance level, and at the 5% significance level as well. From the lower panel, we see that the null of no-causality from LnGINI to LnPCGDP cannot be rejected. The results suggest that there is unidirectional Granger-causality from LnGDP to LnGINI.

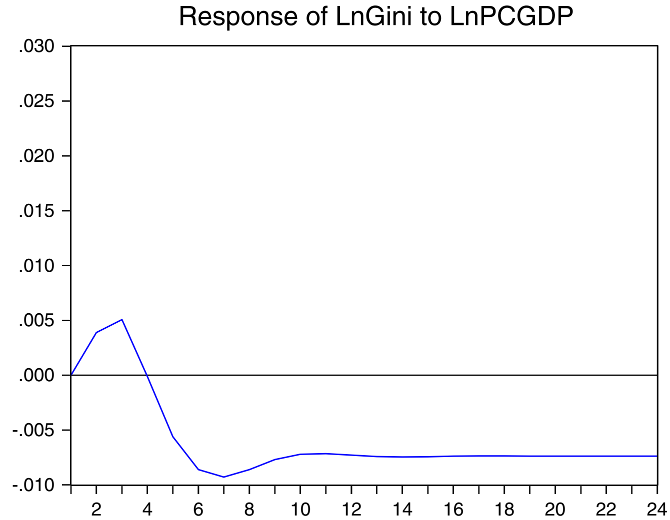

Fig. 2. Response to Cholesky one S.D. innovations. Response of LnGini to LnPCGDP.

4.2. Impulse response functions

Impulse response analysis is important in figuring out the impact of any specific variable on others in the system. It shows how a one standard deviation innovation in a given variable affects the contemporaneous and future values of all endogenous variables. Fig. 2 shows the effect of a Cholesky one standard deviation innovation on LnGINI and LnPCGDP.

From the exogeneity of LnPCGDP in system (1), our interest is in the impulse response of LnGINI to a positive shock onto per capita LnPCGDP. Given such a positive shock, income inequality, LnGINI, shows positive response just in the first 3 years, and then a decline until a negative effect (4th year) which then remains constant after the ninth year.

5. Concluding remarks

This paper has two contributions. First is the study of a relevant question, the relation between inequality and economic growth for a country, Mexico, and of its properties. Second is the use of several different methodologies to produce and confirm empirical results.

The main findings are that i) there is indeed in Mexico (as is almost intuitively true), a long-run (in the sense of cointegrating) relationship between income inequality (measured by the Gini coefficient) and per capita GDP, ii) that such relationship is *negative*, and moreover, iii) the unidirectional causality goes from LnPCGDP to LnGINI. Our findings can be put, e.g., against the *predictions* of Kaldor-type models (where the causality relation is reversed from what we have here) or of the Kutznets curve (where the relation is unstable as it goes through *phases of growth*, while our relation is a long run one).

It is clear that in a country such as Mexico, policies for growth also have broader effects as they deliver a bonus to a wider population. This is consistent with what we know, i.e. that in certain countries, recent growth has gone along with a diminishing concentration of income and a growing middle class. However, while some other less developed countries have seen a re-distribution of the benefits of growth, the contrary has happened in economies that until recently had been known for their better or more even distribution of income and wealth. So, the idea put forward by e.g. Barro (2000) can be reworded as saying that there are distinct "clubs of countries" each club sharing a *model of growth* defined in terms of the relationship distribution-growth. The whole "growth convergence" issue could be re-examined in these terms.

On the other hand, targeting policies would have to be different from club to club. In the Mexico's club, if such a club exists, the target would be growth, the consequence the delivery of a fairer distribution of the benefits from it. The question becomes: what should be listed in an effective growth agenda? In econometric terms there apparently are some explicatory variables behind our per capita growth; they need to be made explicit and become policy instruments and/or objectives of such an agenda. Growth literature in recent years has produced a number of valuable results and many insights. Education, R & D and innovation, openness and international trade institutions are some of the sources of growth. Many emerging countries seem to be following such growth agenda very seriously, and this is the likely reason of their success.

Not all such variables are, however, amenable to speedy adjustment or can be subjected to intervention effective in the short term, institutions being obviously one of them. Thus, while recent work has enhanced our understanding of the interplay between inequality and growth, much remains to be done before we can confidently design an adequate policy mix producing the best chance to grow and at the same time to reduce inequality.

Although in our exercise data seems to speak for itself, nevertheless, as with any other study, we have to recognize that it can be improved along many dimensions. For instance, research could focus on using alternative inequality measures for income and/or wealth, or on levels of education, R & D or other sources of growth. This could prove difficult for the scarcity of long-time series data, so that this is also an area to work on.

However, probably the step to be taken next is to analyze whether distinct *models of growth*, as defined above, exist within emerging economies (and compare with developed ones): does the relation we have found, hold for all countries (such as the BRICS, the early third Millennium success story)? Or our idea of distinct growth clubs is better suited to capture a varied reality?

Table 6
VAR Granger Causality/Block exogeneity Wald tests.

Sample: 1968 2010			
Included observations: 40			
Excluded	Chi-sq	df	Prob.
Dependent variable: LNGINI			
LNGDP	9.5560	3	0.022
Dependent variable: LNPCGDP			
LNGINI	3.6044	3	0.3075

Source: Own elaboration.

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