Does Inequality Benefit Growth? New Evidence Using A Panel VAR Approach

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Abstract

In this paper, we investigate the dynamic relationship between economic growth and income inequality, an issue that has not found yet a clear consensus in the literature. In particular, we implement a panel VAR approach, using state-level data for Brazil, to assess the dynamic effects of inequality on growth and vice versa. We show that inequality shocks lead to higher economic growth, therefore supporting the view that, in poor countries, higher inequality does benefit economic growth. We also present evidence that higher growth leads to lower income inequality, consequently pursuing growth enhancing policies should be translated not only in higher growth, but also in better income distribution. Our results are robust to different inequality measures and also when we include a measure of human capital accumulation.

Keywords: Income inequality; economic growth; panel var.
JEL Classification: O43, C33.

Resumo

Neste trabalho, investigamos a relação dinâmica entre crescimento econômico e desigualdade de renda, uma questão que ainda não encontrou um consenso claro na literatura. Em particular, implementamos uma abordagem VAR Painel, usando dados estaduais para o Brasil, para avaliar os efeitos dinâmicos da desigualdade no crescimento e vice-versa. Mostramos que os choques de desigualdade levam ao crescimento econômico mais elevado, sustentando, portanto, a opinião de que, nos países pobres, uma maior desigualdade beneficia o crescimento econômico. Também apresentamos evidências de que um maior crescimento leva a uma menor desigualdade de renda, consequentemente, ao se buscar políticas que beneficiem o crescimento, os resultados devem ser traduzidos não apenas em maior crescimento, mas também em uma melhor distribuição de renda. Nossos resultados são robustos para diferentes medidas de desigualdade e também quando incluímos uma medida de acumulação de capital humano.

Palavras-chave: Desigualdade de Renda; crescimento econômico; VAR em painel.
Classificação JEL: O43, C33.

Área ANPEC: 6 - Crescimento, Desenvolvimento Econômico e Instituições

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1 Introduction

The relationship between income inequality and economic growth is a long standing issue in Macroeconomics. On the one hand, some authors have found that higher income inequality is beneficial to growth (Partridge, 1997; Galor & Tsiddon, 1997; Li & Zou, 1998; Forbes, 2000) and more recently Brueckner & Lederman (2015) and Cavalcanti & Giannitsarou (2016). On the other hand, there is evidence of a negative relationship with higher inequality being associated with lower growth (Alesina & Perotti, 1996; Persson & Tabellini, 1994; Atems & Jones, 2015). In this paper, we explore the dynamic relationship between income inequality and economic growth, using state-level data for Brazil, a country known by its high level of income disparities. In particular, we investigate what are the effects of shocks to income inequality on growth and vice versa.

In order to investigate this issue, we employ a Panel Vector Autoregression (PVAR) approach and estimate a bivariate PVAR using a measure of income inequality (Gini coefficient) and income data (real GDP per capita). As in traditional Vector Auto-Regressive (VAR) models, the PVAR model is quite flexible and allow us to treat both variables as endogenous. However, PVAR models have an additional advantage over traditional VARs, the possibility to account for time invariant characteristics intrinsic to each unit in our sample. Moreover, given the short time length of our data set, this methodology exploits the panel structure of the data (short T and large N) that is not reliable in a traditional VAR estimation. Orthogonal impulse-response functions (IRFs) are obtained by means of a triangular identification scheme by assuming that real output per capita does not respond contemporaneously to inequality shocks.[1]

Our results show that after an inequality shock the growth rate of real GDP per capita improves and hence higher inequality is beneficial to growth.The effects on the growth rate last for at least 3 years after the initial shock, changing real GDP per capita permanently (level effect).[2] On the other hand, an income shock (i.e. higher GDP growth) is followed by better income distribution (i.e. after a GDP shock income inequality declines). These results are robust when we use a different inequality measure (e.g. Theil Index).

We extend our analysis by estimating a three-variable PVAR to include a measure of human capital. We do this for two purposes. First, to capture the idea that higher economic growth may lower income inequality through higher human capital accumulation (Brueckner et al., 2015).[3] Second, adding a measure of human capital allows us to investigate whether the effects of inequality shocks are indeed a result of a third factor, in our case, shocks to human capital. Our results are robust to introducing human capital.

This paper is related, more directly, to the branch of the literature that investigates the empirical relationship between income inequality and economic growth (Atems & Jones, 2015; Brueckner et al., 2015; Brueckner & Lederman, 2015). Atems & Jones (2015) also employ a PVAR model and show that higher inequality reduces income level and growth in US states. Brueckner et al. (2015), using a panel of 154 countries spanning 1960-2007, show that higher economic growth is associated with lower inequality. Brueckner & Lederman (2015) estimates the effect of income inequality on real gross domestic product per capita using a panel of 104 countries during the period 1970–2010. They find that, on average, income inequality has a

[1] We will discuss the validity of this restriction in section 3.

[2] Galor & Zeira (1993) propose a model where under credit market imperfections and indivisibilities in investment in human capital, higher inequality affects real GDP per capita positively in the short run as well as in the long run.

[3] For instance, Galor & Zeira (1993) argues that, when credit markets are imperfect, higher aggregate income are associated with lower inequality. However, the channel through which the effects of higher income are transmitted to inequality is through higher physical capital accumulation.

significant negative effect on gross domestic product per capita growth and the long-run level of gross domestic product per capita. However, they show that the impact differ by the level of economic development. In particular, in poor countries, income inequality has a significant positive effect on gross domestic product per capita.

The results that higher income inequality can be beneficial to economic growth are in line with the theoretical work by Galor & Zeira (1993). They show that the relationship between inequality and aggregate output in the presence of credit market imperfections and indivisibilities in human capital investment varies across countries initial income levels. While, in rich economies, we should expect a negative relationship between inequality and growth, in poor countries, higher income inequality may be associated with higher economic growth and higher real GDP per capita.[4] This is the result presented in Brueckner & Lederman (2015) and also showed in this paper. Cavalcanti & Giannitsarou (2016), using a concept of network, show that the relationship between growth and inequality is also positive for a given network structure. They show that when the network cohesion is low, the more likely it is to have high growth and inequality in the long run.[5]

The remainder of the paper is organized as follows. In section 2 we give the details on the dataset used. In section 3 we present our empirical methodology. Section 4 discusses the results. Finally, conclusions are presented in section 5.

2 Data

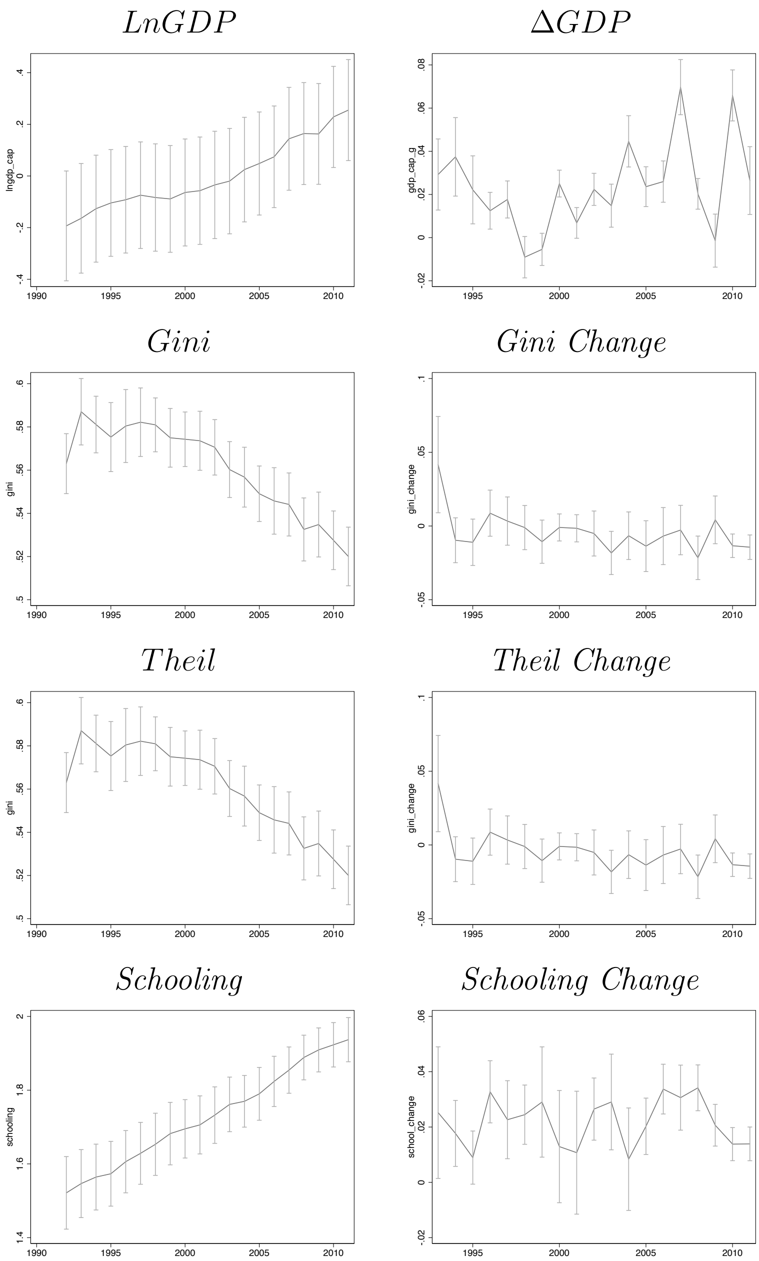
Our income per capita measure is the real GDP per capita from Instituto de Pesquisa e Economia Aplicada (IPEA), while we use two measures of income inequality: a Gini coefficient and Theil index, both from IPEA database. All data ranges from 1992 to 2011.[6] Real state-level GDP is in constant Brazilian Real (R$ 2010). Our measure of human capital accumulation is the average years of schooling for adults who are 25 years of age or older. This is computed as the ratio of the sum of the number of years of study completed by people who are 25 years of age or older and the number of people in this age group. Figure 1 presents the data used in the estimation.

[4] The rationale for the positive relationship between inequality and growth is that under imperfect credit markets, higher inequality channels more resources towards people with higher marginal propensity to save and hence increases capital accumulation and promotes growth.

[5] Network cohesion is a network statistics that can be interpreted as a measure of how uniform or fragmented a network is. See Cavalcanti & Giannitsarou (2016) for details.

[6] For some years (1994, 2000 and 2010) Gini coefficients were not available. For these years, we implement a linear interpolation.

Figure 1: Data used in the estimations



Notes: The column on the left contains the plots of the variables in levels. The column on the right presents the variables in first differences.

A visual inspection of the variables used in the estimation of the PVAR model suggests that a time trend is presented in the variables in levels and such trend seems to be absent when the variables are in first-differences.

3 Methodology

The dynamic relationship among our endogenous variables can be represented as:

$$Y_{it} = \phi_i + A(\ell)Y_{t-l} + \delta_t + u_{it} \qquad i = 1, ..., 27 \quad t = 1992, ..., 2011 \tag{1}$$

where $Y_{it} = [\Delta GDP_{it}, Gini_{it}]'$ is a $\kappa \times 1$ vector of endogenous variables for unit (state) i at time t, ϕ_i is a $\kappa \times 1$ vector of time-invariant state fixed effects, δ_t represents unobservable time effects, $A(\ell)$ are $\kappa \times \kappa$ matrices of lagged coefficients. The fixed effects capture any differences across states that are time invariant (e.g. cost of living, climate, etc.). Finally, $u_{it} \sim iid(0, \Sigma_u)$ is a $\kappa \times 1$ vector of reduced form idiosyncratic disturbances with a nonsingular variance-covariance matrix, Σ_u.

Pooled fixed effects estimation is one possible way to estimate the parameters of the model (1). However, even when N is large, but T is fixed, the pooled estimator is biased. We implement a "Helmet procedure" and employ a GMM approach of Arellano & Bover (1995), which is consistent even when T is small.[7]. The procedure implements a transformation to eliminate the individual fixed-effects. Therefore, before estimation, we rewrite equation (1) in terms of forward orthogonal deviations denoted by:

$$\bar{\bar{y}}_{it} = (y_{it} - \overline{y_{it}}) \sqrt{\frac{T_{it}}{T_{it}+1}} \tag{2}$$

where T_{it} is the number of available future observations for state i at time t and $\overline{y_{it}}$ is its average. Applying this transformation to our endogenous variables, allow us to rewrite the system (1) as:

$$\bar{\bar{Y}}_{it} = A(\ell)\bar{\bar{Y}}_{t-1} + \delta_t + u_{it} \qquad i = 1, ..., 27 \quad t = 1992, ..., 2011 \tag{3}$$

The transformed variables in Equation (3) are orthogonal to the original variables and hence the latter can be used as instruments.

To achieve identification, we assume real GDP per capita (or its growth rate) does not respond contemporaneously to an inequality shock within the year. Therefore the variance-covariance matrix of the residuals, Σ_u, takes the form of a lower-triangular matrix with ΔGDP entering first in the $Y_{i,t}$ vector. This identifying restriction is justified based on the fact that real income is used in the computation of the Gini coefficients, so we would expect that any change in real income will be translated to the Gini coefficient contemporaneously, but not the reverse. That is, changes in Gini coefficient will take at least one year to affect real income (Atems & Jones, 2015).

For the purpose of recovering impulse response functions, equation (3) can be rewritten as $B(\ell)\bar{\bar{Y}}_{it} = u_{it}$, where $B(\ell) = (I_k - A(\ell))$. As long as all eingenvalues of $A(\ell)$ have modulus less than 1, $B(\ell)$ satisfies the stability condition and hence is invertible. Therefore, we can obtain a MA representation of the PVAR model

$$\bar{\bar{Y}}_{i,t} = \Theta(\ell)u_{it}, \tag{4}$$

where $\Theta(\ell) = \sum_{j=0}^{\infty} \Theta_j l^j \equiv B(\ell)^{-1}$. The disturbances u_{it} are correlated contemporaneously and hence we implement a Cholesky decomposition on $\Sigma_u = P'P$, where P is a lower-triangular matrix, such that it is possible to orthogonalize disturbances as $P^{-1}u_{it} \equiv e_{it}$. The vector e_{it} will be the orthogonalized disturbances, which it will give us the orthogonalized impulse-response functions.

[7]The bias is due to the fact that unit specific intercepts, ϕ_i, are correlated with the error term.

4 Results

First, we present the results for a variety of panel unit tests.[8] Second, we present the Impulse Response Functions (IRFs) from our baseline bivariate PVAR specification. Finally, we extend our analysis by introducing a measure of human capital. We do this for two purposes. First, to capture the idea that higher economic growth may lower income inequality through higher human capital accumulation (Brueckner et al., 2015). Second, to investigate whether the effects of inequality shocks are indeed a result of a third factor, in our case, shocks to human capital.

4.1 Panel Unit Root Tests

Table 1 presents the results of different panel unit root tests. Testing unit roots in context of panel data is not as straightforward as in usual time series analysis, but the idea is similar.[9] Consider a variable that can be represented by a single panel-data model with a first-order autoregressive representation such as:

$$x_{it} = \rho_i x_{i,t-1} + W'_{it}\gamma_i + \epsilon_{it} \tag{5}$$

where x_{it} is the variable being tested, the term W_{it} can represent panel-specific means and/or a time trend. Typically, most tests evaluates the null $H_0 : \rho_i = 1$. However, a more common approach is to rewrite the test equation 5 as:

$$\Delta x_{it} = \rho_i x_{i,t-1} + W'_{it}\gamma_i + \epsilon_{it} \tag{6}$$

and to test, alternatively, $H_0 : \rho_i = 0$, where Δx_{it} is the variable being tested in first differences. The specific form of the null hypothesis varies across test, while in Levin-Lin-Chu (LLC) test, Harris-Tzavalis (HT) test, Im-Pesaran-Shin (IPS) test and Fisher (ADF type) test the null is of nonstationarity, in Hadri's test, the null is that all panels are stationary.

We perform each test on the level and on the first difference of each variable in our sample. Therefore, in deciding whether the variable will enter the PVAR model in level or in first differences we take into account the panel unit root test results. Additionally, we also compute the eigenvalues of the $A(\ell)$ matrix to check whether the PVAR model has a stable moving average representation.

A visual inspection of Figure 1 suggests a time trend is present in all variables in levels, so in performing unit root tests we allow for a time trend, while the lag length choices are based on the Akaike Information Criterion when possible. Table 1 presents the results of the panel unit root tests.

[8] We also check the stability condition, i.e., whether the eingenvalues of the matrix of estimated coefficients are strictly less than one. Figure 9 in appendix presents a graphical representation of this condition.

[9] For a recent survey about panel unit root tests and how to interpret these tests in context of panel data see Pesaran (2012).

Table 1: Panel Unit Root Tests

Test	Level	First difference	Level	First difference
	A. Real GDP per capita		B. Gini coefficient	
Levin-Lin-Chu	-4.6113 (0.00)	-11.5132 (0.00)	-5.1537 (0.00)	-17.2605 (0.00)
Harris-Tzavalis	0.652 (0.4306)	0.0319 (0.00)	0.19222 (0.00)	-0.2396 (0.00)
Im-Pesaran-Shin	-1.3558 (0.08)	-12.1682 (0.00)	-4.4639 (0.00)	-17.5632 (0.00)
Fisher (ADF)	-1.3012 (0.9034)	7.2135 (0.00)	2.4348 (0.0074)	19.1049 (0.00)
Hadri	25.1705 (0.00)	1.6083 (0.05)	4.114 (0.00)	-3.1357 (0.99)
	C.Theil Index		D. Schooling	
Levin-Lin-Chu	-7.9997 (0.00)	-18.1705 (0.00)	-5.4139 (0.00)	-20.5806 (0.00)
Harris-Tzavalis	0.1592 (0.00)	-0.2338 (0.00)	0.4215 (0.00)	-0.1022 (0.00)
Im-Pesaran-Shin	-7.1492 (0.00)	-18.6108 (0.00)	-4.2121 (0.00)	-18.7686 (0.00)
Fisher (ADF)	3.6851 (0.00)	19.66 (0.00)	-1.8234 (0.96)	9.8838 (0.00)
Hadri	4.2149 (0.00)	-2.7954 (0.99)	9.9888 (0.00)	-3.2917 (0.99)

Note: Reported values are t statistics and p values are presented in parentheses. Except for Hadri's test, the null hypothesis is for the presence of unit roots. Tests differ in the exact specification of the null and alternative hypothesis.

For the level of real GDP per capita, HT test, IPS test, Fisher test and Hadri's stationarity test indicate non-stationarity. Only LLC test indicates that the level of real GDP per capita is stationary. When the same tests are performed on the first difference, the hypothesis of stationarity cannot be reject at 5% level. Therefore, we will use real GDP per capita in first differences.

For inequality measures (Gini coefficient and Theil index), in four tests (LLC, HT, IPS and Fisher) the null of non-stationarity can be rejected at 5% level. However, the results for Hadri's stationarity test show opposite results, rejecting the null of stationarity. Therefore, in our baseline specification, the inequality measure will enter in level, but we will also use a specification in first differences to assess the robustness of our results.

Finally, for our measure of human capital, Fisher's test and Hadri's test consistently indicate that this variable is not stationary. Therefore, we will use schooling in first differences in our PVAR models.[10]

[10] We also tested PVAR models using schooling in level, but the models failed to satisfy the stability condition and hence did not present a stable moving average representation.

4.2 Impulse Responses

We have used multivariate versions of standard Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) to determine the lag length in our PVAR model. The AIC indicated a model with three lags, while the BIC a model with only one lag. Our choice was to use the most parsimonious model (Andrews & Lu, 2001; Abrigo et al., 2016). Next we present the results regarding our estimated Impulse Response Functions.

4.2.1 Economic Growth and Income Inequality

The results of our baseline specification show that the effects of income shocks on inequality are "positive", but short-lived. That is, in response to a one standard-deviation increase in real GDP per capita growth, income inequality falls and stays below its steady-state value for one-year.[11]

On the other hand, the effects of inequality shocks are a little more persistent. After a positive inequality shock (i.e. higher inequality), the growth rate of real GDP per capita increases and remains above its steady-state level for almost three years. Although the effects of inequality shocks on the growth rate are short lived, there is a permanent, level effect, on real GDP per capita.[12]

Brueckner et al. (2015) in the context of instrumental regressions in a traditional panel model for a large sample of countries, controlling for country and time fixed effects, show that higher real GDP have a significant moderating effect on income inequality. In the context of PVAR models, Atems & Jones (2015) also obtain that an income shock leads to lower inequality as we do in this paper. However, differently from Atems & Jones, our results indicate that after an inequality shock, real GDP growth improves in Brazil. Brueckner & Lederman (2015) obtain a similar result in instrumental regressions using a panel of countries and controlling for initial level of country's income. They show that, in poor countries, higher income inequality is beneficial to economic growth.

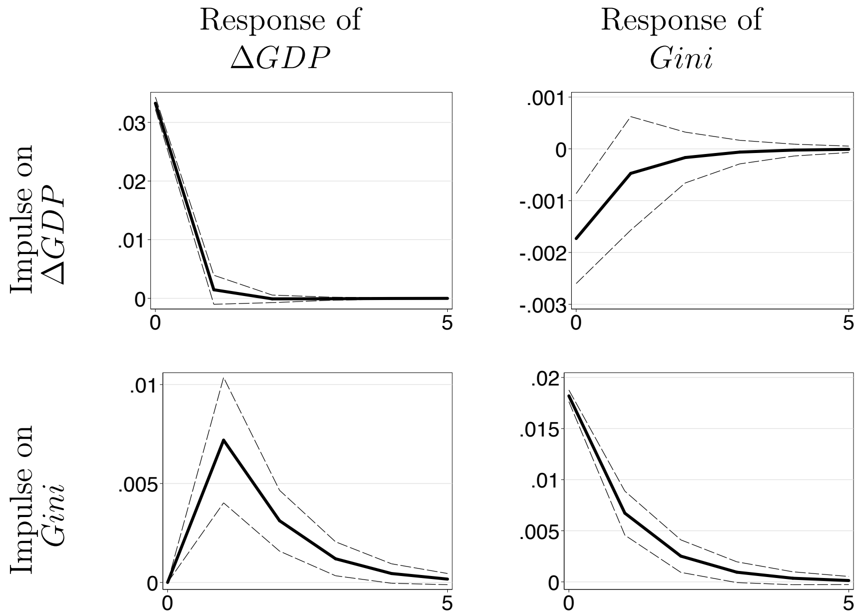
In a theoretical framework, Galor & Zeira (1993) show that higher inequality benefits growth by enhancing higher capital accumulation in an economy with credit market imperfections, which it seems to be the case in Brazil. As saving rates depend positively on wealth, higher inequality channels more resources towards people with high marginal propensity to save, increasing capital accumulation, and fostering higher growth.[13]

[11] The short duration of real income shocks is due to the short lag length of our PVAR model.

[12] It is important to notice that inequality may increase because the poor becomes poorer and/or the rich becomes richer. Although this might be interesting in itself, our data does not allows us to make this differentiation.

[13] However, inequality may also hurt growth. In wealthier economies, more equality alleviates the adverse effects of credit constraints on human capital formation and hence lead to higher growth when human capital is an engine of growth (Galor & Moav, 2004).

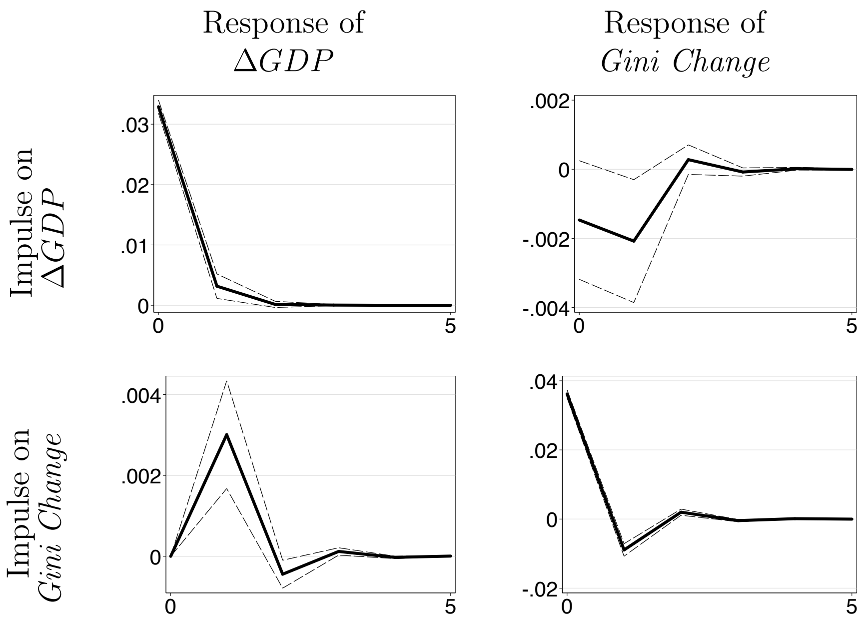
Figure 2: Growth and Inequality: Impulse-Responses



Notes: The column on the left contains the plots of the responses from ΔGDP to a one standard deviation shock in each indicated variable. The column on the right are the responses from $Gini$ to a shock of one standard deviation in each indicated variable. The shadowed area represent the 68% confidence interval using a Monte Carlo procedure with 500 replications.

Using our inequality measure in first differences does not alter the results. In response to an inequality shock (a shock to its growth rate), the growth rate of real GDP per capita still increases. Similarly, in response to an income shock, the growth rate of the Gini coefficient falls. Figure 3 presents these results.

Figure 3: Growth and Inequality: Impulse-Responses



The column on the left contains the plots of the responses from ΔGDP to a one standard deviation shock in each indicated variable. The column on the right are the responses from *Gini change* to a shock of one standard deviation in each indicated variable. The shadowed area represent the 68% confidence interval using a Monte Carlo procedure with 500 replications.

Next we extend our baseline model to include a measure of human capital accumulation.

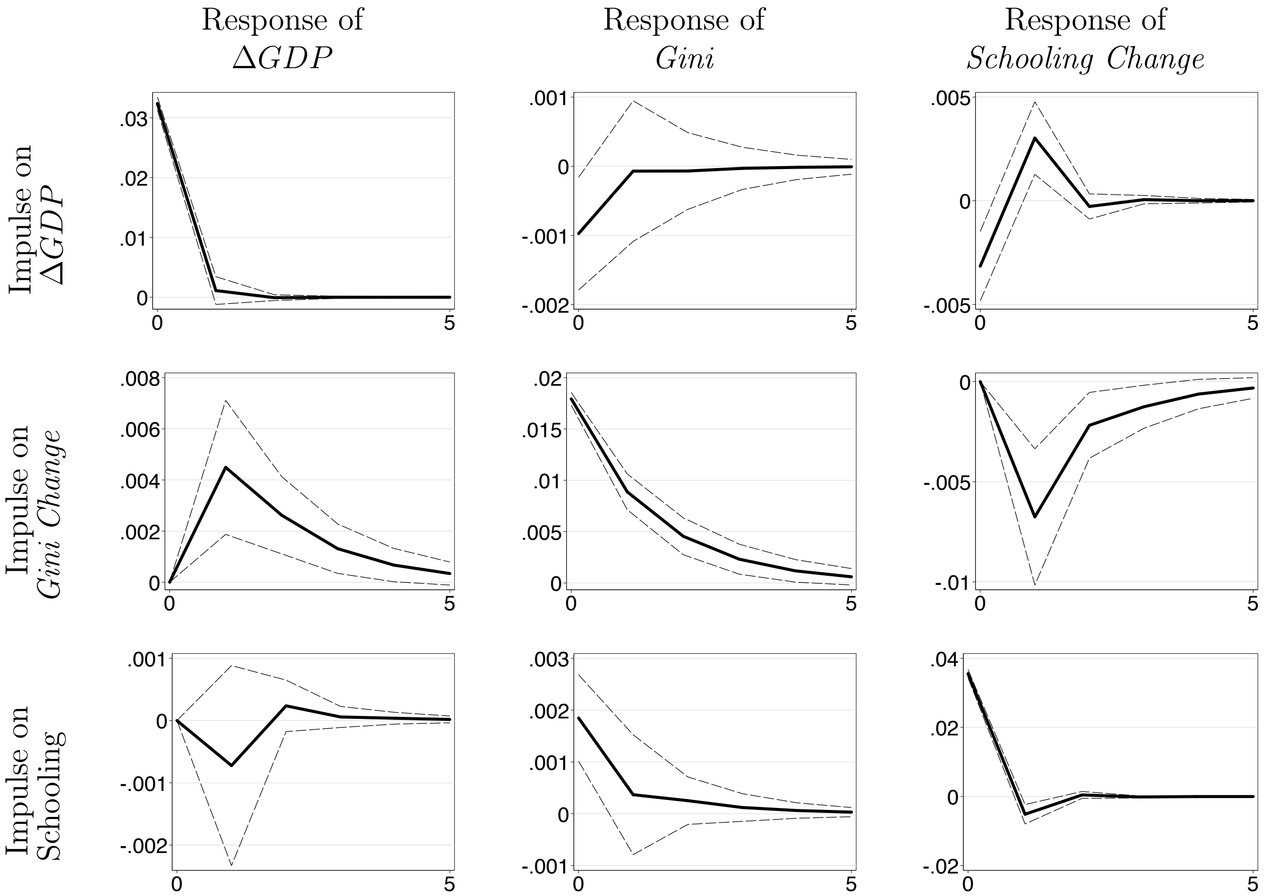
4.2.2 Growth, Inequality and Human Capital

We check our baseline results by extending our PVAR model to include a measure of human capital. The rationale is that higher economic growth may lower income inequality through higher human capital accumulation (Brueckner et al., 2015). Figures 4 to 6 present the results of this exercise. The difference among them is the entry order in the PVAR model.

In Figure 4, we assume real GDP per capita growth enters first, followed by education and then by Gini coefficient. Under this specification, an income shock still lowers inequality but at a lower extent. Our measure of human capital first declines and then increases after the income shock, before returning to its steady-state level.

When we look at the effects of inequality shocks, real GDP still increases as in our baseline specification. However, the mechanism proposed by Galor (2011) that, in poor countries, higher income inequality leads to higher human capital accumulation does not seem to be at work in Brazil, as after an inequality shock human capital accumulation declines. The figure also shows that an education shock does not alter the rate of economic growth, but increases inequality.

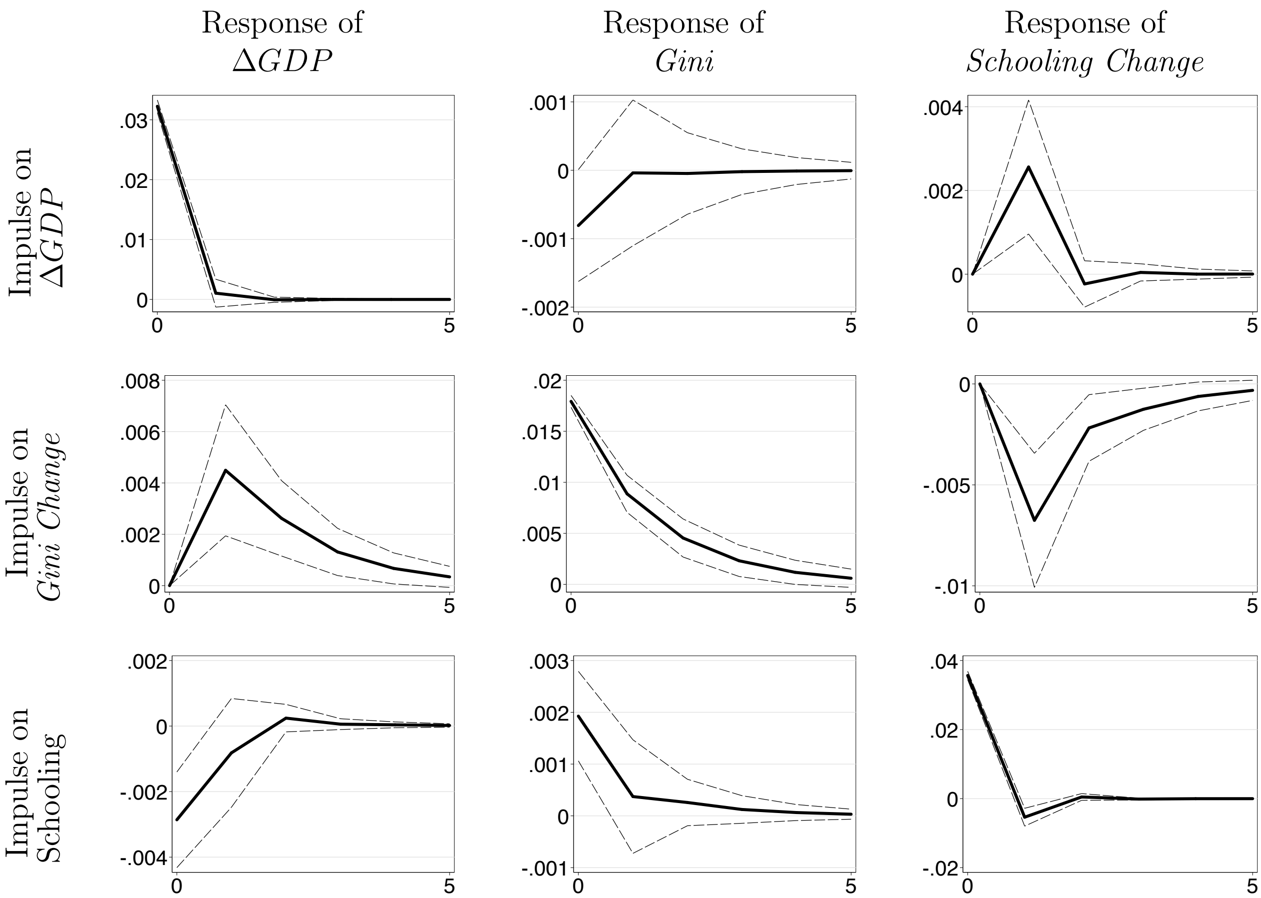
Figure 4: Growth, Inequality and Human Capital



Notes: Ordering:[ΔGDP, *Schooling Change*, *Gini*]. The column on the left contains the plots of the responses from ΔGDP to a one standard deviation shock in each indicated variable. The column in the middle are the responses from *Gini* to a shock of one standard deviation in each indicated variable, while the column on the right the responses from our measure of human capital accumulation. The shadowed area represent the 68% confidence interval using a Monte Carlo procedure with 500 replications.

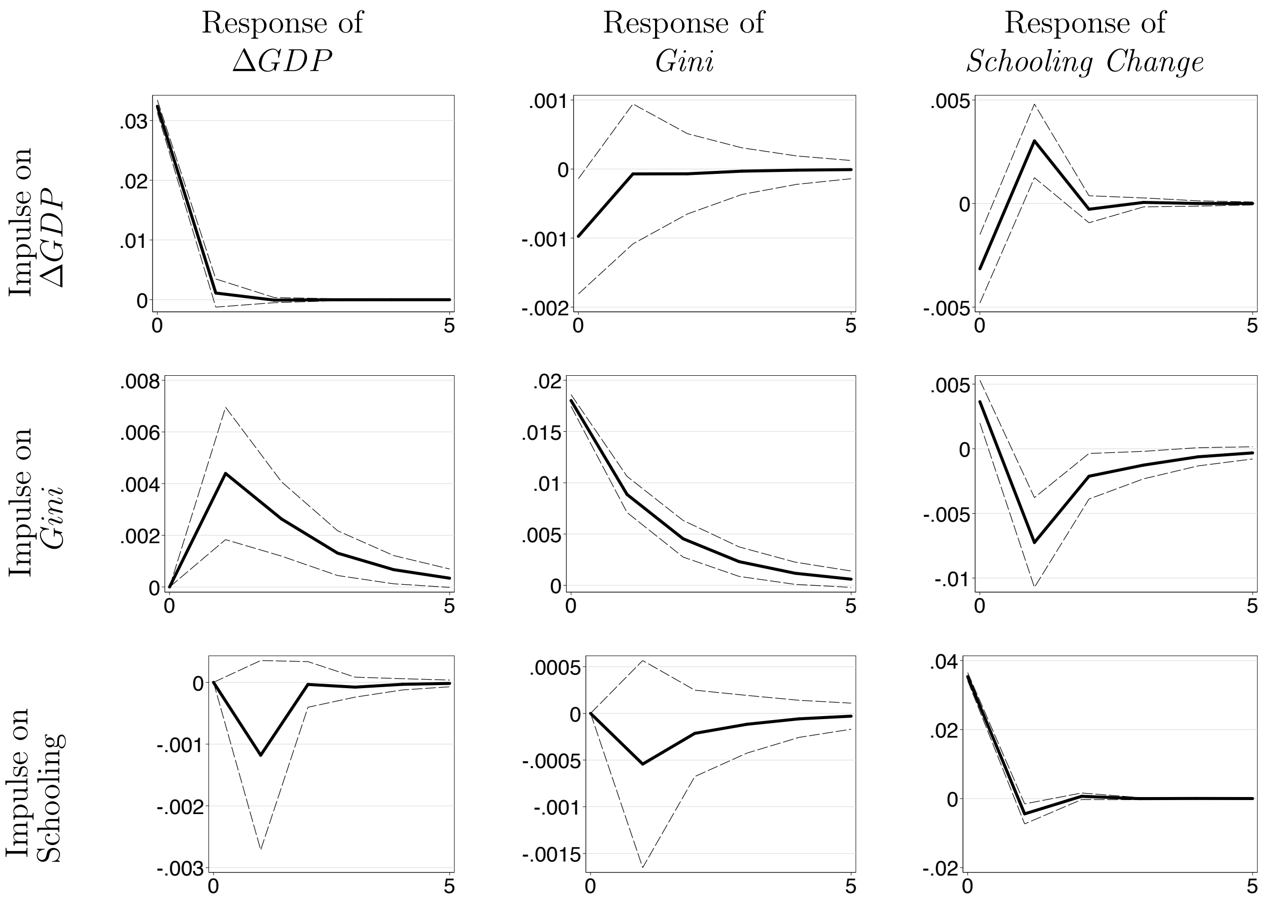
Figure 5 presents the IRF's in a model where education enters first and it is followed by real GDP per capita growth and then by Gini coefficient. The result that an income shock lowers inequality and an inequality shock enhances growth are still present. The same is true in the model when real GDP per capita enters first, followed by Gini coefficient and then by education. Figure 6 presents these results.

Figure 5: Growth, Inequality and Human Capital



Notes: Ordering:[*Schooling Change*, ΔGDP, *Gini*]. The column on the left contains the plots of the responses from ΔGDP to a shock of one standard deviation in each indicated variable. The column on the right are the responses from *Theil* to a shock of one standard deviation in each indicated variable. The solid lines correspond to the median responses to the shocks in a ten period horizon and the dashed lines are 68% confidence interval.

Figure 6: Growth, Inequality and Human Capital

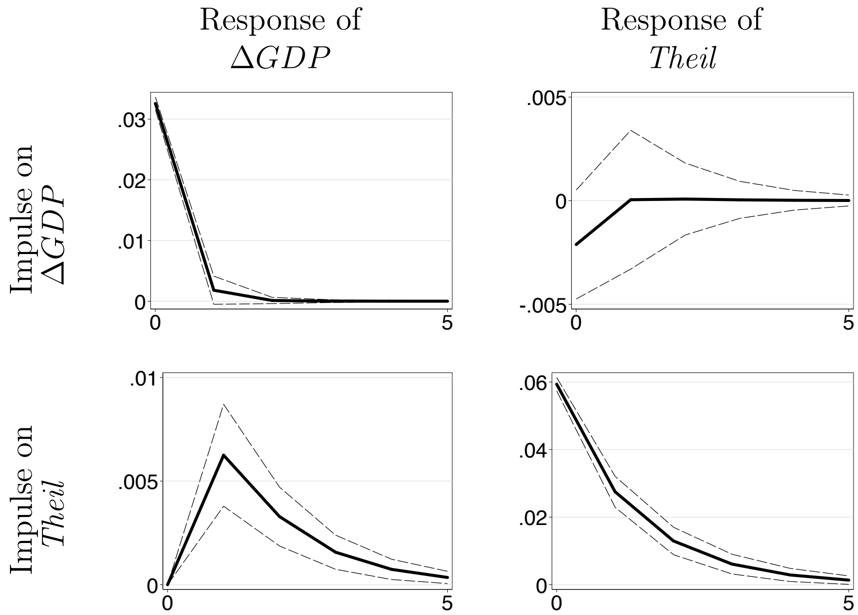


Notes: Ordering:[ΔGDP, *Gini*, *Schooling Change*]. The column on the left contains the plots of the responses from ΔGDP to a one standard deviation shock in each indicated variable. The column in the middle are the responses from *Gini* to a shock of one standard deviation in each indicated variable, while the column on the right the responses from our measure of human capital accumulation. The shadowed area represent the 68% confidence interval using a Monte Carlo procedure with 500 replications.

4.3 Alternative Inequality Measure

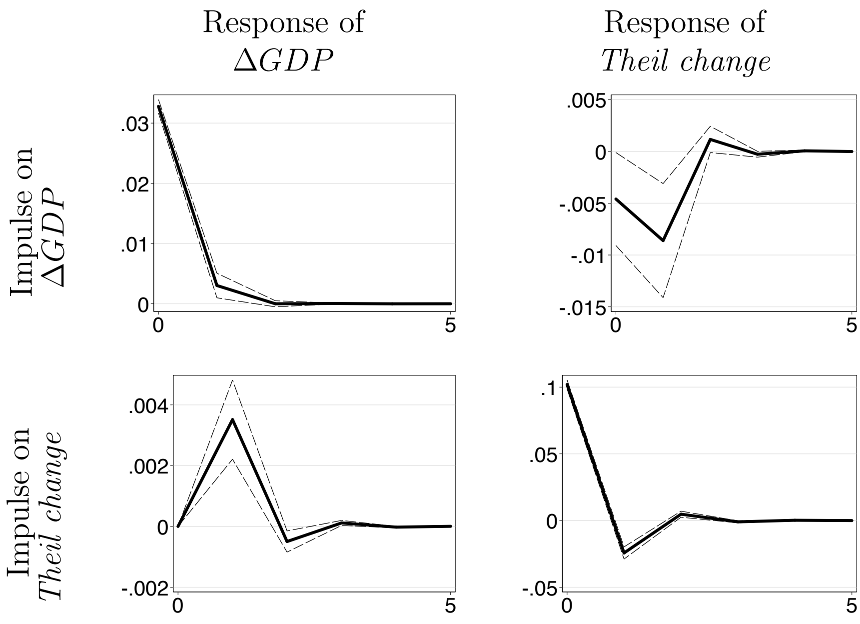
A second robustness exercise is to re-estimate our PVAR model using an alternative inequality measure - a Theil index. Figures 7 and 8 present the results using this alternative measure in levels and in first differences, respectively. Overall, our baseline results are robust when we change the inequality measure.

Figure 7: Growth and Inequality: Theil Index



Notes: The column on the left contains the plots of the responses from ΔGDP to a shock of one standard deviation in each indicated variable. The column on the right are the responses from *Theil* to a shock of one standard deviation in each indicated variable. The shadowed area represent the 68% confidence interval using a Monte Carlo procedure with 500 replications.

Figure 8: Growth and Inequality: Theil Index in First Differences.



Notes: The column on the left contains the plots of the responses from ΔGDP to a shock of one standard deviation in each indicated variable. The column on the right are the responses from *Theil change* to a shock of one standard deviation in each indicated variable. The shadowed area represent the 68% confidence interval using a Monte Carlo procedure with 500 replications.

5 Conclusion

In this paper, we argue that there is no clear consensus in the literature on the dynamic relationship between income inequality and economic growth. We explore this issue by means of a Panel VAR approach, using state-level data for Brazil spanning 1992-2011. We show that inequality is beneficial to growth, that is, after an inequality shock, the growth rate of real GDP per capita increases and stays above its steady state level for at least three years. The temporary change in the growth rate, changes the level of real GDP per capita permanently. On the other hand, after a positive income shock inequality declines. These results are robust either using a different inequality measure (e.g. Theil Index) or by estimating a three-variable PVAR to include a measure of human capital.

The result that higher inequality is beneficial to growth is in line with theoretical analysis by Galor & Zeira (1993) that show that higher inequality benefits growth by enhancing higher capital accumulation in an economy with credit market imperfections. As saving rates depend positively on wealth, higher inequality channels more resources towards people with high marginal propensity to save, increasing capital accumulation, and fostering higher growth.

In sum, we see our results as offering a positive (empirical) analysis of the dynamic relationship between growth and inequality. This is not to say we should pursue policies that increase inequality in order to foster higher growth. On the contrary, as we have shown, the relationship is not symmetric, as higher growth lowers inequality. Therefore, pursing growth enhancing policies should be translated not only in higher growth, but also in better income distribution.

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Appendices

A Additional Figures

Figure 9: Roots of the companion matrix