Is income inequality good or bad for growth? Further empirical evidence using data of all Brazil cities

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Abstract

This paper estimates the impacts of personal income inequality on subsequent growth in a massive spatial dataset for 5564 Brazilian cities observed in 1991, 2000, and 2010 using instrumental variables methods. Instead of assuming exogenous income inequality, we relax this assumption and let the data speak for themselves. Applying Wu-Hausman test data reject inequality exogeneity regarding subsequent growth. Our methods allow identifying causal effects between inequality and subsequent growth in conditional quantiles beyond the average. Income inequality significantly predicts adverse effects on subsequent growth using Brazilian city's data in the conditional mean, and in all considered conditional quantiles below and above average, being larger in more extreme quantiles. In the conditional mean, the magnitude of the estimate implies that lowering personal income inequality by 1 Gini point would translate to an increase in a cumulative economic growth of 2.51 percentage points in the following ten years. Our findings call attention to the risk of following Litschig and Lombardi [*J. Economic Growth*, 2019, vol. 24, pp. 155-187] when studying the influence of inequality on growth neglecting the endogeneity of the former to the latter.
Keywords: Income inequality; Endogeneity; Economic growth; Quantile regression.
JEL classification: D31; C5; O4.

Este estudo investiga se a desigualdade pessoal de renda é favorável ou desfavorável para o crescimento econômico subsequente empregando dados georreferenciados de 5564 cidades do Brasil observados em 1991, 2000 e 2010. Em vez de pressupor exogeneidade, testamos se a desigualdade pessoal de renda é exógena ao crescimento subsequente. O resultado do teste de Wu-Hausman indica rejeição da hipótese de exogeneidade. Testes para relevância e sobreidentificação indicaram a validade dos instrumentos. Desigualdade pessoal de renda afeta negativamente o crescimento econômico subsequente na média, acima e abaixo da média, e nos extremos da distribuição condicional na regressão de crescimento de Forbes. Para a média condicional, estima-se que a redução de uma unidade no índice de Gini corresponda a um aumento acumulado de 2,51% em termos de crescimento econômico na década seguinte. As conclusões não mudam quando os efeitos positivos e negativos de aglomeração em cidades são incluídos no modelo de regressão de Forbes. Endogeneidade negligenciada pode levar a conclusões equivocadas.
Keywords: Desigualdade de renda; Endogeneidade; Crescimento econômico; Regressão quantílica.

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1. Introduction

Whether a country can enjoy higher economic growth with lower income inequality is an issue that dates back to classical political economists. The matter importance relies on that, in some cir-

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cumstances, lower inequality in income can be compatible and even ignite economic activity and growth. Despite being formulated centuries ago, this question is always present in policy circles, governments policy decisions, and academic environments. Recently many authors show a renewed interest in the empirical investigation of whether income inequality is bad, or possibly good for future economic growth (Partridge, 1997; Forbes, 2000; Cingano, 2014; Bourguignon, 2016; Ostry, 2016; Litschig and Lombardi, 2019). The observed rise in inequality in the United States (Piketty and Saez, 2003; Saez and Zucman, 2020), according to Stiglitz (2016) has weakened consumption, a major component of demand in output, because those at the top income share spend a smaller percentage of their income than the rest. A similar pattern is present in China (Qin et al., 2009). By depriving masses of economic development benefits, income inequality also conveys a propensity to erode democracy (Bernstein, 2013). Moreover, Ostry (2016) and Qin et al. (2009) argue that inequality amplifies the potential for financial crises, may bring political instability, discouraging investment, and can cause difficulties for governments to respond to shocks. Besides, if income inequality is slowing economic growth, it also can limit the poverty reduction in countries (Bourguignon, 2003; Ravallion and Chen, 1997).

This paper argues that empirical studies using economic growth and income distribution data designed to inform policymakers and guide policy decisions should better match the data features and the assumptions of employed models to draw inferences more safely (Sickles and Williams, 2008). Nowadays, the existence of a more disaggregated and larger sample, detailed data, and the progress of statistical methods allow one to examine whether income inequality is bad or possibly good for future economic growth with greater precision and accuracy.[2] To the best of our knowledge, this is the first occasion in which the topic of inequality and subsequent growth is investigated using data of all Brazilian cities based on proper methods that match all data features entirely.

Greater personal income inequality is positively associated with future economic growth in Brazil, according to Litschig and Lombardi (2019). Their empirical evidence based on sub-national data implies that income inequality is a favorable factor for growth in Brazil. Places with a higher Gini coefficient exhibit higher subsequent income per capita growth (Litschig and Lombardi, 2019). Lowering the Gini index would lead to slower subsequent growth in Brazil. Thus, policymakers should not be concerned with income inequality regarding future growth in Brazil because the country is already substantially unequal.[3] Given the matter importance for policy in Brazil and other countries with similar characteristics, and all reported gaps in the literature (Forbes, 2000; Reed, 2015; Bourguignon, 2016) untouched by the Litschig and Lombardi (2019) study, this paper further explores the relationship between personal income inequality and subsequent economic growth by choosing a larger sample and more disaggregated, and more informative database from Brazil.

Instead of assuming exogenous income inequality regarding subsequent growth as been done in Litschig and Lombardi (2019) study, we relax the assumption of exogenous income inequality and let the data speak for themselves. We apply the Wu-Hausman test to verify if income inequality is exogenous to subsequent growth based on the recommendations of Forbes (2000), Bourguignon

[2]Since the main objective of this paper is empirical, we refer to the work of Barro (2000) for a summary of theories based on personal income distribution, and Bowles and Boyer (1995) for theories based on functional income distribution. For a more detailed and complete theoretical presentation, see Bertola (2000). Cingano (2014) also presents a summary of predictions from theory. He explains that in developing countries, the most probable effect of inequality on subsequent growth is negative.

[3]Ostry (2016) summarize nine factors generally considered essential for long-run growth and the duration of growth over time. Income inequality is one of them. See also Berg et al. (2012).

(2016), and mainly the simulation study of Reed (2015), according to which the practice of replacing one variable by its lagged value does not prevent endogeneity. The first step using the Wu-Hausman test statistic is essential because when using non-experimental data, neglected endogeneity can lead to inconsistent parameter estimates, invalid inference, and wrong conclusions (Hayashi, 2000; Reed, 2015; Baltagi et al., 2012). In contrast, instrumental variable methods can identify causal effects and generate consistent estimates leading to reliable conclusions when endogeneity is present in data (Hayashi, 2000; Baltagi et al., 2012; Wooldridge, 2010). Based on a massive spatial dataset for 5564 Brazilian cities observed in 1991, 2000, and 2010, we adopt instrumental variable methods because data significantly reject the inequality exogeneity assumption.

Personal income inequality significantly reduces future economic growth in Brazil's cities data. Higher inequality in income leads to significant adverse effects in subsequent growth, not only on average but also in conditional quantiles' in the lower and upper tails. The findings are insensitive when we extend the standard growth regression model of Forbes (2000) to account for agglomeration effects (Krugman, 1999; Rosenthal and Strange, 2020) typically found in cities and regional fixed effects based on three different instrumental variable methods. Because our sample size is more than five and a half thousand observations, we obtain more precise parameter estimates than previous studies. Furthermore, less uncertainty exists in the estimates with the larger sample. Being a large sample, we also get more power to the Wu-Hausman test. All these features enhance the reliability of our conclusions.

The essential contribution of the paper is to express, quantitatively, how important income inequality is for future economic growth in Brazil. In all estimated growth regressions of Forbes (2000) designed to study the influence of inequality on subsequent growth, we account for the endogeneity of the regressor, omitted variable bias, and substantial heterogeneity. According to Wu-Hausman test results, Brazilian data for cities is similar to countries in this aspect (see Forbes, 2000) and does not support the exogeneity assumption of inequality regarding subsequent economic growth. Most previous studies assume that units of analysis behave independently as "float islands" (Fujita and Thisse, 2009). Cities and regions are connected not only by trade but also by labor and capital mobility, beyond commuting relationships (Baltagi et al., 2012). Our findings also account for this typical dependence observed in data.

When using a massive spatial dataset for all Brazilian cities, correcting for the reported gaps in the literature (Forbes, 2000; Bourguignon, 2016; Reed, 2015) by choosing proper methods to match all features present in data, the empirical evidence suggests that lowering income inequality faster subsequent economic growth, not only on average but also in conditional quantiles.

The structure of the paper is the following. Section two briefly presents a summary of the literature, discusses some limitations, and presents the study's motivations. Section three presents the econometric models and describes the data. Section four presents and discusses the main findings, Section five provides brief conclusions.

2. Literature review

According to the aggregative data level, the literature studying the influence of inequality on future economic growth use data for countries (national entities) or sub-national entities (states, regions, cities). When fully considered, the reported findings lead to mixed conclusions. We briefly discuss the limitations of the literature at the end of this Section, providing some motivations for the present paper. Persson and Tabellini (1994) study nine countries using annual data to the period 1830 to 1985. They find that greater income inequality reduces future economic growth. Barro (2000) use data for developed and developing countries finding a negative relationship between inequality and growth in the former and a positive relationship in the latter.

Forbes (2000) found a positive relationship between inequality and subsequent growth in a sample of 45 countries over the period 1966-1995. An important contribution of Forbes (2000) is providing a standard growth regression model to study the influence of inequality on subsequent growth in countries. Nonetheless, Roodman (2009) have detected some issues of instrument proliferation in the methods employed by Forbes (2000). Using the same dataset of Forbes (2000), Roodman (2009) shows that the coefficient on the income Gini loses significance as the number of instruments falls. Cingano (2014) employ the growth regression of Forbes (2000) using data of 31 OECD countries over the period 1970-2010, correcting the problem of instrument proliferation, and found a significant negative relationship between income inequality and subsequent growth. Ostry et al. (2014) apply the standard growth regression of Forbes (2000) using data of OECD and non-OECD countries from Penn World Table and report empirical evidence that income inequality is bad for future growth. Ostry (2016) report several studies and present empirical evidence that income inequality is a robust predictor for growth, and more inequality is associated with less sustained growth in countries. Berg et al. (2012) use a sample of 140 countries and have found similar conclusions.

In the second category of studies that uses sub-national data, Partridge (1997) review the findings of Persson and Tabellini (1994) using more disaggregated data from a panel of US states to the period 1960 to 1990. He concludes that states with more income inequality at the beginning of the period experience greater subsequent economic growth. His findings are supported by the work of Frank (2009) who employ annual state-level data to find a positive relationship between inequality and growth in the US economy. While Partridge (1997) found a positive correlation between the Gini index and subsequent growth using data of US 48 states from 1960 to 1990, our results support the conclusion of Barro (2000), Persson and Tabellini (1994), Cingano (2014): personal income inequality is significantly damaging for future growth. They strongly contrast with the findings of Litschig and Lombardi (2019) that found a positive correlation between the Gini coefficient in 1970 and income per capita in 1980, 1990, and 2000 using Brazilian data in the conditional mean distribution.

One possible explanation for these contradictory results relies on differences in the dataset, for instance. First, Litschig and Lombardi (2019) have used more aggregated data for areas of the Brazilian economy rather than data for cities, which is less informative. Second, beyond the more disaggregated data level, our data set is available for more recent periods: 1991, 2000, and 2010. While Litschig and Lombardi (2019) have used more aggregated data for the years 1970, 1980, 1991, and 2000. Besides, there are differences in the sample size as well, since they used only 3659 *Áreas Mínimas Comparáveis* (66% of our sample size), while we employ 5564 cities data.

Another difference relies on the specification. Litschig and Lombardi (2019) strongly departs from Forbes (2000) growth regression model designed to study the influence of inequality on subsequent growth by including a large number of explanatory variables. Two issues come with this change. The first problem in doing this is the increasing uncertainty (dispersion) leading to inefficient parameter estimates (LeSage and Fischer, 2008). Second, by departing from the standard growth regression model, the priors of the researcher and a bigger number of free parameters to be estimated will put more weight on the evidence. This issue poses an additional challenge to the identification. To avoid these problems, as been done in Hall and Jones (1999), we employ structural models. The advantage of this approach is that the specification need not be complete: not all exogenous variables must enter into the model (Hall and Jones, 1999). Ostry et al. (2014) and Cingano (2014) are examples of the Forbes growth regression model applied in countries. As the statistical tests below show, the main differences between our and Litschig and Lombardi (2019) conclusions likely rests upon neglected endogeneity since the methods they employ presuppose exogenous income inequality beyond sphericity of residuals. Our findings are free of both restrictive assumptions.

While the growth regression model of Forbes (2000) was initially designed for examining income inequality and subsequent growth in heterogeneous countries, it likely applies much more to cities than to countries. Specifically, while countries exhibit tremendous heterogeneity in political and institutional systems, trade barriers, higher transport costs, and different currencies featuring much lower mobility of capital, labor, and goods, cities located within countries are precisely the opposite. Cities are open economies in nature with common currency by enjoying immense mobility of factors and goods, and the democratic political process is equally democratic across cities. These features also suggest that endogenous growth models that predict a negative relationship between inequality and growth apply better to cities than to countries and help to explain why cities grow consistently at different rates (Partridge, 1997; Persson and Tabellini, 1994; Galor and Zeira, 1993).

A deeper question in an empirical study is neglected endogeneity because it can drastically alter the conclusions, as can be easily seen below in Figure 2. Litschig and Lombardi (2019) completely ignore the warns by Forbes (2000) and related literature, summarized in words of Bourguignon (2016), "the point is that not even the inequality of market incomes can really be considered as an exogenous determinant of economic growth." As the simulation study of Reed (2015) has made clear and the application of Wu-Hausman test documents in this paper, the practice of replacing one variable by its lagged value does not avoid the endogeneity. When it is not handled correctly by the employed methods, the endogeneity of the regressor can change the sign, magnitude, and significance of the estimates (Forbes, 2000; Hayashi, 2000).

In this regard, beyond the older, more aggregated, and lower sample data, Litschig and Lombardi (2019) employ the Least Squares estimator that delivers inconsistent estimates and unreliable conclusions when inequality is endogenous to subsequent growth (Forbes, 2000; Hayashi, 2000). The conclusions of Litschig and Lombardi (2019) rest upon the untested assumptions of exogenous inequality and the sphericity of the residuals. Brazilian sub-national data strongly reject both assumptions (see Table 2 and the discussion of results). Besides, as well know since the introduction of quantile regression methods (Koenker and Bassett, 1978), and even before, the Least Squares method cannot describe all parts or tails of the conditional distribution of the dependent variable consistently (Koenker and Bassett, 1978; Konker and Xiao, 2004; Heckhman, 1979).

In this context, Forbes (2000) reports three main problems to be solved when one wishes to verify whether inequality affects subsequent economic growth - the likely error measurement in variables, the omitted variable bias, and simultaneity between inequality and growth. All these data features lead to the endogeneity of inequality regarding subsequent economic growth, which comes out to be evident by the Wu-Hausman test statistic. All these three regression problems reported by Forbes (2000) when present in data can lead to a significant correlation between the explanatory variable and the error term (Wooldridge, 2010). When this correlation is present, the Least Squares estimator renders inconsistent estimates, and likely wrong conclusions.[4]

This paper fills all the three reported gaps by Forbes (2000). Further, it provides more reliable and robust conclusions regarding Litschig and Lombardi (2019), for instance, because our methods

[4]Many variables have a simultaneous character in macroeconomics, leading to difficulties in identifying causal effects—for example, production and consumption, exports and imports, inflation, and interest rates. Thus, the assumptions of regressors' exogeneity and the residuals' sphericity in the Least Squares method are unwarranted restrictive assumptions. Because empirical studies deal with a small fragment of macroeconomics, the simultaneous character of inequality and growth tends to be the rule rather than the exception in this field.

match all the data features entirely and can model all parts of the conditional distribution of the dependent variable consistently without relies upon the untested assumptions of exogenous inequality and sphericity of residuals (Koenker and Bassett, 1978; Kim and Muller, 2004; Konker and Xiao, 2004). Besides, departing from the previous studies concentrated only on the conditional mean, our methods consistently measure the impacts of personal income inequality in all considered conditional quantiles beyond average using a single criterion. Quintiles share does not correlate with the Gini index in the mean and lower tail of the distribution (Barro, 2000; Partridge, 1997).

Besides the above-reported gaps in the literature, the empirical motivation for the paper comes from Figure 1, which shows our measure of personal income inequality in 1991 and 2010 in all Brazilian cities. The Brazilian economy has passed through considerable structural reforms in the 1990s. It began with openness to trade in 1989, the stabilization of prices based on the Real Plan in 1994, and the adoption of the inflation targeting regime in 1999.[5]

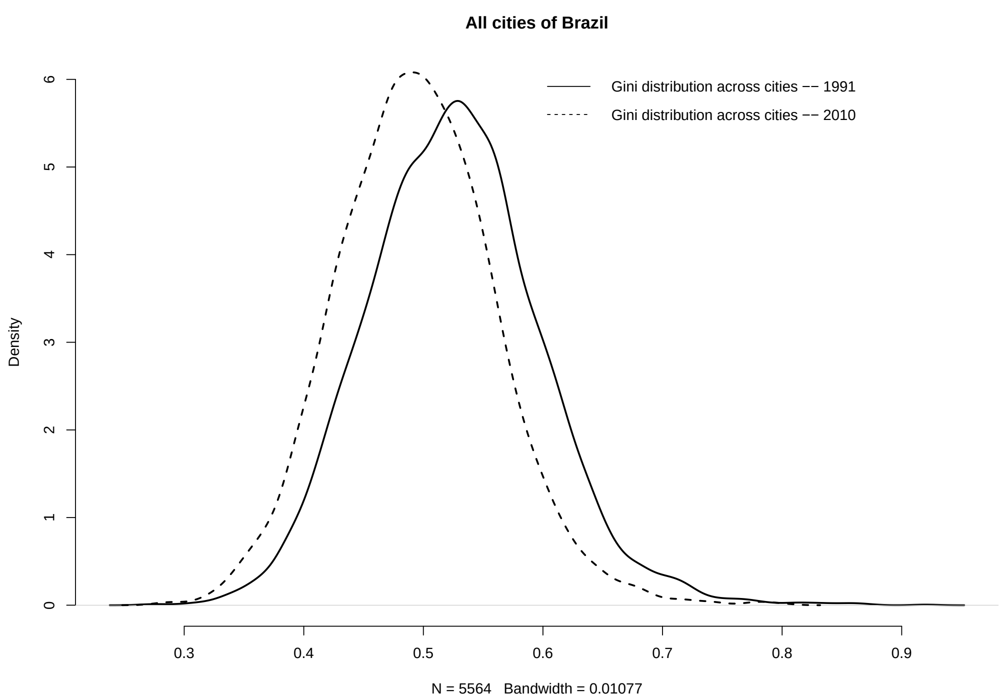

Figure 1: Overall decline in personal income inequality – all cites of Brazil, 1991 and 2010.

Along with macro reforms, poverty reduction and distributive policies come to the forefront in that decade. One noteworthy aspect is the significant reduction in personal income inequality as measured by the decline of the Gini index in all country cities (Figure 1), which is the same inequality index employed by Forbes (2000), Barro (2000), Partridge (1997), and Litschig and Lombardi (2019). We choose the Gini index because it is the most commonly published by the statistical agencies (Atkinson and Bourguignon, 2015), is available for all Brazil cities and have been used in much important paper

[5]Moreira and Correa (1997), Franco (1998), and Afonso et al. (2016) provides a historical background and data description of all these developments in Brazil.

on the issue (Partridge, 1997; Barro, 2000; Forbes, 2000).[6] The average Gini index had declined from 0.5255 in 1991 to 0.4944 in 2010 in Brazil, as an opposed movement in the Chinese economy when it opens to trade, faces globalization, and implement economic liberalization reforms in the 1990s (see Fujita and Hu, 2001). Regarding the historical higher levels of this index over the decades in Brazil, this accomplishment is a piece of strong good news. A simple test for the difference of means across the two groups of cities is significant a the $p < 0.001$ level.[7] Important drivers of this observed change, according to Atkinson and Bourguignon (2015), were the decline in wage inequality due to expansion of skilled workers, increases in the minimum wage, and cash transfers, like the *Bolsa Família*. After examining long series of Gini index, Ferreira et al. (2008) concludes that, from 1993 onward, a secular decline in average returns to schooling, convergence in household incomes between rural and urban areas, a widespread cash-based social assistance, and the stopping hyperinflation produced by the Real Plan in 1994 are the main factors explaining the decline in personal income inequality in Brazil.

3. Econometric methodology

3.1. Econometric models

According to Forbes (2000), the relationship between inequality and subsequent economic growth, in a conditional mean regression model, can be examined using the model given by

$$Growth_i = \alpha + \beta Inequality_{i,t-1} + \theta Income_{i,t-1} + \gamma Education_{i,t-1} + u_i, \tag{1}$$

$i = 1, \ldots, 5564$; where $Growth_i$ denote the subsequent per capita income growth rate for city i between 2000 and 2010, β is the inequality elasticity measure and can be zero, positive or negative. $Income_{i,t-1}$ is the initial level of income for city i, and θ is expected to be negative, controlling for convergence across cities. $Education_{i,t-1}$ is the average years of schooling for inhabitants of the city i. It is expected that subsequent economic growth and labor force initial level of human capital are positively related, $\gamma > 0$. Using the Least Squares estimator, the causal effect of the personal income inequality on subsequent growth measure by β is identified only if $E(u_i/Inequality_{i,t-1}) = 0$ (Hayashi, 2000). The Wu-Hausman test statistic assesses whether data support this assumption or not. The source of endogeneity in data comes from the correlation of $Inequality_{i,t-1}$ and the structural error u_i because $E(u_i\varepsilon_i) \neq 0$, such that:

$$Inequality_{i,t-1} = \gamma Z_i + \varepsilon_i, \tag{2}$$

where Z_i is a vector of instrumental variables used to identify the impact of the inequality on subsequent economic growth. ε_i is an error term with mean zero and constant variance. When data reject assumption $E(u_i/Inequality_{i,t-1}) = 0$ the regressor is not strictly exogenous. Thus, one can use a set of instruments Z_i, in which $E(u_i/Z_i) = 0$. The set of instruments must be uncorrelated with the error term. The F-statistic been greater than ten indicates that the instruments are not weak and are relevant for estimation (Staiger and Stock, 1997). Lastly, the Sargan statistic tests the null hypothesis of whether the chosen instruments are valid. Staiger and Stock (1997) recommends considering instruments being relevant only when F-statistic is greater than 10. In a more general framework, to model

[6] Piketty and Saez (2003) focuses on income shares in the United States, France, and the United Kingdom over 1913-1998. Partridge (1997), Barro (2000) and Litschig and Lombardi (2019) use Gini index and shares of income. Each one of these measurements of inequality reflects different aspects of inequality (Atkinson and Bourguignon, 2015; Partridge, 1997; Barro, 2000).

[7] The calculated t-statistic is 27.185 with 5563 degrees of freedom.

a conditional distribution of cities growth applying a conditional quantile regression model, a corresponding quantile regression function to express the relationship between inequality and subsequent economic growth reads

$$Q_{Growth_i}(\tau|X) = \alpha(\tau) + \beta(\tau) Inequality_{i,t-1} + \theta(\tau) Income_{i,t-1} + \gamma(\tau) Education_{i,t-1}, \tag{3}$$

where $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. The parameter of interest is β, and the method allows it to be quantile-specific, and it can be zero, negative or positive. This flexibility is absent in the traditional conditional mean regression model and allows us to describe all parts of the conditional distribution of cities' economic growth consistently.

We follow the suggestion of LeSage and Fischer (2008), Forbes (2000), and Partridge (1997) in using the dependent variable measured a decade after (per capita income growth was measured by ten-year growth in real per capita income between 2000 and 2010) and the explanatory variables and instruments at the beginning of the period (1991). However, as the simulation study of Reed (2015) shows, this common practice does not prevent endogeneity. Even proceeding with this based on theoretical reasons, to avoid biased and inconsistent estimates, one cannot simply assume exogeneity of inequality regarding economic growth in which $E(u_i/Inequality_{i,t-1}) = 0$ without testing it. As the empirical evidence reported in this paper documents, missing this step in the analysis can produce significant impacts in drawing invalid inferences and quite the opposite conclusions regarding the response of future growth to inequality changes (Forbes, 2000; Reed, 2015).

The economic and social interaction across cities provides the natural instruments for identification. Using valid instruments derived from spatial interactions, it also minimizes the omitted variable bias (LeSage and Fischer, 2008; LeSage and Pace, 2009). The homogeneity of the data source minimizes the chance of measurement error in variables. The use of spatial lagged values of the exogenous variables (WX) as instruments in regression models initially proposed by Kelejian and Prucha (1999) and Kelejian and Prucha (2010) is now widely used in economic analysis when one or more regressors are endogenous (Baltagi et al., 2012). In this paper, we follow the approach of Kelejian and Prucha (1999), Kelejian and Prucha (2010), and Baltagi et al. (2012) in this regard. The W matrix is an n by n non-stochastic inverse great circle distance, non-negative spatial weight matrix whose elements expresses the strength of connections between cities. If the city i is related to city j, then $w_{ij} > 0$. Otherwise, $w_{ij} = 0$, and the diagonal elements of W are set to zero as a normalization standard. Because row-sums to unity, WX contains a linear combination of exogenous variables from related cities.

When we observe a significant statistic value in the Wu-Hausman test, this suggests that Least Squares regression method is inconsistent and invalid for drawing inferences, and the IV estimator is consistent and shall be preferred (Hayashi, 2000; Wooldridge, 2010). Further, we follow Staiger and Stock (1997)'s approach in detecting weak instruments in the usual IV estimator. Lastly, we verify whether our instruments are valid using both the Sargan test and the score test statistic for overidentification that is robust to heteroskedastic errors (Hayashi, 2000; Wooldridge, 2010).

Introduced by Koenker and Bassett (1978), the quantile regression method can provide valuable insights into heterogeneous effects of policy variables, even in the context of pervasive endogeneity in economics (Kim and Muller, 2004). We employ the IV estimator for detecting impacts in conditional quantiles based on the methods of Kim and Muller (2004), we also use the Limited Information Maximum Likelihood (LIML) and the standard IV estimator for detecting effects in the conditional mean. Lastly, we also employ one IV instrument-free method based on heteroskedastic errors for estimating effects with endogenous regressors without external instruments (Lewbel, 2012).

We deal with spatial autocorrelation present in data following the works of Anselin and Rey (1991), Kelejian and Prucha (2010), and Baltagi et al. (2012). Because the main interest is on the direct impacts of personal income inequality on future economic growth, we do not model the potential spillovers. As explain Anselin and Rey (1991), substantive spatial dependence and spatial heterogeneity are intricated and complex phenomena difficult to separate themselves. Our methods capture these features present in data in two specific ways. First, we employ the variance-covariance estimator of Cribari-Neto (2004) accounting for substantial heterogeneity and the quantile regression method that handles it robustly (Konker and Xiao, 2004). Second, following Baltagi et al. (2012) and Kelejian and Prucha (2010), we use spatial autocorrelation present in data to identify the impacts of inequality on growth. When applied simultaneously, both ways to deal with spatial heterogeneity can describe large variations in data.

3.2. Data description

Table 1 presents the summary statistics of the main variables of the paper. All cities data used in this study come only from two sources. First, the economic attributes of cities are freely available in the Atlas do Desenvolvimento Humano home page at `http://www.atlasbrasil.org.br/acervo/biblioteca`. The Instituto de Pesquisa Econômica Aplicada homepage provides the shapefile for all Brazilian cities. The shapefile conveys all geographical information to generate choropleth maps of economic attributes, create the W matrix and spatial instruments used in the analysis. These geographical information are freely available at `https://www.ipea.gov.br/ipeageo/malhas.html` from Instituto de Pesquisa Econômica Aplicada. Thus, we have cross-sectional spatial data for 5564 Brazilian cities observed in 1991, 2000, and 2010 that vary within the cities and space.

Table 1: Summary statistics: Gini index and the real per capita income growth between 2000 and 2010.

Statistic	$Gini_{i,1991}$	$Gini_{i,2010}$	$Growth_{i,2000-10}$
Mean	0.5255	0.4944	0.5525
75th percentile	0.57	0.54	0.7291
25th percentile	0.48	0.45	0.3219
CV	0.1370	0.1337	0.6141

Notes: The Gini index measures the degree of income inequality existing in per capita household income. The real per capita income is given by the ratio between the sum of all individuals' income at constant August 2010 national prices in a given household and the total number of these individuals. Coefficient of Variation (CV) measures variability around the mean given by the ratio of standard deviation to the sample mean. The interquartile range (IQR) given by the difference between the 75th percentile and 25th percentile is another measured of dispersion not affected by the heterogeneity of cities. Per capita income growth is given by $(Y_{i,2010} - Y_{i,2000})/Y_{i,2000}$, where $Y_{i,t}$ is the real per capita income level in city i at year t.

The reported summary statistics suggest a decrease in average income inequality regarding all cities data of Brazil. But, the CV and IQR do not suggest a huge decline in the dispersion. Thus, sigma convergence is absent in these data.

4. Results and Discussion

Following Litschig and Lombardi (2019) in assuming exogenous personal income inequality regarding subsequent economic growth with more disaggregated and larger sample size in Brazil subnational data, no significant empirical relationship exists between income inequality and subsequent economic growth. This conclusion emerges when ignoring the recommendations of Reed (2015) and the warns of Bourguignon (2016) and Forbes (2000): the Least Squares estimate (β) of the conditional mean function as the solid black shows it in Figure 2.

On the other hand, if we follow the advice of Reed (2015) simulation study, Bourguignon (2016), and Forbes (2000) testing for the endogenous inequality regarding subsequent growth by applying the Wu-Hausman statistic (the second and third columns from Tables 2 and 3 show that LS estimate is inconsistent) and use relevant instruments (Staiger and Stock, 1997) for the income inequality, the conclusion drastically changes. The dashed red, orange, and blue lines in Figure 2 display the consistent estimates of negative impact (β) of inequality on subsequent economic growth for all Brazilian cities data, which is significant at the 1% level. This conclusion is invariant regarding both the spatial instruments (Kelejian and Prucha, 2010) or internal instruments (Lewbel, 2012) for identification.

In both the standard IV and using the heteroskedastic errors (IVHET) method proposed by Lewbel (2012) the impact is negative, significant, and close to or higher than two (second and third columns from Table 2). The same conclusion applies to the LIML estimator results when we extend the growth regression model of Forbes (2000) to account for agglomeration effects and regional diversity across cities, including regional dummy variables (see the third column of Table 3).

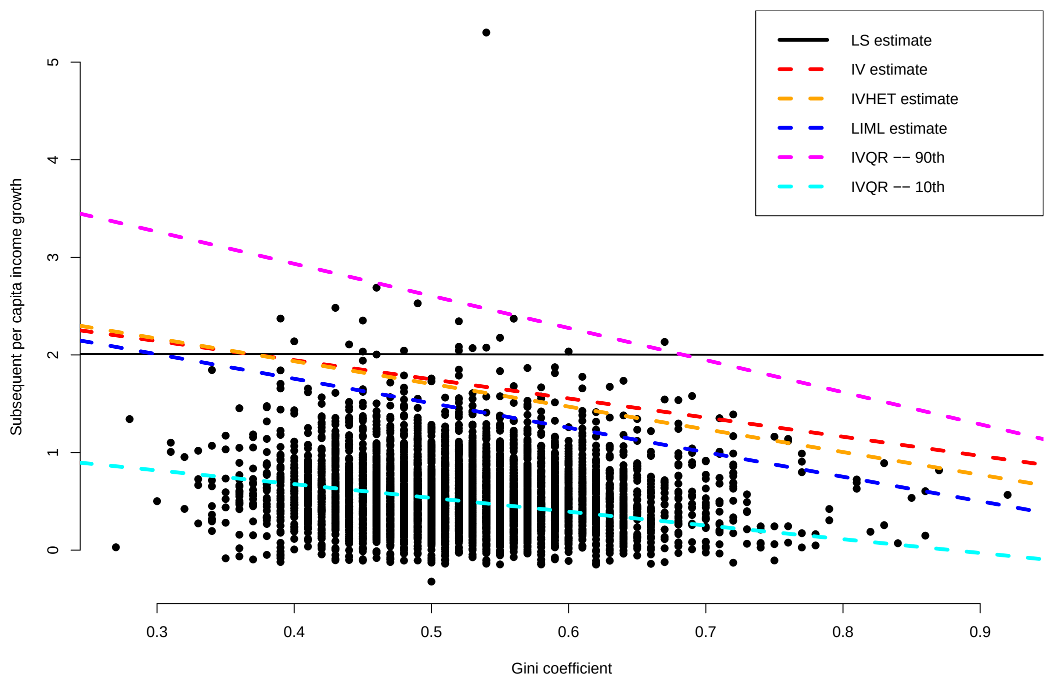

Figure 2: We follow Partridge (1997) in using the dependent variable per capita income growth measured by ten-year growth in real per capita income between 2000 and 2010. Explanatory variables were measured in 1991. We use the growth regression of Forbes (2000). The data is drawn from 5564 cities of Brazil observed in 1991, 2000, and 2010 (`http://www.atlasbrasil.org.br/acervo/biblioteca`). The scatterplot shows the regression fit using LS, IV, IVHET, and LIML estimates. Superimposed on the plot are the least-squares estimate of the conditional mean function as the solid black, the instrumental variable estimate of the conditional mean function as the dashed red, orange, and blue lines. The scatterplot also shows the regression fit using IVQR estimates. Superimposed on the plot are the $\{0.10, 0.90\}$ quantile regression fit dashed lines in cyan and magenta.

Based on our more complete model that includes control for regional differences and agglomeration effects whose results appear in the third column of Table 3, in the conditional mean, the impact of inequality on subsequent growth is noticeable. The magnitude of the estimate (-2.51) implies that lowering inequality by 1 Gini point would translate to an increase in the cumulative economic growth of 2.51 percentage points in the following ten years. It means an increase of 0.25 percent point by year in per capita income growth. This finding is similar in magnitude found by Cingano (2014) and Ostry et al. (2014) for OECD countries.

Regarding the impacts in conditional quantiles, the dashed cyan and magenta lines in Figure 2 display the consistent estimates of negative impact (β) of inequality on subsequent economic growth for all Brazilian cities data in the extreme lower ($\tau = 0.10$) and extreme upper ($\tau = 0.90$) tails of the dependent variable, respectively. These findings are consistent, statistically significant, robust to heterogeneity and endogeneity of the regressor (Kim and Muller, 2004). We observe that at the extreme upper tail, the impact is more prominent than on average.

Table 2 presents the parameter estimates of the standard Forbes (2000) growth regression model based on the four different methods: LS, IV, IVHET, and LIML, measuring the impact of inequality on subsequent growth only in the center of the conditional distribution. Based on Least Squares regression, the Breusch-Pagan test for the absence of heteroskedasticity in data is significant at the $p < 0.001$ level.[8] Thus, we adopt in all regression models based on LS and IV the robust standard errors suggested by Cribari-Neto (2004).

Table 2: Subsequent growth response to income inequality estimates - Equations 1 and 3.

Dependent: Growth	**LS**	**IV**	**IVHET**	**LIML**
Const	2.01***	2.73***	2.87**	2.76***
	(42.76)	(13.73)	(14.78)	(13.32)
$Ineq_{1991}$	**-0.02**	**-1.96*****	**-2.33*****	**-2.05*****
	(-0.29)	(-3.76)	(-4.55)	(-3.76)
$\ln Inc_{1991}$	-0.31***	-0.24***	-0.23***	-0.24***
	(-29.68)	(-10.80)	(-10.45)	(-10.31)
$Educ_{1991}$	0.03***	0.02***	0.02***	0.02***
	(8.34)	(3.96)	(3.92)	(3.80)
Weak instruments	—	**32.80*****	**46.62*****	**32.79*****
Wu-Hausman test	—	**19.96*****	**26.76*****	—
Sargan statistic (p-value)	—	**0.126**	**0.193**	**0.126**
Score test statistic (p-value)	—	**0.201**	—	—
Anderson-Rubin test (95% CI)	—	—	—	**[-3.11;-1.15]**
Cond. Likelihood Ratio test (95% CI)	—	—	—	**[-3.14;-1.13]**
N	5564	5564	5564	5564
F-statistic	468.70***	395.40***	371.5***	—

Notes: (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are in parentheses. We measure the average skill (education) by the average years of schooling of people 18 years or more. We use as valid instruments for the endogenous Gini index in 1991, the Gini index in neighboring cities in 1991 ($WG1991$), the average number of years of schooling of people 18 years or more in neighboring cities in the same year, $WAEST91$, and the illiteracy rate of people 18 years or more in neighboring cities in the same year, $WANALF18$. All the explanatory and instruments enter into the regression at the beginning of the period: 1991. The Sargan test statistic has null the validity of instruments. The Wu-Hausman statistic tests the absence of correlation between the covariate and the error term under the null of exogenous income inequality. The weak instruments statistic tests the null of the absence of correlation between the instruments and the endogenous variable. In LS, IV, and LIML estimates, we use robust standard errors. IVHET delivers the parameter estimates with robust standard errors by the method proposed by Lewbel (2012) that constructs valid instruments as simple functions of the model's data. The score test statistic for overidentification tests the null of validity of instruments and is robust to heteroskedasticity (Wooldridge, 2010).

The first column presents the Least Squares estimation results. The β is statistically equal to zero. The assumption is exogenous inequality regarding subsequent growth, following Litschig and Lombardi (2019). Initial income level and human capital have signs and significance as predicted by theory. From this finding, no empirical evidence exists in sub-national Brazil data with a larger and more dis-

[8] The calculated statistic is 39.188 with 3 degrees of freedom

aggregated sample regarding the effect of inequality on subsequent growth. The second column from Table 2 presents the results of statistical tests and the parameter estimates using standard IV estimator with spatial lagged exogenous variables instrumenting inequality. First, data reject the assumption of exogenous inequality regarding growth based on the Wu-Hausman test at a 1% level. Thus, the β estimate based on Least Squares in the first column is inconsistent and invalid for inference. The F-statistic (32.80) greater than 10 indicates no problem with weak instruments in data. Both p-values (0.126 and 0.201) of the overidentification tests support the validity of spatial instruments at a 1% level. Accounting for endogeneity of the regressor and using robust standard errors, the β is negative and statistically significant at the 1% level. Lastly, initial income level and human capital have signs and significance as predicted by theory.

The third column from Table 2 presents the findings based on the IVHET method of Lewbel (2012) that do not require external instruments by constructing valid instruments for inequality as simple functions of the model's data. Again, we observe that applying the Wu-Hausman test data reject the assumption of exogenous inequality regarding growth at a 1% level. The F-statistic (46.62) greater than 10 indicates no problem with weak instruments in data. The p-value (0.126) of the overidentification test supports the validity of instruments at a 1% level. Both Wu-Hausman test results confirm that the estimate of the β based on Least Squares is inconsistent and invalid for inference. Yet, accounting for endogenous inequality, the β is negative and statistically significant at the 1% level. Again, initial income level and human capital have signs and significance as predicted by theory. The parameter estimates based on the LIML estimator and the Anderson-Rubin and Conditional Likelihood Ratio tests reject the null of no effect of inequality on subsequent growth at a 5% level. No weak instruments problem exist and the Sargan test support the validity of spatial instruments in IV and LIML estimators.

In sum, the findings of the standard IV method, LIML and using the Lewbel (2012) IVHET method that does not depend on external instruments, in the conditional mean of the distribution, income inequality is significantly damaging for future growth in Brazil. Regarding the conditional mean regression models, this result supports the findings of Barro (2000) for developing countries and Cingano (2014) for OECD countries. However, it strongly contradicts the conclusions of Litschig and Lombardi (2019) that employ Least Squares regression for sub-national Brazilian data under the untested assumptions of exogenous inequality and sphericity of residuals.

An obvious criticism of the above results based on the standard growth regression model of Forbes (2000) come to the absence of observed control for the potential agglomeration effects typically found in cities (Krugman, 1999; Rosenthal and Strange, 2020; LeSage and Fischer, 2008; Chen and Partridge, 2013). Agglomeration effects, when statistically significant, can give rise to productivity increases or decreases that help to explain why some cities are more or less productive than others (Chen and Partridge, 2013; LeSage and Fischer, 2008) and may interfere with the relationship between inequality and subsequent growth. Besides, as Brazil displays great geographical differences across regions, we follow Partridge (1997) including regional dummies for the South, Southeast, Northeast, Midwest, and North, where Midwest and North are merged and is the omitted category.[9]

Table 3 presents parameter estimates capturing the net effects of inequality on subsequent growth in the conditional quantiles and in the conditional mean regression models. We adopt the same variable of LeSage and Fischer (2008) and Chen and Partridge (2013) to measure agglomeration effects

[9]To focus on the results, we put the statistical tests conducted to define the dummy variables and the model used for this end in the Appendix. The statistical tests indicate no significant difference between the Midwest and North regions of Brazil.

into the Forbes model: the population density (population/km^2). We also employ the conditional likelihood ratio (CLR) test of Moreira (2003) and the Anderson-Rubin test statistic designed for structural models. The null hypotheses of both test statistics are that the Gini coefficient does not affect future economic growth: H0: $\beta = 0$ in Eq. 1. The p-value and the 95% confidence interval of the test is based on Andrews et al. (2006). Regarding the extended Forbes growth regression model accounting for agglomeration and regional fixed effects, we extract the following conclusions from Table 3. The spatial instruments are valid (the Sargan test p-value is 0.44), and the Wu-Hausman test statistic rejects income inequality exogeneity assumption at 1% level. Thus, we observe that the Least Squares estimator generates inconsistent parameter estimates even when accounting for significant negative congestion effects and regional unmeasured fixed effects, as shown by the statistical significance of the Wu-Hausman test statistic.

Table 3: Subsequent growth response to income inequality estimates - Extended equations 1 and 3.

Dependent: Growth	**LS**	**IV**	**LIML**	$IVQR_{\tau=0.50}$	$IVQR_{\tau=0.75}$	$IVQR_{\tau=0.90}$	$IVQR_{\tau=0.10}$	$IVQR_{\tau=0.25}$
Constant	1.89***	2.75***	2.76***	2.52***	3.08***	4.25***	1.23***	1.81***
	(28.40)	(11.11)	(11.07)	(10.13)	(11.92)	(9.46)	(6.80)	(7.53)
$Ineq_{1991}$	**-0.052**	**-2.49*****	**-2.51*****	**-2.46*****	**-2.11*****	**-3.29*****	**-1.41****	**-1.84****
	(-0.87)	(-3.74)	(-3.75)	(-3.44)	(-2.99)	(-3.14)	(-2.33)	(-2.50)
$\ln Inc_{1991}$	-0.27***	-0.18***	-0.18***	-0.15***	-0.21***	-0.17**	-0.14***	-0.16***
	(-20.77)	(-6.00)	(-5.96)	(-4.97)	(-5.10)	(-2.70)	(-6.44)	(-6.03)
$Educ_{1991}$	0.014***	0.007	0.007	0.02***	-0.004	-0.04***	0.03***	0.025***
	(3.50)	(1.48)	(1.47)	(2.81)	(-0.569)	(-3.03)	(6.37)	(5.62)
$\ln Den_{1991}$	-0.010**	-0.01*	-0.01*	0.0003	-0.01***	-0.03***	0.02***	0.012***
	(-3.95)	(-1.80)	(-1.79)	(0.09)	(-3.97)	(-6.34)	(4.34)	(3.11)
DU_2	0.0377**	0.028	0.028	0.048***	-0.020	-0.087**	0.15***	0.12***
	(2.18)	(1.47)	(1.47)	(2.65)	(-1.02)	(-2.50)	(8.45)	(6.65)
DU_3	-0.04***	-0.10***	-0.10***	-0.10***	-0.11***	-0.15***	-0.02	-0.033
	(-2.62)	(-4.24)	(-4.25)	(-4.93)	(-4.56)	(4.93)	(-0.75)	(-1.26)
DU_4	0.134**	0.098***	0.098***	0.055***	0.099***	0.21***	0.048	0.07***
	(7.49)	(4.40)	(4.38)	(2.88)	(4.59)	(4.48)	(1.57)	(2.93)
Weak instruments	—	**33.346*****	**33.346*****	—	—	—	—	—
Wu-Hausman test	—	**21.821*****	—	—	—	—	—	—
Sargan test (p-value)	—	**0.44**	**0.44**	—	—	—	—	—
Score test (p-value)	—	**0.49**	—	—	—	—	—	—
N	5564	5564	5564	5564	5564	5564	5564	5564
F-statistic	239.9***	183.2***	—	—	—	—	—	—

Notes: (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are in parentheses. The Anderson-Rubin test result (95% CI) is **[-4.23;-1.24]**. The CLR test result (95% CI) is **[-3.92;-1.42]**. We measure the average skill (education) by the average years of schooling of people 18 years or more. In the IV and LIML regression model we use as valid instruments for the endogenous Gini index in 1991, the Gini index in neighboring cities in 1991 ($WG91$), and the average number of years of schooling of people 18 years or more in neighboring cities in the same year, $WAEST91$. All the explanatory and instruments enter into the regression at the beginning of the period: 1991. The Sargan test statistic has null the validity of instruments. The Wu-Hausman statistic tests the absence of correlation between the covariate and the error term under the null of exogenous income inequality. The weak instruments statistic tests the null of the absence of correlation between the instruments and the endogenous variable. In LS, IV, and LIML estimates, we use robust standard errors. The score test statistic for overidentification tests the null of validity of instruments and is robust to heteroskedasticity (Wooldridge, 2010. In conditional quantiles, we employ the IVQR estimation procedures suggested by Kim and Muller (2004) using the same instruments from the standard IV method based on 10000 bootstrapped standard errors.

In contrast, IV and LIML methods provide consistent estimates as indicated by the Sargan test statistic p-value and the absence of weak instruments problem in data (F-statistic greater than 10). Besides, based on the 95% confidence interval, both Anderson-Rubin and the CLR test statistics reject the assumption of no effect of income inequality on subsequent growth in Brazilian cities at a 5% level. The second and third columns of Table 3 represent our best specification to the conditional mean regression models.

The remaining columns from Table 3 present the findings based on the IVQR method of Kim and Muller (2004) for five portions of the conditional distribution of the dependent variable (Koenker and Machado, 1999). We employ precisely the same spatial lagged exogenous variables instrumenting inequality as been done in standard IV and LIML estimators. The β estimate is negative and statistically significant at the 5% level for all conditional quantiles considered. Brazil's income inequality is significantly harmful to future economic growth in the center of conditional distribution and lower and upper tails. Interestingly, the impact is negative, and more substantial for the upper tail of the conditional quantiles, as can be seen by the magenta ($\tau = 0.90$) and cyan ($\tau = 0.10$) dashed lines in Figure 2.

We observe that all the above conclusions based on findings from Table 2 employing the standard growth regression of Forbes (2000) remain valid. In the conditional mean, holding constant the agglomeration effects and regional diversity, the magnitude of the estimate in the standard IV estimator (-2.5) suggests that lowering 1 Gini point would translate to an increase in the cumulative economic growth of 2.5 percentage points in the following ten years. In other words, this means a rise of 0.25 percentage points per year in per capita income, given a decrease in 1 Gini point previously.

One remarkable difference comes from the significantly *favorable* agglomeration effects impacting the cities that grow below the average in $\tau = 0.10$ and $\tau = 0.25$. Symmetrically, *adverse* significant congestion effects impact cities that grow above the average in $\tau = 0.75$ and $\tau = 0.90$. This pattern of heterogeneous agglomeration effects seem to be not documented previously yet in other works (Chen and Partridge, 2013; LeSage and Fischer, 2008; Rosenthal and Strange, 2020). Two essential advantages come from applying quantile regression in this framework. First, it distinguishes which cities benefit more in reducing personal income inequality. Second, the method avoids using double criteria (Barro, 2000; Partridge, 1997) by using a single measure to compare impacts in all parts of the conditional distribution: the Gini index. The reported evidence does not depend on quintiles' share measures used to compare the impact on the center to the tails (Litschig and Lombardi, 2019). It is not reliable to use double criteria because the Gini index only correlates with Q_5 and not to other quintiles share (see the details in Barro, 2000; Partridge, 1997).

Notice that the benefit in reducing personal income inequality is heterogeneous across quantiles in which $|\beta(0.90)| > |\beta(0.50)|$. For instance, for each point decrease in the Gini index, the response of future economic growth of cities that grow faster (-3.29) is higher than that of cities that grow on median (-2.46). Nonetheless, because β is negative and statically significant in $\tau = \{0.10, 0.25, 0.50, 0.75, 0.90\}$, cities growing on average, below and above it benefits significantly from reducing personal income inequality regarding future economic growth using Brazil cities data. In some circumstances, it may be relevant for a whole country to make differences across more or less affected cities regarding public policies designed to change personal income inequality to affect future growth. In the present case, cities in the extreme upper tail would benefit more than the average when facing a one-point reduction in the Gini index.

In sum, net personal income inequality effects on subsequent growth are adverse and significant in the conditional mean, and all considered conditional quantiles of the dependent variable for all cities of Brazil data. They are statistically significant, negative, and heterogeneous across quantiles, been larger in more extreme quantiles. Knowing that personal income inequality is harmful to future economic growth in Brazil, a set of available policies for policymakers and government decisions exists. A complete discussion of policy options and the analysis of their costs and benefits is beyond the scope of this study. It constitutes a limitation of the present paper that focuses only on seeking empirical evidence of whether personal income inequality is damaging or possibly good for future economic growth.

According to the findings of the present paper, policymakers *should be concerned* with personal income inequality in Brazil when they take into consideration future economic growth, as argued by Ostry (2016), Bourguignon (2016), Bernstein (2013), and Stiglitz (2016). This also indicates that those drivers identified by Atkinson and Bourguignon (2015) that explain income inequality decreases in Brazil can be further explored. In sum, in Brazil, personal income inequality shall be a concern in policy decisions not only for economic reasons (Berg et al., 2012; Ostry, 2016) (e.g., higher future economic growth) but also for political and social reasons, as argued in Persson and Tabellini (1994) and Partridge (1997). Future economic growth is a multi-factor phenomenon (Hall and Jones, 1999; Krugman, 1999), and income distribution is one of them (Berg et al., 2012; Ostry, 2016) as the findings of this paper show. Because Brazil still has high-income inequality, it represents an opportunity for well-informed policy decisions; lowering personal income inequality may significantly help accomplish better economic performance in the coming years.

All empirical works have their limitations. The paper does not distinguish for which channel future economic growth positively responds to lower personal income inequality. Nonetheless, being a statistically significant negative factor for future growth, Brazil could take advantage and learn from the experience of other countries. For instance, Bénabou (1996) provides a rich discussion and analysis of contrasting routes conditional on different initial conditions followed by the Philippines and South Korea regarding the impact of inequality on long-term growth. Another source of learning for Brazil could be the study of Acemoglu and Robinson (2012) when comparing which specific institutions provides the right economic incentives to more equitable growth, shaping the economic development in Asian countries in contrast to the ones experienced by Mexico, a country similar to Brazil in many aspects (Bacha and Bonelli, 2016).

Besides, the reliability of the conclusions depends on the right choices of methods regarding the data features and the quality of source data (Atkinson and Bourguignon, 2015). We are using data from the demographic census of 1991, 2000, and 2010; the homogeneity of the source and comparability across cities provide credibility to the findings. Regarding the heterogeneity of data, the endogeneity of the inequality regarding growth, the weight of the influential observations, all the estimation procedures we have chosen are suit methods for dealing with. The employed methods match all data features; the parameter estimates present much higher precision than previous studies because we use more than five and half thousand observations. Besides, the Wu-Hausman test has more power as the sample size is large. As can be seen from Appendix A, the conclusions are invariant when considering the parameter estimates of a Cliff-Ord general spatial model with endogenous regressors and heteroskedasticity of unknown form.

5. Conclusions

This paper estimates the impacts of personal income inequality on subsequent growth in a massive spatial dataset for 5564 Brazilian cities observed in 1991, 2000, and 2010 using instrumental variables methods. Instead of assuming exogenous inequality, we relax the assumption of exogenous income inequality and let the data speak for themselves. Wu-Hausman's test rejects inequality exogeneity regarding growth. Our methods allow identifying causal effects between inequality and subsequent growth in conditional quantiles beyond the average. Sargan and the score test statistics show the validity of employed instruments.

The benefit of reducing personal income inequality goes beyond the conditional average. For each point decrease in the Gini index, the response of future economic growth of cities that grow faster is higher than that of cities that grow on average. Nonetheless, cities below and above average benefit significantly from reducing personal income inequality regarding future economic growth in Brazil.

When we extend the growth regression model of Forbes (2000) to account for agglomeration effects and significant regional diversity across cities, the magnitude of the estimate implies that lowering inequality by 1 Gini point would translate to an increase in the cumulative economic growth of 2.51 percentage points in the following ten years. It means an increase of 0.25 percent point by year in per capita income growth given a previously reduced income inequality. The conclusions are invariant when considering the parameter estimates of a Cliff-Ord general spatial model with endogenous regressors and heteroskedasticity of unknown form.

Because Brazil still has high-income inequality, it represents an opportunity for well-informed policy decisions; lowering personal income inequality may significantly help accomplish better economic performance in the coming years. Neglected endogeneity leads to wrong conclusions.

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Appendix A: SARAR model with heteroskedastic disturbances and regional dummies

Substantive spatial dependence and heteroskedasticity are common phenomena in spatial data, mainly because cities openly interact in space but can diverge in size, physical geography, location, and other relevant aspects. Beyond the endogeneity of the regressor, all these city characteristics may affect quantifying a parameter of interest as the response of future growth to personal inequality changes. The model specified below is general enough to accommodate all these possibilities and provide a way to verify how sensitive our previous conclusions are. It represents an extreme form of heterogeneity across cities.

The model proposed by Kelejian and Prucha (2010) and Drukker et al. (2013), termed Cliff-Ord model or SARAR, is a generalization of the previous versions because it permits estimation parameters of interest consistently even when some *additional endogenous explanatory variables* (e.g., inequality level) beyond the (endogenous) spatial lagged dependent variable (Wy) be present in the model. Beyond this critical property for the present problem at hand, the model is robust against misspecification of the disturbances and allows for heteroskedasticity of unknown form. The general Cliff-Ord spatial model can be specified as:

$$y = \lambda Wy + \beta Inequality_{i,t-1} + \Gamma X_{i,t-1} + \eta \tag{4}$$

where y is an N x 1 vector of observations on the dependent variable as a function of the endogenous explanatory personal income inequality plus initial income, population density and the regional dummies (omitted to save space). W is the N x N spatial weights matrix of know constants in which the diagonal is set to zero, and λ is the spatial autoregressive parameter measuring the strength of spatial autocorrelation in data. The innovations are spatial autocorrelated and are assumed to be heteroskedastic of unknown form:

$$\eta = \rho W\eta + \varepsilon, \varepsilon \sim N(0, \sigma_i^2). \tag{5}$$

We define the dummy variables verifying whether or not exists a statistical difference between the rate of economic growth across the five geographic regions of Brazil. We estimate the model given by

$$y_i = \beta_1 + \beta_2 D_{2,i} + \beta_3 D_{3,i} + \beta_4 D_{4,i} + \beta_5 D_{5,i} + v_i, \tag{6}$$

$i = 1, \ldots, 5564$; where y_i denote the subsequent per capita income growth rate for city i between 2000 and 2010. The categorical variable $D_{2,i}$ assumes value one if the city belongs to Northeast and zero otherwise; $D_{3,i}$ assumes value one if the city belongs to Midwest and zero otherwise; $D_{4,i}$ assumes value one if the city belongs to Southeast and zero otherwise; and $D_{5,i}$ assumes value one if the city belongs to South and zero otherwise. The omitted category (reference) is the North region.

The estimation of the model 6 delivery the following results: $\hat{\beta}_1 = 0.5018$ with t-statistic 26.08; $\hat{\beta}_2 = 0.1879$ with t-statistic 9.14; $\hat{\beta}_3 = -0.0110$ with t-statistic -0.4246 (statistically no significant); $\hat{\beta}_4 = -0.0916$ with t-statistic -4.51; and $\hat{\beta}_5 = 0.0863$ with t-statistic 3.98. These findings indicate that the wealthier cities of the country located at Southeast grow less than poorer cities located at North. The Southeast cities had grow 9.2% less than reference category.

Because no statistical difference exists between Midwest and North (reference category) regions in model 6, we merge both regions and use them as the reference category in the following analysis. In sum, after verifying no statistical difference between Midwest and North, the regional dummies used are such that: $DU_{2,i}$ assumes value one if the city belongs to Northeast and zero otherwise; $DU_{3,i}$ assumes value one if the city belongs to Southeast and zero otherwise; $DU_{4,i}$ assumes value one if the city belongs to South and zero otherwise.

Table 4 display the parameter estimates of the SARAR (HET), LIML and Least Squares alternative methods. The objective is to observe how much our previous conclusions change when considering a more extreme form of heterogeneity across all Brazil cities' data. The λ estimate is positive and significant at the 1% level. It indicates spatial autocorrelation present in data, in which the economic growth in city i affects the economic growth of neighboring cities positively. The CLR test of Moreira (2003) and the Anderson-Rubin test statistic reject the null hypotheses (H0: $\beta = 0$ in Eq. 1) of both test statistics that the Gini coefficient does not affect future economic growth at a 5% level. The spatial instruments are valid (the Sargan test p-value is 0.47), and the Wu-Hausman test statistic rejects income inequality exogeneity assumption at 1% level.

The Least Squares estimator still generates inconsistent parameter estimates, as shown by the statistical significance of the Wu-Hausman test statistic. However, SARAR (HET), standard IV, and

LIML estimators provide consistent estimates as indicated by the Sargan and the score test statistic p-values (0.47 and 0.51, respectively) and the absence of weak instruments problem in data (F-statistic greater than 10). By comparing the sign, statistical significance, and the magnitude of β delivered by SARAR, IV, and LIML estimators, we do not observe abrupt changes that could lead to different conclusions, even when allowing the extreme form of heterogeneity across cities beyond the endogeneity of the regressor. In contrast, if one follows Litschig and Lombardi (2019) in assuming that income inequality is exogenous without testing it, the conclusions would be quite misleading in these data as the Least Squares β estimate show it in the last column of Table 4 since the parameter is not significantly different from zero.

Table 4: Subsequent growth response to income inequality estimates - Extended equation 1.

Dependent: Growth	**SARAR (HET)**	**IV**	**LIML**	**LS**
Constant	2.46***	2.79***	2.80***	1.86***
	(12.34)	(11.39)	(11.46)	(28.02)
λ	0.40***	—	—	—
	(3.91)	—	—	—
$Ineq_{1991}$	**-2.23*****	**-2.63*****	**-2.65*****	**-0.06**
	(-4.47)	(-4.09)	(-4.10)	(-1.05)
$\ln Inc_{1991}$	-0.18***	-0.16***	-0.16***	-0.24***
	(-8.83)	(-6.44)	(-6.43)	(-22.18)
$\ln Den_{1991}$	-0.003	-0.006*	-0.005*	-0.010***
	(-0.78)	(-1.66)	(-1.65)	(-3.82)
DU_2	-0.03	0.028	0.03	0.04**
	(-1.12)	(1.44)	(1.44)	(2.22)
DU_3	-0.06**	-0.09***	-0.09***	-0.018
	(-2.38)	(-3.84)	(-3.86)	(-1.36)
DU_4	0.12***	0.11***	0.11***	0.17***
	(5.98)	(5.04)	(5.09)	(10.84)
ρ	0.19	—	—	—
	(1.40)	—	—	—
N	5564	5564	5564	5564
Weak instruments	—	**36.46*****	**36.46*****	—
Wu-Hausman test	—	**26.51*****	—	—
Sargan test (p-value)	—	**0.47**	**0.47**	—
Score test (p-value)	—	**0.51**	—	—

Notes: (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are in parentheses. The Anderson-Rubin test result (95% CI) is **[-4.32;-1.41]**. The CLR test result (95% CI) is **[-4.01;-1.61]**. We exclude education from this specification because the computational algorithm of estimation for the SARAR (HET) model cannot deliver parameter estimates when both highly correlated variables, income, and education, enter simultaneously into the equation. In the SARAR (HET), IV, and LIML regression models we use as valid instruments for the endogenous Gini index in 1991, the Gini index in neighboring cities in 1991 ($WG91$), and the average number of years of schooling of people 18 years or more in neighboring cities in the same year, $WAEST91$, as done previously. For the endogenous variable Wy the optimal matrix of instruments H is $[X, WX, W^2X^2]$. All the explanatory and instruments enter into the regression at the beginning of the period: 1991. The Sargan test statistic has null the validity of instruments. The Wu-Hausman statistic tests the absence of correlation between the covariate and the error term under the null of exogenous income inequality. The weak instruments statistic tests the null of the absence of correlation between the instruments and the endogenous variable. In IV, LIML, and LS estimates, we use robust standard errors. The score test statistic for overidentification tests the null of validity of instruments and is robust to heteroskedasticity (Wooldridge, 2010).