Effects of fiscal consolidation on income inequality: narrative evidence from South America[1]

Dante Cardoso (Universidade de São Paulo – USP)
Laura Carvalho (Universidade de São Paulo – USP)

ABSTRACT

Based on a narrative dataset constructed by David and Leigh (2018) that covers nine South American economies in the period 1982-2017, this paper estimates dynamic effects of fiscal consolidations on income inequality from Jordá (2005)'s local projections method. Results suggest that fiscal consolidations lead to a rise in income inequality in all specifications and data panels. When decomposing fiscal shocks, spending-based fiscal consolidations appear to significantly increase the Gini index, while tax-based fiscal consolidations do not show statistically significant effects on income inequality. The rise in the Gini index for disposable income caused by a spending-based fiscal adjustment of 1% of GDP varies between 1.74 and 3.22% in five years depending on the selected data panel (country-years). The magnitude of this effect is higher than in most of the previous studies carried out for OECD countries.

Keywords: income inequality; fiscal consolidation; fiscal austerity; South America; local projections.

RESUMO

Partindo da base de dados narrativa construída por David e Leigh (2018), que cobre economias Sul-Americanas entre 1982 e 2017, este artigo estima os efeitos dinâmicos das consolidações fiscais sobre a desigualdade de renda a partir do método de projeções locais de Jordà (2005). Os resultados sugerem que as consolidações fiscais levam a uma elevação na desigualdade de renda em todas as especificações e painéis de dados. Quando se faz a decomposição dos choques fiscais, as consolidações fiscais baseadas em gastos parecem elevar o índice de Gini com significância estatística, enquanto as consolidações fiscais baseadas em tributos não mostram efeitos estatisticamente significantes sobre a desigualdade de renda. A elevação no índice de Gini para a renda disponível causada por um ajuste fiscal baseado em gastos de 1% do PIB varia entre 1,74 e 3,22% em cinco anos, dependendo do painel de dados selecionado (país-anos). A magnitude deste efeito é maior do que na maioria dos estudos anteriores realizados para países da OCDE.

Keywords: desigualdade de renda; consolidação fiscal; austeridade fiscal; América do Sul; projeções locais.

Área 4 – Macroeconomia, Economia Monetária e Finanças.

Classificação JEL: D30; D63; E60; E62.

[1] Appendix available upon request.

1 – Introduction

As the world emerges from the Covid-19 economic crisis with higher levels of public debt, countries in the Global South seem more likely to engage in a new round of fiscal consolidation programmes amid strong market pressures. Known as the most unequal region in the world (IMF, 2014), Latin America has suffered a relatively strong impact of the pandemic in the health, social and economic fronts (OECD, 2020) after a decade of low growth and rising inequality. The potential implementation of new austerity measures aimed at achieving debt sustainability in the short- to medium-run in these countries are thus raising concerns over the impact of these policies on poverty and inequality levels in a context of high social vulnerability.

Indeed, since the end of the commodity price boom of the 2000s and the political shift away from the so-called Pink Tide governments in South American countries (LOUREIRO, 2018), the implementation of austerity measures has been accompanied by a reversal in previously declining levels of income inequality in the region. After reaching its lowest level in the 21st century in 2015 (0.519), the Gini index for income in Brazil, for instance, has risen to 0.538 in 2018 according to World Bank estimates. Other South American economies have experienced a similar reversal, as shown in Figures 6, 7 and 8 in the Appendix.

Especially after the Global Financial Crisis, a growing empirical literature has delved into estimating the effects of fiscal shocks on economic growth and public debt in developed and developing countries, with varying results depending on the adopted methodology, the type of adjustment programme and the macroeconomic context. On the methodological front, the econometric literature can be classified into two main groups: studies using cyclically adjusted fiscal variables in VAR estimations (BLANCHARD AND PEROTTI, 2002; ALESINA AND ARDAGNA, 2010) and studies based on the construction of narrative datasets containing specific historical episodes of fiscal shocks (ROMER AND ROMER, 2010; ALESINA, FAVERO E GIAVAZZI, 2019; CARRIÈRE-SWALLOW, DAVID AND LEIGH, 2021). Using both empirical approaches, a smaller number of authors have investigated the impact of fiscal shocks on income inequality in OECD countries (WOO ET AL., 2013; HEIMBERGER, 2020; AGNELLO AND SOUSA, 2012). Evidence so far suggests that inequality has widened as a consequence of fiscal consolidations in advanced economies.

Fiscal shocks may affect income inequality through several channels. Starting with indirect channels, wage disparities may increase as wages at the bottom respond more intensely to economic recessions caused by a fiscal consolidation, for instance. Another indirect effect involves a change in income composition: households at the top of the distribution earn a relevant share of their income from capital while poor households receive wages or informal jobs earnings. As economic recessions tend to weaken the bargaining power of workers and, consequently, reduce the share of wages in the functional distribution of income, fiscal adjustments tend to disfavor families at the bottom of the distribution.

Regarding the direct impacts of fiscal policy on income inequality, results may depend on the type of adjustment measures. Cuts in social transfers, for instance, tend to disfavor individuals at the bottom of the distribution. Increases in tax rates on capital income, wealth or inheritance may directly reduce income inequality by decreasing the share of national income that goes to the top of the distribution.

Based on the narrative dataset constructed by David and Leigh (2018) for estimating macroeconomic effects of fiscal shocks in Latin America, this paper aims at measuring the effects of fiscal consolidation on inequality in South American

economies. As the region is characterized by a relatively low distributive power of its tax system (GOÑI, LÓPEZ, and SERVÉN, 2011) and inequality-reducing social expenditures, our study will additionally distinguish the impact of tax-based versus spending-based fiscal consolidation programmes on inequality.

The next section describes our dataset and methodology after a brief review of the related empirical literature. The following section presents our econometric results. A discussion of these results concludes the paper.

2. Data and Methodology

2.1 Identification of fiscal shocks: statistical vs narrative approach

Until the end of the first decade in the 21st century, the empirical literature on macroeconomic impacts of fiscal shocks usually employed the so-called statistical approach (MCDERMOTT AND WESCOTT, 1996; LAMBERTINI E TAVARES, 2005; ALESINA AND ARDAGNA, 2010) or the Cyclically-Adjusted Primary Balance approach (CAPB). The CAPB calculates the budget balance that would be observed if the economy operated at the level of potential GDP and, as a second step, adjusts the budget balance to consider the effects of the business cycle on government revenues and expenditures. If the observed GDP is lower than potential GDP, then the fiscal balance is adjusted downwards, accounting, for instance, the negative impacts on tax collection. If the observed GDP is higher than the estimated potential GDP, considering the opposite movement, the fiscal balance is adjusted upwards.

However, this approach has been questioned since the beginning of the 2010s. Using the statistical approach to estimate the impact of fiscal adjustments on income inequality, Agnello and Sousa (2012) recognize its limitations and the need for using other ways to identify these shocks. According to the authors, variables capturing economic cycles can be correlated with fiscal data leading to CAPB measurement errors. Thus, policymakers may be committed to "sustainable" fiscal consolidation, but in the event of a recession, the fiscal adjustment will be associated with unfavorable economic results. On the other hand, policymakers may decide to implement consolidation measures at the time of an economic recovery, generating an association between fiscal consolidation and favorable economic results.

Devries et al. (2011) highlight that cyclical adjustment methods suffer from measurement errors due to the intrinsic correlation between such measures and economic fluctuations[2]. In addition, even if fluctuations in the CAPB accurately reflect discretionary changes in fiscal policy, the intrinsic motivation for these movements may be related to a response to cyclical fluctuations (causality, in this case, runs from the economic cycle to fiscal policy). For instance, governments may cut spending when the economy overheats. In addition, unemployment insurance and other categories of social benefits respond to the economic cycle, linking recessions to an increase in these types of spending.

Based on the case of Finland in the 2000s, which implemented a fiscal consolidation programme in a context of strong economic growth and a boom in asset

[2] Cyclical adjustment methods fail to remove the impact of strong fluctuations in economic activity and asset prices from fiscal data, generating changes in the CAPB not necessarily linked to fiscal policy. A boom in the stock market, for instance, raises CAPB through tax revenues derived from capital gains. A commodity price boom can stimulate private investment and raise government cyclically adjusted revenues (DAVID AND LEIGH, 2018).

prices, Ball et al. (2013) also argue that the use of the CAPB is not appropriate for it ignores the motivations behind fiscal actions[3].

Moreover, Agnello and Sousa (2014, 2016) consider the degree of arbitrariness involved in the statistical smoothing technique used to extract the automatic impact of the economic cycle on fiscal indicators as problematic. In addition, they highlight the fact that CAPB estimates assume elasticities of budgetary components relative to economic activity as constant while empirical evidence suggests that these vary over time and are highly volatile.

Other authors of this stream of literature develop similar criticisms to the statistical approach and chose to use alternative methods to identify fiscal shocks (WOO ET AL., 2013; SCHALTEGGER AND WEDDER, 2014; FURCERI, JALLES AND LOUNGANI, 2016, 2018; JALLES, 2017; KLEIN AND WINKLER, 2018; HEIMBERGER, 2020). Among these alternatives, the most widespread is the so-called narrative approach. Based on the work of Devries et al. (2011) inspired by Romer and Romer (2010), this approach aims to reduce the recognized endogeneity problems in the CAPB method by focusing on specific historical episodes of fiscal consolidation. Such episodes are identified based on the actions and intentions of policymakers as described in official documents that are explicitly motivated by the main objective of reducing the fiscal deficit and respond to retrospective economic conditions (not to prospective conditions)[4].

The identification of these episodes is drawn through the examination of the accounts and historical records of the government economic policy intentions such as IMF Recent Economic Development and Staff reports, OECD Economic Surveys and others (AGNELLO and SOUSA, 2014, 2016). In addition, the effect of fiscal consolidation on the budget balance is recorded in the year in which the adjustment actually occurs. Hence, announced policy measures that end up not being implemented are not included in the database, providing greater accuracy to the measurement of fiscal shocks. Such episodes, as advocated by Ball et al. (2013), are exogenous to the economic cycle because they only include policy actions taken by governments that intend to reduce the fiscal deficit.

In sum, this procedure aims at eliminating endogenous responses of fiscal policy to economic fluctuations, thus capturing the decision components of policymakers primarily related to the reduction of the budget deficit and excluding other political, economic, and institutional factors that may motivate consolidation programs. In addition, this approach allows for the decomposition of fiscal adjustment episodes into "spending-based" or "tax-based", enabling greater qualification on the impacts of fiscal shocks. Even authors that used CAPB (AGNELLO E SOUSA, 2012; JALLES, 2017[5]) recognize a higher degree of exogeneity in the narrative approach.

It is worth mentioning that the approach taken by Devries et al. (2011) also has disadvantages. Jordà and Taylor (2016) point out that the strategy depends on the judgment of those who build the database and may not completely eliminate the endogeneity to the economic cycle. Escolano et al. (2014) express concern over the use of many different sources to obtain estimates of the budgetary impact of fiscal policy

[3] If a fiscal adjustment is a response to pressures generated by the heating of domestic demand, then it is not valid to estimate the effects of fiscal policy.

[4] The fiscal shocks identified from this strategy, therefore, should not be the result of other economic fluctuations.

[5] Although the author recognizes the weaknesses of the statistical approach (CAPB), he argues about the impossibility of using the narrative approach because Devries et al. (2011)'s research covers only 17 advanced economies, while his sample involves 27 emerging economies.

actions because it may put together data based on incompatible methodologies. Furceri et al. (2018) highlight that narrative datasets are mostly restricted to OECD countries, hindering estimations for emerging economies.

2.2 Database

Inspired by Romer and Romer (2010) and Devries et al. (2011), David and Leigh (2018) built a narrative dataset for 14 Latin American economies between 1989 and 2016. The authors emphasize that the objective of building an exogenous fiscal shock measure is to obtain a policy instrument that correlates with the CAPB, but that is not correlated with prospective conditions (i.e., exogenous to business cycle fluctuations and short-term developments). Thus, if there are measurement errors caused by the use of several sources to estimate the episodes of consolidation, it only matters if the conditions of exogeneity to the cycle are affected, which does not seem to be the case.

Historical sources examined by the authors include multilateral institutions reports, such as IMF Staff Reports and OECD Economic Surveys, budget documents (*Informe de Finanzas Publicas* from Chile and Paraguay, *Marco Fiscal de Mediano Plazo* from Colombia, *Criterios Generales de Política Económica* from Mexico and *Marco Macroeconomico Multianual* from Peru), as well as central banks reports. In some cases, these sources have been supplemented by information from Working Papers or other research documents.

The database constructed for our study puts together the narrative dataset built by David and Leigh (2018) with data on inequality and GDP per capita for South American countries. Considering that income inequality estimates at the national level are based on sources that, in general, are also national - such as household sampling surveys or household budget surveys -, there are difficulties in making international comparisons. The literature that focuses on distributional impacts of fiscal shocks, although using other databases to verify the robustness of the results, seems to converge on the use of the Standardized World Income Inequality Database (SWIID) which, in its version 8.2, provides information on the Gini index for market income and for disposable income for a sample of 196 countries from 1960 to 2018 (SOLT, 2019).

Based primarily on the Luxembourg Income Study (LIS) data, this database is constructed by using a Bayesian approach to standardize observations obtained from sources such as OECD Income Distribution Database, Socio-Economic Database for Latin America and the Caribbean - CEDLAS, Eurostat, World Bank PovcalNet, and others. It is thus possible to compare the evolution of the trajectories of income inequalities in the countries of the sample over the last decades.

Although Furceri, Jalles, and Loungani (2016) and Furceri et al. (2018) highlight downsides in the use of modeling to estimate missing information from the LIS in the construction of SWIID, it is the best available database when taking into account its coverage and quality (WOO ET AL., 2013). Among the authors who estimated the impacts of fiscal consolidations on income inequality (AGNELLO E SOUSA, 2012, 2014, 2016; BALL ET AL., 2013; WOO ET AL., 2013; SCHALTEGGER AND WEDER, 2014; FURCERI, JALLES E LOUNGANI, 2016; FURCERI ET AL., 2018; KLEIN AND WINKLER, 2018; HEIMBERGER, 2020), only Agnello and Sousa (2016) used a different database due to their focus on European regional inequality.

Based on data availability for the Gini index for disposable income, fiscal shocks, and GDP per capita (the latter being obtained from the World Bank) in South American countries, three balanced panels are constructed (see Table 1). As can be observed in Table 1, there is a trade-off between increasing the number of countries and

the number of years in the panel. Panel 3 has nine countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru e Uruguay) but only for the period 1991-2017. Panel 1 has six countries (Argentina, Brazil, Chile, Colombia, Peru e Uruguay) for a longer time period (1982-2017). Panel 2 can be seen as intermediate, as it contains 7 countries with data from 1988-2017. All estimations will be conducted with the three data panels.

A detailed description of the fiscal shocks is available in the Appendix (Table 1), which sets out the countries, years, what measures were implemented and the estimated budgetary impact for each episode. The empirical relationship between fiscal shocks and the Gini index for disposable income in the 9 countries of the sample is shown in Figures 6, 7, and 8 in the Appendix.

Table 1 – Data panels

Panel	Years	Country (number)	Obs. Gini[6]	Consolidation(spending-based)	Consolidation (tax-based)	Expansion (spending-based)	Expansion (tax-based)
Panel 1	1982-2017	6 [7]	216	10	22	1	3
Panel 2	1988-2017	7[8]	210	11	25	1	3
Panel 3	1991-2017	9[9]	243	13	29	1	5

Own elaboration.
* Some of the episodes refer to spending-based and tax-based adjustments applied concomitantly.

2.3 Econometric strategy

Regarding econometric methods for estimating the distributive impacts of fiscal adjustments, one can distinguish between static models such as Seemingly Unrelated Regressions (SUR) and panel data with fixed effects estimators; and dynamic models such as Autoregressive Distributed Lag (ARDL), Panel Vector Autoregressive (PVAR) and Local Projections (LP) method (JORDÀ, 2005) to estimate Impulse Response Functions (IRFs). This section shows how the literature has evolved over the past few years, converging to the widespread use of Jordà's method (2005).

To estimate the contemporaneous impacts of fiscal consolidation on income inequality, several authors use static models. While Agnello and Sousa (2012, 2014) employ Seemingly Unrelated Regressions (SUR) as a baseline model, Jalles (2017) and Woo et al. (2013) use SUR only as a complement to their main strategies. This method consists of estimating two regressions, one for the Gini index for disposable income and the other for the Gini index for market income (the errors of these equations are considered correlated). Thus, if the unobserved determinants of these two indexes are correlated, the SUR estimator is an efficient and plausible strategy.

Other authors use panel data models with fixed effects as their main strategy (WOO ET AL., 2013; SCHALTEGGER AND WEDDER, 2014). This method allows us to take into account unobservable factors that are invariant over time for each sample unit or that are invariant between countries for each temporal unit. However, as distributional impacts of fiscal consolidation dynamically change over time, static approaches, while useful, are incomplete to capture these impacts.

[6] With the first differencing of the variables, one unit of time is lost for each cross-sectional unit.
[7] Argentina, Brazil, Chile, Colombia, Peru e Uruguay.
[8] Argentina, Brazil, Chile, Colombia, Ecuador, Peru e Uruguay.
[9] Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru e Uruguay.

Hence, among available alternatives to capture dynamic effects of fiscal consolidations, one possibility is to estimate Impulse Response Functions (IRFs) through Panel Vector Autoregressive models (PVAR). This method has several weaknesses. Jalles (2017) considers that some intrinsic characteristics of the PVAR models, such as the fact that all relevant regressors are considered endogenous, generate narrowness, engendering the necessity of ordering each regressor accurately in the estimation of the system while economic theory rarely provides such arrangement[10]. In addition, as a VAR model represents a linear global approach to the real data-generating process, it is optimally designed for the projection of a period ahead, causing the shift of all measurement errors or misspecifications of the model ahead over time, hindering the interpretation of IRFs. Thus, as highlighted by Heimberger (2020), the PVAR traditional approach may suffer from identification problems and length limitations.

The possibility of using Autoregressive Distributed Lag (ARDL) is also mentioned by several authors of this empirical literature as a way to take into account dynamic effects (BALL ET AL., 2013; FURCERI, JALLES AND LOUNGANI, 2016; JALLES, 2017; FURCERI ET AL., 2018; HEIMBERGER, 2020). As stated by these authors, however, the IRFs derived from this approach tend to be sensitive to the number of lags in the model, generating potential instability in the face of slight changes. Furthermore, when the dependent variable is extremely persistent (this is the case for the Gini index), the statistical significance of long-term effects can occur from one-type-of-shock models - i.e., the response of the dependent variables is always the same, regardless of the presence of shocks in the system.

To address these issues on the estimation of IRFs, there is a recent convergence and strong adherence in the empirical literature to the estimation of dynamic impacts of fiscal shocks on income inequality using the Local Projections approach (BALL ET AL., 2013; FURCERI, JALLES E LOUNGANI, 2016; JALLES, 2017; FURCERI ET AL., 2018; KLEIN AND WINKLER, 2018; HEIMBERGER, 2020). This method was developed by Jordà (2005), who derived the local projections from sequential regressions of the endogenous variable that is shifted several steps ahead – similarly to the direct forecasts of several stages. Impulse responses, in this way, are calculated from a sequence of projections of the endogenous variable.

Thus, these projections are local to each forecast horizon and have greater robustness than the PVARs misspecifications of an unknown data generating process (KLEIN AND WINKLER, 2018). As opposed to ARDL models, Jordà (2005)'s method does not use lags of the dependent variable to derive the IRFs (BALL ET AL., 2013; JALLES, 2017) and allows confidence intervals of these impulse responses to be estimated directly from the standard errors of the estimated coefficients, without the need for Monte Carlo simulations (FURCERI, JALLES, AND LOUNGANI, 2016; HEIMBERGER, 2020).

In VARs, the estimation of the model is based on the sample and represents a global linear approximation, being designed optimally for a period ahead even when badly specified. An impulse response, however, is a function of predictions in increasingly distant horizons, causing the aggravation of the specification errors over time. Local projections, on the other hand, are based on sequential regressions of the dependent variable shifted to horizons ahead, generating consistent estimates of the impulse response coefficients. Jordà argues that the use of the Local Projections method is advantageous because they may be estimated with usual techniques such as Ordinary

[10] Choleski decomposition is often used as a solution to this issue, but it has no value to provide structural information to a VAR.

Least Squares (OLS) and are robust to specification errors[11].

Thus, the baseline model of the econometric estimation in this paper is based on Jordà (2005), as previously applied in several studies on the same topic (see Table 2).

Table 2 – Summary of econometrics studies on the impact of fiscal policy on income inequality

Authors	Gini Database	Identification of Fiscal Shocks	Sample (Years)	Econometric Method
Agnello and Sousa (2012)	SWIID	CAPB	18 OECD economies (1970 - 2010)	SUR
Ball et al. (2013)	SWIID	Narrative approach	17 OECD economies (1978 - 2009)	IRFs from LPs
Woo et al. (2013)	SWIID	Narrative approach	17 OECD economies (1978 - 2009)	FEE, SUR
Agnello and Sousa (2014)	SWIID	Narrative approach	18 OECD economies (1978 - 2009)	SUR
Schaltegger and Weder (2014)	SWIID	Narrative approach	17 OECD economies (1978 - 2009)	FEE
Agnello et al. (2016)	ERD	Narrative approach	13 European countries (1980 - 2008)	FEE
Furceri, Jalles and Lougani (2016)	SWIID	Narrative approach	17 OECD economies (1978 - 2009)	IRFs from LPs
Jalles (2017)	Milanovic (2014)	CAPB	28 emerging economies (1980 – 2014)	SUR / IRFs from LPs
Furceri et al. (2018)	SWIID	Forecast errors in goverment spending[12]	103 emerging economies (1990 – 2015)	IRFs from LPs
Klein and Winkler (2018)	SWIID	Narrative approach	17 OECD economies (1980 – 2011)	IRFs from LPs
Heimberger (2020)	SWIID	Narrative approach[13]	17 OECD economies (1978 - 2013)	IRFs from LPs

* CAPB: Cyclically-Adjusted Primary Balance approach.
* WIID: World Income Inequality Database.
* SWIID: Standardized World Income Inequality Database.
* ERD: European Regional Database.
* IRFs from LPs: Impulse Response Functions (IRFs) from Local Projections (LPs) (JORDÀ, 2005).
* SUR: Seemingly Unrelated Regressions model.
* FEE: panel data with Fixed Effects Estimator.

Own elaboration.

Regressions are estimated using Ordinary Least Squares (OLS) in a panel with fixed effects for countries and time and considers Driscoll-Kraay standard errors to account for heteroscedasticity, and serial and spatial autocorrelation, as below:

$$\sum_{h=0}^{H} y_{i,t+h} - y_{i,t+h-1} = \alpha_i^h + \gamma_t^h + \beta^h X_{t-1} + \beta^h X_{t-2} + \beta^h X_{t-3} + \delta^h Z_{t-1} + \delta^h Z_{t-2} + \delta^h Z_{t-3} + \varepsilon_{i,t}^h .$$

[11] In this way, the impulse responses calculation for a time series vector based on local projections does not require a specification identical to that of the Data Generating Process (DGP). This is very useful when the DGP is unknown.

[12] Auerbach e Gorodnichenko (2013).

[13] He uses Devries et al. (2011) and Alesina et al. (2015) databases.

Where:

y: income inequality measure (Gini for disposable income, in log).
X: fiscal adjustment measure.
Z: GDP per capita – ppp 2017 (1st difference of the log).
$\mathbf{y}^{h}_{t}$ e $\boldsymbol{\alpha}^{h}_{i}$: fixed effects for time and countries.
$\boldsymbol{\beta}^{h}$: corresponds to the estimated multiplier; cumulative response of income inequality to the fiscal shock in a given horizon.
h: time horizon chosen, represented as a notation on the right side of the model equation, to the analysis of the impact of fiscal adjustment.
$\boldsymbol{\varepsilon}^{h}_{i,t}$: Driscoll-Kraay standard errors.

Table 3 shows information on the explanatory variables of the model. The model specification was inspired by previous studies that applied Jordá (2005)'s method for the same purpose (BALL ET AL., 2013; FURCERI, JALLES E LOUNGANI, 2016; FURCERI ET AL., 2018; KLEIN E WINCKLER, 2018; HEIMBERGER, 2020).

Table 3 – Our explanatory variables

Expected sign	Variable	Description	Source
(-)	Change in real GDP per capita - ppp[14]	First difference of the log of real GDP per capita	WDI – World Bank.
(+)	Fiscal consolidation measure	Fiscal shock measures (total, spending-based, or tax-based, as a % of PIB) for 9 South American countries between 1989 and 2016.	David and Leigh (2018).

Own elaboration.

However, since the dependent variable (variation in income inequality) is the first difference of the log of the Gini index for disposable income, its lags are not used as explanatory variables of the baseline model. Our approach is based on the idea that changes in income distribution are engendered by structural determinants, so that variations in inequality by themselves do not catalyze new variations in inequality. Milanovic (2016) argues that decreases/increases in income inequality are generated by idiosyncratic events such as wars, civil conflicts, epidemics, strong social pressures, changes in the demographic structure, technological changes, and other political-institutional ruptures. In the case of fiscal policy, if the changes are permanent, it may be considered that the impact in income inequality is also permanent.

3. Estimation and results

3.1 Diagnostic tests

Considering the panels indicated in Table 1, unit root tests were implemented to verify the stationarity of the Gini index and GDP per capita[15]. It was not necessary to apply unit root tests to the fiscal variables given that they represent episodes of shocks and that, in their absence, their expected value is equal to zero. Results of the Levin-

[14] The GDP per capita is expressed in purchasing power parity and denominated in US dollars at 2017 prices.

[15] Tests were applied to the variables "Gini for disposable income (in log) - with and without trend", "GDP per capita (in log) - with and without trend", "1st difference of the log of Gini for disposable income (in log)" and "1st difference of the log of GDP per capita (in log)" series.

Lin-Chu[16] (LLC) tests are presented in Table 2 in the Appendix.

Based on these results, the Gini index was introduced in logarithmic form of the first difference in all estimations[17]. Even though the presence of a unit root to "Gini (in log) – disposable income – with the trend" is rejected, the graphical analysis of Figures 6, 7, and 8 in the Appendix did not suggest a linear temporal trend. All countries in the sample, except for Paraguay, reduced their level of income inequality between 1990 and 2017 (Figure 2 in the Appendix). However, the trajectory of this variable fluctuates for the region as a whole, so that the most appropriate specification are the changes in inequality (represented by the "1st difference of the log of Gini index for disposable income"), as shown in Figures 6, 7 and 8 in the Appendix.

The Levin-Lin-Chu test presents unequivocal results on the use of the first difference of the log of GDP per capita. While there is a possibility of unit roots in the other specifications for this variable, test results and Figures 9, 10, and 11, considering the countries and years in this sample, indicate stationarity to changes in GDP per capita.

Models were estimated with Driscoll-Kraay standard errors, accounting for heteroscedasticity and serial and spatial autocorrelation, so that Ordinary Least Squares estimators are consistent and unbiased.

3.2 Results

Results for Panel 1, which includes observational units for Argentina, Brazil, Chile, Colombia, Peru, and Uruguay between 1982 and 2017, indicate a strong and statistically significant impact of spending-based fiscal consolidations on income distribution, while the impact of tax-based fiscal adjustments on inequality is not statistically significant. Figure 1 presents the impulse response functions of fiscal consolidations of 1% of GDP on the Gini index for disposable income.

Results presented in Table 3 in the Appendix indicate that the Gini index for disposable income increases by about 0.2% in the short-run (in year one) after a fiscal consolidation episode of 1% of GDP. In the medium-run (in year five), the increase in inequality reaches almost 1.4%, being statistically significant at the level of 10%. As can be seen in Table 4 in the Appendix, a spending-based fiscal adjustment of 1% of GDP generates an increase of about 0.2% in the short-run (in year one), while in the medium-run (in year five) it rises almost 3.22%, with statistical significance at the level of 0.1%. The impact of a tax-based consolidation, shown in Table 5 in the Appendix, seems to be less intense and has no statistical significance. In year one, a fiscal adjustment of 1% of GDP generates an increase of 0.46% in income inequality. In year five, the Gini index for disposable income increases by 1.3%.

[16] It has an alternative hypothesis of stationarity. This test is recommended if "(n/t) → 0" and panels are balanced, which is the case in our study.

[17] It avoids the violation of statistical assumptions such as the constancy of the mean and the variance in the series – which occurs in the presence of unit root.

Figure 1 – Cumulative Response of Inequality to a fiscal consolidation of 1% of GDP in Panel 1

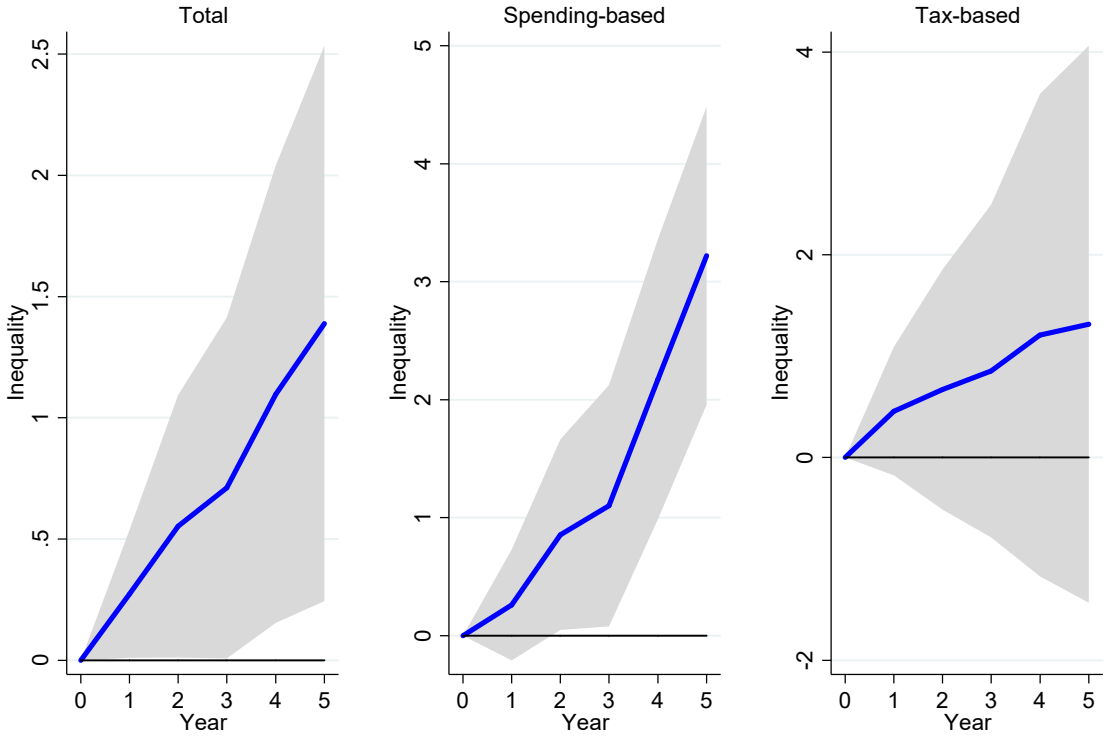
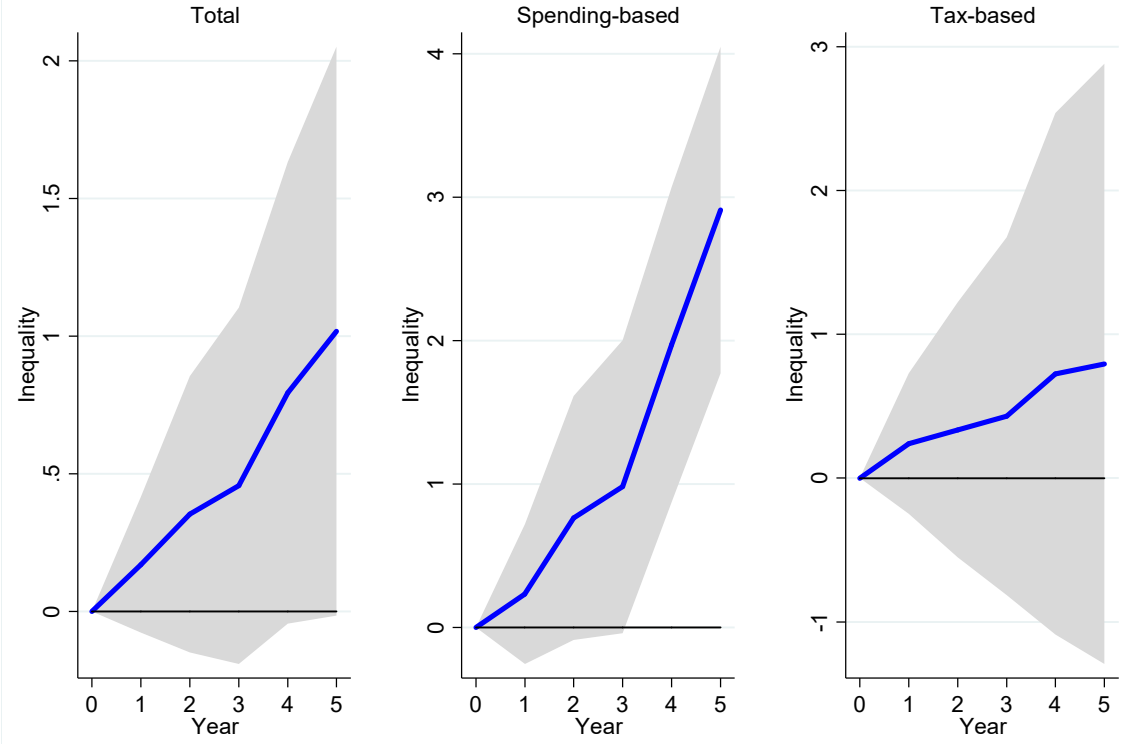


Figure 2 – Cumulative response of inequality to a 1% of GDP fiscal consolidation in Panel 2



Focusing on Panel 2, which includes observational units for Argentina, Brazil, Chile, Colombia, Ecuador, Peru, and Uruguay between 1988 and 2017, results are

similar to those found for Panel 1. While there are strong and statistically significant effects of spending-based fiscal consolidation on income distribution, the same does not happen to the impact of tax-based adjustments on inequality. The impulse response functions of a fiscal consolidation of 1% of GDP for Panel 2 are shown in Figure 2.

As shown in Table 6 in the Appendix, a fiscal consolidation episode of 1% of GDP engenders an increase of 0.17% in inequality in year one. In the medium run (in year five), income inequality rises by 1%. There is no statistical significance to these results. As observed in Table 7 in the Appendix, spending-based fiscal adjustments of 1% of GDP generate an increase of 0.23% in the Gini index for disposable income in year one, while in the medium-run (in year five) the change in inequality may reach +2.91%, being statistically significant at the level of 0.1%. The impact of tax-based consolidation is shown in Table 8 in the Appendix and, such as in Panel 1, it is less intense and has no statistical significance. In year 1, an adjustment of 1% of GDP generates an increase of 0.2% in income inequality. In the medium-run (in year five), the Gini index for disposable income rises by 0.7%.

Considering Panel 3, which includes data for Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, and Uruguay between 1991 and 2017, results slightly differ from those presented for Panels 1 and 2 but maintain major qualitative conclusions. The impact of spending-based fiscal consolidations on income inequality remains statistically significant, albeit less intense. Analyzing the distributive consequences of the tax-based fiscal consolidations, results are inverted (i.e., a tax-based adjustment tends to generate a decrease in inequality), but with no statistical significance. The impulse response functions of fiscal consolidation of 1% of GDP for this panel are shown in Figure 3.

Figure 3 – Cumulative response of inequality to a 1% of GDP fiscal consolidation in Panel 3

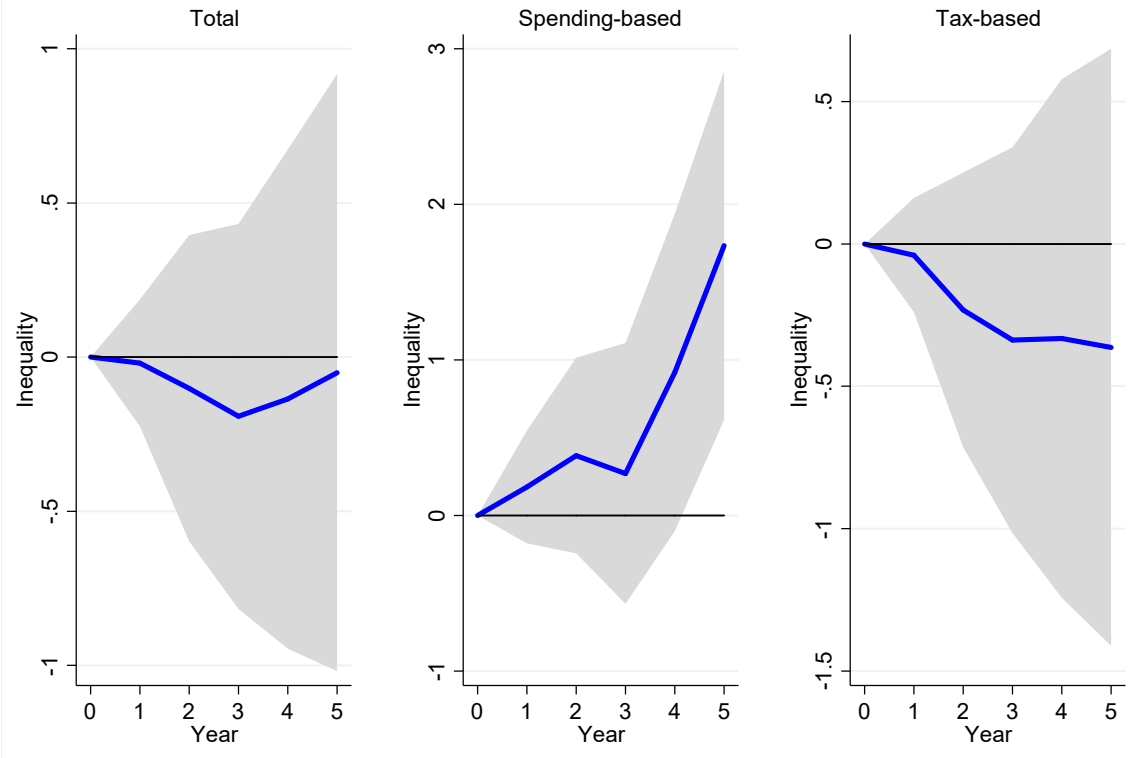


Table 9 in the Appendix shows a decrease of 0.02% in the Gini index for disposable income in the short-run (in year one) after a fiscal consolidation of 1% of

GDP, while in the medium-run (in year five) there is a decline of 0.05% in inequality. These results do not have statistical significance. As shown in Table 10 in the Appendix, spending-based fiscal adjustments of 1% of GDP generate an increase of 0.18% in the Gini index for disposable income in year one, while in the medium-run (in year five) the change in the inequality may reach +1.74%, being statistically significant at the level of 5%.

The impact of tax-based fiscal consolidation shocks is shown in Table 11 in the Appendix. Such as in Panels 1 and 2, the effect of these shocks has no statistical significance. However, differently from the previous panel, tax-based adjustments show a negative effect on inequality. In year 1, an adjustment of 1% of GDP generates a decrease of 0.039% in income inequality. In the medium-run (in year five), the Gini index for disposable income diminishes by 0.36%.

3.3 Discussion

Our econometric results can be interpreted as additional evidence of a potential positive effect of fiscal austerity on income inequality, as results for Panels 1 and 2 show a statistically significant rise in inequality caused by fiscal consolidation episodes in South American countries. In particular, our results unambiguously point towards the significant increase in income inequality generated by spending-based fiscal consolidation episodes in South American countries. The estimated effect of a reduction in government expenditures of the magnitude of 1% of GDP five years after the shock varies between a rise of 1.74% in inequality measured by the Gini index found for Panel 3 (9 countries, 1991-2017) and a rise of 3.2% in inequality found for Panel 1 (6 countries, 1982-2017). Finally, our results also show a lack of statistical significance of the effect of tax-based fiscal consolidation episodes on inequality for all three data panels. In Panel 3, which contains data for more countries in a more recent time period, the impact of a tax-based adjustment on inequality is even negative.

Table 14 – Results observed in the empirical literature

Authors	Consolidation of 1% of GDP or dummy for consolidation episode	Spending-based adjustment (1% of GDP or dummy for consolidation episode)	Tax-based adjustment (1% of GDP or dummy for consolidation episode)
Agnello and Sousa (2012)	Reduction of 0.011 in the Gini index.	-	-
Ball et al. (2013)	Increase in the Gini index for disposable income: 0.3% (after 2 years); 1.5% (after 8 years).	Increase in the Gini index for disposable income: 1% (after 8 anos).	Increase in the Gini index for disposable income: 0.6% (after 8 years).
Woo et al. (2013)	Increase in the Gini index for disposable income: 0.6-0.7% (after 1 year).	Increase in the Gini index for disposable income: 1.5%-2% (after 1 year).	Negative relationship, but without statistical significance.
Agnello and Sousa (2014)	Increase in the Gini index for disposable income: 0.026.	Increase in the Gini index for disposable income: 0.035.	Increase in the Gini index for disposable income: 0.004.
Schaltegger and Weder (2014)	Increase in the Gini index for disposable income: 0.4% (after 1 year).	Increase in the Gini index for disposable income: 0.609% (after 1 year).	Increase in the Gini index for disposable income: 0.28% (after 1 year).
Agnello et al. (2016)	Increase in the Gini index: 0.1 (after 1 year); 0.3 (after 5 years).	Increase in the Gini index: 0.2 (after 1 year); 0.5 (after 5 years).	Fiscal consolidations seem to be neutral both in the short and medium terms, without statistical significance.
Furceri, Jalles and Lougani (2016)	Increase in income inequality: 0.2 (after 1	Increase in income inequality: 0.24% (after 1	Increase in income inequality: 0.09% (after 1

	year); 0.9 (after 8 years).	year); 1.05% (after 8 years).	year); 0.13% (after 8 years).
Jalles (2017)	Increase in income inequality: 0.65 (after 1 year); 0.8 (after 3 years).	Increase in income inequality: 2.3 (after 1 year); 3.2 (after 4 years).	Increase in income inequality: 0.8 (after 1 year); 2.6 (after 4 years).
Furceri et al. (2018)	Increase in income inequality: 3.38% (after 5 years).	-	-
Klein and Winkler (2018)	Increase in the Gini index for disposable income: 0.42 (after 4 years).	Increase in the Gini index for disposable income: 2.9 (after 4 years).	Increase in the Gini index for disposable income: 1.5 (after 4 years).
Heimberger (2020)	Increase in the Gini index for disposable income: 0.35% (after 3 years); 0.6% (after 5 years).	Increase in the Gini index for disposable income: 0.5% (after 3 years); 0.6% (after 5 years).	Increase in the Gini index for disposable income: 0.2% (after 3 years); 0.4% (after 5 years).
This study (Panel 1)	Increase in the Gini index for disposable income: 0.27% (after 1 year); 1.39% (after 5 years). With statistical significance.	Increase in the Gini index for disposable income: 0.26% (after 1 year); 3.22% (after 5 years). With statistical significance.	Increase in the Gini index for disposable income: 0.45% (after 1 year); 1.3% (after 5 years). Without statistical significance.

Own elaboration.

Our results for Panel 1 are compared to other results in the empirical literature on the effect of fiscal consolidation on income inequality in Table 14. In general, South American economies seem to show a higher effect of fiscal consolidation on inequality than obtained in most empirical studies for OECD countries, with the exception of Ball et al (2013) and Furceri et al (2018). When it comes to spending-based adjustments, the increase in inequality found in our study is higher than in 7 out of 9 studies in our literature review and very similar to those in Jalles (2017) and Klein and Winkler (2018). As for tax-based consolidation episodes, two other studies had found no statistical significance: Woo et al (2013) and Agnello et al (2016).

4. Conclusion

This paper intended to contribute to the empirical literature on the effect of fiscal consolidation episodes on income inequality by focusing on South American economies. By building on the narrative dataset on spending-based and tax-based fiscal consolidation episodes by David and Leigh (2018), we have estimated impulse response functions using Jordá (2005)'s Local Projections method for a panel covering nine countries in the period between 1982 - 2017. Our results indicate that fiscal austerity measures have significantly increased inequality as measured by the Gini index for disposable income when based on cuts in government expenditures. Fiscal consolidation episodes based on an increase in taxes seem to show no statistically significant effects on inequality.

Results show that the Gini index for disposable income after a spending-based fiscal adjustment of 1% of GDP rises by 0.18-0.26% after one year and by 1.74-3.22% in year 5 with statistical significance in all specifications, with the exact estimate depending on the chosen data panel (number of countries and years). Changes in income inequality after a tax-based fiscal adjustment of 1% of GDP in year one are between -0.03 and 0.45% and -0.36% and 1.3% in year 5 depending on the chosen data panel according to our estimations, but no statistical significance appears in this type of shock.

Given the adverse socioeconomic effects of the Covid-19 pandemic currently faced by South American countries, the potential implementation of a new round of spending-based fiscal consolidation plans raises concerns. Our results suggest that if a fiscal adjustment is required for external or macroeconomic stabilization purposes, a

tax-based strategy would be preferable.

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