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"The dynamic effects of fiscal discretion on income distribution in the EU-27"

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ABSTRACT

Based on a panel data for EU-27 from 1990 to 2017, this paper develops a novel three-steps framework to assess the dynamic effects of discretionary fiscal policy on income distribution and inequality. The steps are the following: 1) extract the discretionary fiscal component by estimating a well-known fiscal rule model, 2) use that component to estimate the dynamics of income distribution given a discretion's shock by ARDL models and 3) investigate the short-, medium- and long-term effects by computing IRFs via Local Projections method by Jordà, 2005. Overall, I find supportive evidence on the heterogeneity in the response of income distribution to discretionary changes in government spending and a weak performance of discretion in terms of income redistribution durability. Such heterogeneity is shown as i) a positive, yet transitory, income redistributive power of discretion and ii) a persistent and detrimental impact on the top 1 share of the distribution. In addition, these results complement with persistent inequality alleviation in the long-run. Such results are robust to multiple specifications regarding lag selections criteria, time indicators inclusion and sign non-linearities (asymmetries).

Keywords: Discretionary fiscal policy; Autoregressive Distributed Lag Model; Local projections method; Income redistribution

JEL: C23, C26, D31, E26, H50

DEDICATION

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1. INTRODUCTION

Over the past decades, the academia, governments and policymakers have been attracted towards the role of fiscal policy due to relevant events. The set of fiscal consolidations that occurred in Europe following the Maastricht convergence criteria, the creation of the Economic and Monetary Union (EMU) and the extraordinary fiscal stimulus packages implemented during and after the Great Recession, *inter alia*, entailed a shift in the vision of fiscal policy in the European Union (EU). Consequently, a debate arose regarding the real influence of fiscal policy on economic stabilization and recovery (Agnello & Sousa, 2011; Andrikopoulos et al., 2004; Brunila et al., 2003; Buti & Van den Noord, 2003).

Complementary to the regular fiscal tool used by governments, automatic stabilizers; an additional component dictating the fiscal stance of the policymaker gained importance during and after the crisis. Related with that, an extra debate arose based on questioning the influence of the components of fiscal policy on multiple economic and social indicators, specifically after the Great Recession. Not only output volatility and economic stabilization were directly affected by these components (Buti & Van den Noord, 2003; Şen & Kaya, 2020), but also income distribution (Bargain et al., 2017; De Agostini et al., 2016; Hills et al., 2019; Mulas-Granados et al., 2005; Paulus et al., 2020; Paulus & Tasseva, 2020), inequality (Anderson et al., 2017; Davoodi et al., 2000; Joumard et al., 2012; Martinez-Vazquez et al., 2012; Paulus et al., 2017; Sidek, 2021) and their redistributive impact (Immervoll et al., 2006; Joumard et al., 2012; Martinez-Vazquez et al., 2012; Paulus et al., 2017).

The main goal of this paper is to shed light on the dynamic effects of discretionary fiscal policy on the way income is distributed in the EU-27 during the period 1990-2017 and complementary, on inequality. To do so, I will first extract the estimated discretionary fiscal component from the estimation of a well-known in the literature fiscal rule model (Afonso et al., 2010; Agnello et al., 2013; Fatás & Mihov, 2003, 2006; Lane, 2003). Then, I will estimate the dynamic effects of discretion on different segments of the income distribution and on inequality by estimating Autoregressive Distributed Lag (ARDL) models that will explain the average response of income distribution to lagged values of discretion, and finally, I will estimate the short-, medium- and long-term impulse responses functions (IRFs) to discretion via local projections method by Jordà, 2005. In turn, I will also estimate the cumulative version of Jordà, 2005's method with the aim of providing answers on the persistence of the effects of discretion in the long-run.

To the best of my knowledge, the novelty of this paper relies on the application of dynamic and macroeconomic frameworks to study the impact of discretionary fiscal policy on a complete segmentation of European income distribution. Differently from the microeconomic approach applied by Bargain et al., 2017; De Agostini et al., 2016; Hills et al., 2019; Paulus et al., 2020 in the study of the effects of tax-benefit stimulus packages implemented by selected European governments after the Great Recession on income distribution and inequality, and to the general usage of inequality coefficients as indicators of changes in the income distribution (Agnello et al., 2013; Balseven & Tugcu, 2017; Martinez-Vazquez et al., 2012; Mulas-Granados et al., 2005).

Overall, I find supportive evidence that discretionary fiscal policy: i) has a transitory income redistributive power, ii) provokes persistent inequality alleviation in the long-term, and iii) persistently harms the top 1 share of the income distribution. Hence, since great part of the effects on the poorest and the middle class are transitory, discretionary fiscal policy weakly performs in terms of persistent income redistribution.

The rest of this paper is organized as follows; Section 2 will present a brief retrospective view of the role of fiscal policy in the EU, together with a presentation of the historical importance of fiscal policy components; Section 3 will show the existing literature and evidence on the power of fiscal policy to alleviate inequality and redistribute income, in addition to a search for gaps in the literature in these manners; Section 4 will present the data set I have used in this paper; Section 5 will explain in detail the applied methodology; Section 5 will consist of the presentation and discussion of the results, along with a set of robustness checks; and finally Section 6 will provide the reader of some concluding remarks and potential further research items [1] [2].

[1]This is the download link for the Stata code developed for this paper.
[2]This is the data set utilized in this paper ready to be used in Stata.

2. FISCAL POLICY IN THE EU: INSTRUMENTS, COMPONENTS AND ELEMENTS.

Fiscal policy, seen as an instrument for economic stabilization, became unpopular in the academia and among policymakers partly due to the collapse of the Keynesian consensus in the middle of the 1970's and opened questionings about its functioning such as Barro, 1974's seminal paper on Ricardian equivalence. At that time, as stated in Brunila et al., 2003, monetary policy was meant to deal with short-term stabilisation, whilst fiscal policy should be harnessed to medium-term structural issues and the achievement of long-term sustainability of public finance.

Budgetary imbalance issues and cooperation necessities were key convergence criterion of the Maastricht Treaty in 1992. Simultaneously, the Economic and Monetary Union (EMU [3]) was launched with clear policy assignment and institutional arrangements; a united and common monetary policy in charge of stabilisation against symmetric shocks, and national fiscal policies committed to smooth asymmetric shocks and diverging cyclical conditions. Thus, fiscal policy for EU members was the only remaining instrument controlling local macroeconomic stabilization conditions. This crucial shift in the fiscal policy paradigm implied a clear turnaround in the views regarding its cyclical fluctuations smoothing potential (Brunila et al., 2003).

Albeit, the existence of great budget deficits and debt relative to GDP entailed the arrival to a new agreement between the EMU members in 1998; The Stability and Growth Pact (SGP). This pact pursued retraining fiscal expansion and eliminating fiscal influence on the price level, thus assigning full responsibility for price stability to the European Central Bank (ECB) (Daniel & Shiamptanis, 2008). Under the SGP, EMU members were committed to attain medium-term positions close to balance or in surplus and were constrained to a ceiling of a 3% deficit to GDP ratio.

Components of fiscal policy

Consequently, a different discussion arose regarding which fiscal policy component was in charge of contributing to economic stability. Firstly, the decomposition of fiscal policy needs to be conducted. In theory, and following the definitions by Fatás and Mihov, 2003 and Galı and Perotti, 2003, fiscal policy can be thought of consist-

[3] The list of current members is the following (note that the year of commencement is in parenthesis): Austria (1999), Belgium (1999), Cyprus (2008), Estonia (2011), Finland (1999), France (1999), Germany (1999), Greece (2001), Ireland (1999), Italy (1999), Latvia (2014), Lithuania (2015), Luxembourg (1999), Malta (2008), Netherlands (1999), Portugal (1999), Slovakia (2009), Slovenia (2007) and Spain (1999).

ing of two main components; automatic stabilizers and discretionary measures. The first is the "cyclical" or "non-discretionary" variations due to causes out of control by the fiscal authorities; for instance, changes in tax revenues due to income variations and in primary expenditures, such as unemployment benefits increase due to output fluctuations. Additionally, debt interest payments can also be seen as an element of this automatic component affecting the balance of payments. The second component, as referred by Galı and Perotti, 2003, are the "structural", "cyclically adjusted" or "discretionary" variations observed in case output is at some "potential" level, meaning that the cyclical component is controlled. As such, this component pretends to be capturing the fiscal stance chosen by the policymaker.

Discretionary policy elements

In turn, the discretionary component firstly consists of a "systematic" or "endogenous" element. Conforming to Fatás and Mihov, 2003, this element reacts to the state of the economy and as stated in Galı and Perotti, 2003, it is a result of a deliberate policy decision responding to changes in the actual or expected cyclical conditions of the economy. Secondly, there is a discretionary element that is implemented for reasons different from current macroeconomic conditions; as referred by Galı and Perotti, 2003; the "non-systematic" or "exogenous" element. It is the consequence of exogenous political processes or extraordinary non-economic circumstances (Galı & Perotti, 2003). In consonance with Fatás and Mihov, 2003, it can be interpreted as "changes in the cyclically adjusted fiscal policy stance" and with Galı and Perotti, 2003, as "the element of fiscal policy whose variations do not result from the automatic influence of the cycle or other non-policy influences". Further on in this paper, for simplicity reasons, I will refer to this last "non-systematic" element as the discretionary component of fiscal policy, and as the only element non-reacting against the state of the economy.

"Automatic stabilizers" vs "Discretion": The stabilization debate

Recapturing the fiscal policy components discussion, politicians and institutions positioned against the usage of discretion to fine tune the business cycle (European-Commission, 2002). Therefore, automatic stabilizers were chosen as the main tool for fiscal stabilisation and cushioning of the business cycle. Moreover, conforming to Brunila et al., 2003, this "non-discretionary" strategy would be guaranteeing counter-cyclical budget balance reactions [4], and hence, contributing to economic stability. Thus, discretionary fiscal policy was expected to be the exception rather than the

[4] Counter-cyclicality of a macroeconomic indicator means opposite movements with respect to output fluctuations. In times of recessions, and therefore, output falls, the macroeconomic indicator should go upward. For instance; government expenditure increases after the 2009 financial crisis, both in terms of "systematic", "non-systematic" and "non-discretionary" expenditures.

rule in the EMU. Indeed, this statement was studied in the fiscal literature. Buti and Van den Noord, 2003 found how powerful were automatic stabilizers in the event of shocks to private consumption, although less effective in the cases of private investment and exports. From a different perspective, Şen and Kaya, 2020's results suggest the short-run economic stabilization power and the counter-effect on output volatility of taxes and government spending's automatic stabilizers. Albeit, when widening the temporal scope, the long-run effect of these stabilizers alleviates and leads to conclude the non-alternative character of automatic stabilizers compared to discretionary policy.

The eruption of the Great Recession posed serious economic challenges to the EMU. Among them, the need for efficiently combining automatic stabilizers and discretionary policy changes. The urgent character of the crisis was demanding the quick response of automatic stabilizers, especially when it comes to unemployment. And simultaneously, rescue and stimulus packages were created and subsequently implemented. A quite interesting and recent work by Paulus and Tasseva, 2020 conducted a comparison between the effects of both fiscal policy components during the Great Recession in the EU. Results suggested a greater effect of discretionary policy changes on the increase of income and related with that, both components shown the importance to redistribute incomes and alleviate inequality in equal shares in terms of effect's size. Hence, here we see that there are effects of these components beyond economic stabilization and output volatility; inequality, income distribution and poverty are other factors directly affected by these fiscal policy components.

3. THE REDISTRIBUTIVE POWER OF FISCAL POLICY

The implications of fiscal policy for income inequality and distribution have been extensively covered in the literature. Most of them focus on the direct effect of fiscal policy on income inequality, without considering the responses of different segments of the distribution. In general, historical trends in income inequality can be partly explained by the level and progressivity of tax and spending policies (Coady et al., 2012; Davoodi et al., 2000).

Does fiscal policy alleviate inequality?

Overall, there is an agreement in the literature based on claiming the significant role played by fiscal policy in reducing income inequality. Coady et al., 2012 stated that, in 2005, fiscal policy reduced income inequality approximately 20 points in Belgium, Denmark, Germany, Italy, Luxembourg, Poland, and the Slovak Republic, and less than 10 points in Korea, Iceland, Ireland, Switzerland, and the United States. A quite recent study by Sidek, 2021 supported the inversed U-shaped Kuznet curve where, after a certain threshold, government expenditure brought about a positive effect on inequality for 32 developed countries. When differentiating between taxes and spending as potential inequality alleviators, direct taxes and social spending are found to successfully alleviate inequality, whilst indirect taxes tend to rise it (Davoodi et al., 2000; Joumard et al., 2012; Martinez-Vazquez et al., 2012; Paulus et al., 2017). Additionally, Anderson et al., 2017 conducted a meta-regression analysis [5] and concluded that both the magnitude and direction of the estimated relationship between income inequality and government expenditure depends on the country composition of the sample, the set of control variables included in the model, the analytical approach applied and the government spending measure used. Albeit, the predicted relation is negative in some cases, which means an inequality alleviation power of government spending. Also, larger magnitudes and hence, greater improvements of inequality are provoked by social welfare spending and general social spending.

Differently, there is a modest amount of literature which treats the inequality effects of fiscal consolidation periods [6]. Mulas-Granados et al., 2005 found that,

[5] See Anderson et al., 2017 for a detail explanation of the method based on the identification of 84 separate studies counting with over 900 estimates of the effect of one or more measures of spending on one or more measures of income inequality.

[6] As stated in OECD, 2011, fiscal consolidation is defined as concrete policies aimed at reducing government deficits and debt accumulation. From the expenditure side, operational savings (defined as containing governments' running costs), wage cuts and staff reductions appear to be the most frequent expenditure cut measures in the OECD (OECD, 2011). From the revenue side, raising consumption taxes followed by reducing tax expenditures and increasing income taxes, are the most frequent measures.

after expenditure-based adjustments, inequality is detrimentally affected in a panel of 15 EU countries in 1960-2000. Similar conclusions were obtained by Agnello and Sousa, 2014 in the study of fiscal consolidation episodes in 18 OECD countries in 1978-2009. Indeed, they found inequality increases when financial turmoil periods were followed by consolidation episodes.

Does fiscal policy really redistribute income?: Searching for the empirics

In addition, fiscal consolidations and expansions have consequences on income redistribution. The theoretical and empirical literature in this manner was almost inexistent as Mulas-Granados et al., 2005 stated at that time [7]. The study concluded that fiscal consolidations involving spending cuts were detrimental to European income distribution. Later on, other works appeared to explain the overall redistributive impact of specific fiscal policies. In a comparison between spending and taxes, Joumard et al., 2012; Martinez-Vazquez et al., 2012; Paulus et al., 2017 found that spending, in the form of family and housing benefits, had a higher redistributive impact than taxes. In Nordic economies of Europe [8], conforming to Immervoll et al., 2006; Paulus et al., 2017, non-means-tested transfers [9] were positioned as the main contributor to the redistributive impact of the expenditure-based side. Complementary, other works have focused on the influence of in-kind transfers [10] and pointed that health and education transfers accounted for virtually all the impact on income redistribution (Paulus et al., 2010).

From a more specific view on the effect of discretionary fiscal policy, a large body of microeconomic literature has studied the importance of discretion on the income distribution in selected countries of Europe during the Great Recession (Bargain et al., 2017; De Agostini et al., 2016; Hills et al., 2019; Paulus et al., 2020; Paulus & Tasseva, 2020). Overall, with the exception of Hills et al., 2019 whose work predicted detrimental effects for poverty and inequality of discretionary actions, the tax-benefit policy developments as discretion measures helped reduce poverty and inequality in the first stage of the crisis (2008-2011), whilst the contrary occurred with the stimulus packages implemented later on.

[7] In that work, the author theoretically insisted on the trade-off idea between economic growth promoting policies and fairer income distribution promoting policies. Also, he remarked that the long-term sustainability of public transfers from richer strata to the poorer strata of the population distribution highly depended on the imposition of associated taxes required for the financing of these policies that do not harm domestic productivity and the capital's net rate of return. Conditions required for the maintenance of today's welfare states in Europe.

[8] Austria, Belgium, Poland, and Hungary.

[9] Government spending transfers not subjected to the economic and social conditions of the individual or household. For instance, universal child benefits are delivered to the whole income distribution.

[10] This part of government spending transfers refers to the provision of education, health care, housing, and food transfers to the population.

The representatives of income distribution

In this section, I would like to emphasize the range of indicators used as representatives of income distribution in the existing works. Part of the literature in this manner mainly utilizes inequality indexes; Mulas-Granados et al., 2005 made use of the Gini and Theil indexes, Martinez-Vazquez et al., 2012 used consumption based Gini coefficients, Agnello et al., 2013 used the Gini coefficient as well and Balseven and Tugcu, 2017 introduced in a multivariate model the market Gini and the net Gini coefficients. Differently, other works have applied a multi-country tax-benefit microsimulation model, named EUROMOD [11] that uses household micro-level data extracted from European national household budget or income surveys. For instance, Paulus et al., 2017 calculate, as an output from the EUROMOD model, equivalised household disposable incomes and consequently, compute Gini coefficients of the distribution. Similarly, Immervoll et al., 2006 calculate differences in disposable incomes before and after the implementation of a tax or benefit instrument [12]. Thus, the redistributive effect of the instrument is computed as the difference in the Gini coefficient before and after.

Complete segmentation, dynamics and macroeconomics: The existing gap

Hence, when analyzing the existing literature, I have observed a clear gap in the study on the segmentation of the income distribution, contrary to the usual usage of inequality indexes; mostly Gini coefficient and derivatives. In addition, the aggregate and dynamic study of the effects of discretion on income inequality is conspicuous by its absence. Only microeconomic approaches have addressed these effects. Hence, a wider image of the events occurring after changes in fiscal policy (specifically discretion) can be analyzed if we study the complete segmentation of income distribution. Thus, with this paper, I aim to humbly fill that space by making use of multiple income shares to study the dynamic effects of the discretionary component of fiscal policy on income distribution. Additionally, and concurring with the existing literature, I will complement this study with the analysis of inequality measured by the Gini coefficient.

[11] EUROMOD is a static tax-benefit model covering the 15 Member States of the pre-May 2004 European Union. It provides measures of direct taxes, social contributions and cash benefits, where benefits may be categorised according to function or other characteristics. See more information in http://www.iser.essex.ac.uk/msu/emod .

[12] Additionally, other above mentioned microeconomic works studying the effect of discretion on income distribution and inequality have made use of this model; (Bargain et al., 2017; De Agostini et al., 2016; Hills et al., 2019; Paulus et al., 2020)

4. DATA

I gather the annual data, from 1990 to 2017, for 27 European countries (EU-27). The choice of this sample is dictated by data availability. Note that the list of countries is presented in Table 7.1 in the annex. Additionally, Table 7.2 in the annex presents the main descriptive statistics of all variables. In overall, the data can be divided into 2 groups; macroeconomic and, inequality and income distribution data.

Starting with the first group, I use data for real GDP in 2011 US$ from by the Maddison Project Database (2020). General government final consumption expenditure (% of GDP) is extracted from World Bank Data (WDI), except the case of Poland (1990-1994), which was extracted from the IMF Data Fiscal Affairs Departmental Data (Public Finances in Modern History; PFMH). Inflation as measured by the annual growth rate of the GDP implicit deflator [13] was collected from WDI as well. Additionally, central government debt (% of GDP), total population and trade openness [14] are extracted from WDI. Although government debt of Netherlands (1990-2010) comes from OECD Data, (2011-2017) from Eurostat Data (EU), of Slovak Republic (1993-2005) from OECD Data, of Estonia (1995-1999) from Eurostat Data and Romania (1990-1994) from IMF, Historical Public Debt Database.

Regarding inequality and income distribution, I use data for Gini coefficients from by the Standardized World Income Inequality Database (SWIID). This database combines information from the United Nations World Income Database (UNWIDER) and the Luxembourg Income Study (LIS). Theoretically, the Gini coefficient is bounded between 0 and 100. In my sample, it ranges from 17.5 to 37.3, denoting moderate levels of inequality of European countries during the last 30 years. Income distribution data is extracted from the World Income Inequality Database (WIID) and the variable selected is the income share of equal-split adults. In this paper, I particularly use income share quintiles and the top 1 share of the income distribution.

A clear overview of the evolution of the income distribution and inequality is reported in Figures 7.1 and 7.2 in the annex. I computed the mean per year of all EU-27 countries of the 1^{st} quintile, the middle class (see the note of Figure 7.1), the 5^{th} quintile and the Gini coefficient. Apparently, there is a clear loss, in terms of income share, of the poorest and the middle class over the last 30 years (Figure 7.1), which is complemented with the improvement of the richest and the progressive increase of the Gini coefficient (Figure 7.2).

[13] The GDP implicit deflator is the ratio of GDP in current local currency to GDP in constant local currency. This measure of inflation is selected following the recommendations by Fatás and Mihov, 2003

[14] Trade openness is measured as the sum of exports and imports of goods and services measured as a share of gross domestic product, according to the World Bank Data.

5. METHODOLOGY

5.1. Fiscal policy rule model

Firstly, I intent to focus only on government expenditure as representative of fiscal policy, following the recommendations of Fatás and Mihov, 2003. As they mentioned, simultaneity issues arising in the determination of output and the budget deficit used as a cyclical adjusted fiscal policy measure produce a bias in the estimations. To reduce it, government expenditure is used, although, I need to state at the outset that there is an existing debate on the most appropriate measure of fiscal policy. Following again Fatás and Mihov, 2003, one argument in favor of the usage of government expenditure against the budget deficit is that the latter is largely affected by macroeconomic conditions and instability, and thus, highly vulnerable to endogeneity issues. Also, Chalk, 2002 gives support to his idea, and finds government expenditure as the most accurate matching indicator of observable changes in fiscal policy. Hence, once that fiscal policy has been represented, a fiscal model that explains changes in government expenditure due to macroeconomic conditions can be constructed.

Following the existing literature with regard to the study of government expenditure responsiveness, also named cyclicality, (Afonso et al., 2010; Agnello et al., 2013; Brückner & Gradstein, 2014; Fatás & Mihov, 2003, 2006; Ilzetzki & Végh, 2008; Jaimovich & Panizza, 2007; Lane, 2003), I will estimate the following fiscal rule model:

$$\Delta g_{i,t} = \alpha_i + \delta_i \Delta y_{i,t} + \lambda_i \Delta g_{i,t-1} + \sum_{s=1}^{j} \gamma_s Z_{s,i,t} + \epsilon_{i,t}, \tag{5.1}$$

where g is the natural logarithm of real government expenditure measured as a share of GDP, y is the natural logarithm of real GDP, Δ is the first-differences operator, α is the country fixed effects, Z is a vector of controls and $\epsilon_{i,t}$ is an error term clustered at the country level. Note that i stands for country level and t for time (annual frequency). The choice of controls follows Fatás and Mihov, 2003 and Agnello et al., 2013's recommendations. The firsts include a time trend, inflation [15] and inflation squared [16]. While the seconds include additionally the logarithm of real public debt. Thus, vector Z will be composed by a time trend, inflation, inflation squared, the logarithm of real public debt and additionally, to solve potential and posterior identification issues, the natural logarithm of the Gini coefficient to account for the effect of inequality on the first stage of this paper. Thus, this part of the variation gov-

[15] Inflation is included to ensure that results are not partially driven by high inflation periods. Indeed, during the first half of the 90s, eastern Europe countries experienced high inflation episodes.

[16] The inclusion of inflation squared is due to the need for controlling for a possible nonlinear relationship between inflation and government expenditure.

ernment expenditure, that collects information of the automatic stabilizers and the fraction of discretion provoked by changes of the state of the economy, will depend on aggregated inequality. And, hence, I assume that the remaining exogenous effect on government expenditure, discretionary policy, will not react due to changes in inequality, only due to political and unexpected reasons. This statement coincides with Anderson et al., 2016 and De Giorgi and Gambetti, 2012's idea of, in principle, unidirectional effect of unexpected spending on consumption inequality. Against the application of this unidirectional idea in this paper, it can be argued that the aim of the stimulus packages implemented after the Great Recession was to reduce inequality. In response, these stimulus packages were introduced in the economy due to vital and primary necessities, instead of specific inequality and income distribution goals. Along with these primary needs, the macroeconomic stance at that time demanded counter-action of governments in spending terms.

The estimation of this baseline model is simple in case we ignore the obvious issues concerning endogeneity and reverse causality between the core variables [17]. Hence, causal interpretations will not be an option when estimating by OLS. Yet, a cautious hint of the cyclicality of government expenditure can be obtained by estimating this model by OLS.

Counting on these reverse causality issues, the baseline model is required to be estimated by Instrumental Variables (IV). I instrument current output growth with two lags of output growth and one lag of inflation growth, which partially matches with Fatás and Mihov, 2003's selection. In this manner, the first stage equation will be the following:

$$\Delta y_{i,t} = \pi_{0,i} + \sum_{s=1}^{3} \pi_s I_{s,i} + \sum_{l=1}^{j+1} \gamma_l Z'_{l,i,t} + \nu_{i,t}, \tag{5.2}$$

where I is the vector of 3 instruments, Z' the same vector of controls of model (5.1), although the first lag of the growth of government expenditure is included as an exogenous regressor as well. Additionally, the joint significance of the instruments will be tested by imposing the following null hypothesis on model (5.2):

$$H_0 : \pi_1 = \pi_2 = \pi_3 = 0. \tag{5.3}$$

Thus, the $F-test$ will dictate whether, jointly, the instruments used are valid or not.

Hence, equation (5.1) will be estimated by TSLS and the residuals from that estimation will be interpreted as the discretion component of fiscal policy, following Fatás and Mihov, 2003. Although, instead of using the volatility of the residuals (standard deviation) as the quantitative estimate of discretion, as they do, I will

[17]Ilzetzki and Végh, 2008 present a contemporaneous fiscal rule model to think about issues of reserve causality between the cyclical components of government expenditure and output. Also, they reflect the expected sings of the model parameters and explain the different types of cyclicality based on the simultaneous equations model

maintain the residual in levels. The reason behind this choice is the aim of estimating a panel data setting, keeping the time dimension, as Agnello et al., 2013 indeed do. Thus, this estimated residual from equation (5.2) in levels will reflect unexpected variation in fiscal policy due to discretion. The next section will explain more in detail other ways of constructing discretion and further interpretations.

5.2. Measuring discretion

The discretionary shock's extraction comes as a result of isolating the estimated shock series preceded by estimating model (5.1) by TSLS and using the IV approach. What is required to avoid endogeneity issues from shock's estimation and extraction. Expression (6.4) *per se* provides a suitable interpretation of the shock: the fraction of the government expenditure variation that does not react to income shocks when controlling and subtracting the effect of influencing macroeconomic indicators.

$$\hat{\epsilon}_{i,t} = \Delta g_{i,t} - \hat{\alpha}_i - \hat{\delta}_i \Delta y_{i,t} - \hat{\lambda}_i \Delta g_{i,t-1} - \sum_{s=1}^{j} \hat{\gamma}_s Z_{s,i,t}, \tag{5.4}$$

Thus, this measure is interpreted as the typical size of a discretionary change in fiscal policy for country i in time t.

Alternatively, existing work presents other ways of measuring and utilizing discretionary fiscal policy. Debrun and Kapoor, 2010 apply a similar residual approach, although estimating previously the relation between the cyclically adjusted balance (CAB) and the output gap. More directly, Silgoner et al., 2003 extract the discretionary component by estimating an unobserved components model following A. Harvey, 1989; A. C. Harvey, 1985. They separate a trend, a cyclical component and an irregular part from the expenditure series, which is assumed to represent the discretionary component. A more complex empirical approach was developed by Agnello et al., 2013. First, they estimate a fiscal rule, as model (5.1). Then, they use the residuals as measures of discretion to assess the existence of crowding-in and/or crowding-out effects, and additionally, to investigate the trade-off between such effects in the short and medium term. And finally, they analyze the heterogeneity of the macroeconomic response to discretionary fiscal policy. Agnello et al., 2013 clearly differentiate from the rest of the existing work in the dynamic panel equations estimated in the second step, which includes lagged residuals.

Ultimately, there is a "narrative approach" that measures discretionary policy from policy interventions or intentions, taken directly from laws, government enforcement, presidential speeches and alike. Ramey and Shapiro, 1998 used this approach by utilizing data from historical accounts and economic details of policy decisions, specifically data on defense government spending in the U.S.. Such approach was also adopted by Romer and Romer, 2010 in a context of postwar reconstruction of tax legislation in the U.S.. They used presidential speeches, executive-branch documents, and congressional reports data to construct discretion action in taxation. Later on, Ramey, 2011 introduced a new narrative measure of exogenous episodes of government spending that meant to fix timing lags issues of the 1998's approach. By reading periodicals with the aim of gauging the public's expectations, an updated time series of U.S. government expenditures on defense was used as a proxy of unexpected spending.

Conducting an exercise of comparison between discretion extraction approaches, the limiting factor of data availability encourages the researcher to apply the residual approach. Instead, as stated in Coricelli and Fiorito, 2013, the "narrative approach" is promising, as it measures directly policy decisions. However, there are relevant caveats concerning this approach. The mechanism that joins intentions and budget decisions is not quite transparent, meaning that policy intentions identified by policy statements and laws not always result in approved budget decisions. Also, the unclear relation between political proposal and the enough funding required approval. And finally, the analysis of government spending in relation to GDP is truly complicated by accrual accounting.

5.3. Dynamic effects on income distribution

In this section, I will evaluate the dynamic effects of discretionary fiscal policy on income inequality and distribution. However, differently from almost all the existing work on the study of inequality, I will unravel income distribution. I will use quintile income shares and the top 1 share of the distribution. The existing literature does not strongly recommend any specific income shares' frequency. This quintile choice is due to the greater homogeneity between groups compared with a quarter frequency and due to the non-feasibility of dealing with gigantic table results when using deciles. Additionally, the top 1 share has been selected to isolate the effects of discretion on the richest share of the distribution. Hence, quintiles seem to offer the most appropriate and duable frequency. Thus, the main goal here is to offer a wide picture of the effects of discretion on income inequality and distribution.

The dynamic impact of discretionary fiscal policy on income distribution is assessed by implementing an Autoregressive Distributed Lag (ARDL) approach, which was formed by Pesaran, Shin, et al., 1995 and Pesaran, 1997, and further advanced by Pesaran et al., 2001. This approach is ideal to estimate dynamic relationships between variables. I use this approach due to the multiple advantages that offers. Firstly, and in consonance with Pesaran, Shin, et al., 1995; Pesaran et al., 2001, variables that are I(0) or I(1), or a combination, can be employed in the model, although I(2) are not allowed. Thus, the restriction that all variables must be stationary in levels is relaxed. Secondly, its lagged structure, as it will be shown subsequently, offers an option for the dynamic study, which perfectly suits for the focus of this paper. Thirdly, by conducting simple $F - tests$, it allows for the study of short- and long-run relationships in case all the independent variables are in first differences. And fourthly, it allows for small data sets, which is the case here, and simultaneously, offers efficient performance.

This approach has been used in the study of the influence of discretion on different macroeconomic indicators [18] by Agnello et al., 2013. Also, in a Chinese context, Khan et al., 2015 evaluated the dynamic effects using the ARDL approach of government expenditure on private consumption, and estimating the existence of short- and long-run relations. Focusing on the European Monetary Union (EMU), Papageorgiou et al., 2016 studied the determinants of business cycles using this approach as well. From a disparate perspective, albeit making use of the ARDL approach, Stoian and Iorgulescu, 2020 assessed the effects of fiscal policy, represented by the budget balance, on the stock market returns. Finally, Nuru and Gereziher, 2021 recently studied the asymmetric relationship between fiscal policy, measured as the natural logarithm of government expenditure, and economic growth, albeit they estimate a non-linear ARDL (NARDL), a technique created by Pesaran et al., 2001 and Shin et al., 2014.

After this brief introduction on the application of ARDLs in the literature, I present the following linear autoregressive distributive lag model that relates discretionary fiscal policy and, income distribution and inequality:

$$S_{a,i,t} = \kappa_i + \sum_{j=1}^{l_1} \rho_j S_{a,i,t-j} + \sum_{j=0}^{l_2} \phi_j \hat{\epsilon}_{i,t-j} + \sum_{j=0}^{l_3} \theta_j X_{i,t-j} + \xi_{i,t}, \tag{5.5}$$

where κ_i denotes country-fixed effects, $\xi_{i,t}$ is the disturbance term, S is the natural logarithm of the set of income shares, $\hat{\epsilon}_{i,t}$ the discretionary component of fiscal policy extracted from estimation of model (5.1) by TSLS and X is a vector of control variables. The transformation of income shares into natural logarithms arises from recommendations from the literature on the usage of income shares as measures of unbundled inequality (Beck et al., 2004; Beck et al., 2007). Note the subindex a; it denotes the income share quintile and the top 1 share. Thus, $a \in [0-20, 20-40, 40-60, 60-80, 80-100, 99-100]$ and therefore, I will estimate 6 different ARDLs. Additionally, I will estimate the effect on aggregate inequality using the natural logarithm of the Gini coefficient with the aim of providing a broad view of inequality. Hence, an additional ARDL will be estimated and presented, for a total of 7 models.

The vector of control variables will be composed by, following the recommendations of Agnello et al., 2013, the growth rate of population, the growth rate of trade openness and the natural logarithm of inflation [19]. Following again Agnello et al.,

[18] Agnello et al., 2013 estimate the dynamic effects of discretionary fiscal policy on GDP growth, private consumption growth and private investment growth.

[19] The usage of growth rates is due to necessity of turning variables to stationary. Note as well

2013, I will use the same number of lags for the control variables, which will be 0. Thus, only the contemporaneous value of these controls will affect the different income shares [20]. Finally, every ARDL model will be estimated by Fixed-Effects (FE) estimator with the aim of controlling for country characteristics.

The model includes lag operators for the dependent variable (l_1) and for the regressors (l_2, l_3) [21]. I use the Schwarz Information Criteria (SIC) to identify the optimal lag length of the 7 dependent variables and the discretionary component. SIC is selected against the Akaike Information Criteria (AIC) because the second tends to select greater lag lengths and the sample used in this paper does not allow for that loss of values. Hence, since I work with a panel data setting, 7 different ARDLs will be estimated and 7 different combination of lags will be applied. By selecting a maximum lag length in the software of reference in this paper (Stata) equal to 4, the criteria is based on selecting the maximum lagged combination found by the SIC on each ARDL estimation of the panel. The results is homogeneous, and l_1 and l_2 will be equal to 4 in every ARDL model.

With regard to stationarity and the integration order constraints of the ARDL application, Table 7.3 in the annex reports the descriptive integration order properties of the variables. Integration order and the existence of non-stationarity is tested using the Augmented Dickey-Fuller test (ADF) (Dickey & Fuller, 1979) and the Im-Pesaran-Shin test (IPS) (Im et al., 2003). The ADF test is applied in this case in panel data thanks to the Fisher-type unit root test. The statistic used in this particular test will be the inverse normal Z statistic, following the suggestions from Choi, 2001's simulations [22]. Differently, the statistic used in the IPS test will be the t statistic [23]. Looking at the statistics in Table 7.3 in the annex, all variables are stationary at I(0) or I(1), which was necessary for the proper ARDLs estimation.

5.4. Short-, medium- and long-term effects on income distribution

In this section I will investigate the short-, medium- and long-term term dynamic reactions of the different income shares given a shock of discretionary expenditure by computing Impulse Response Functions (IRFs) and thus, complement the previous results. I will use a new and currently-used in the literature methodology to compute IRFs developed by Jordà, 2005 via the local projections (LP) method. This approach

that these variables seem to have been used in levels in Agnello et al., 2013, although it is not fully specified.

[20] By using only the contemporaneous value of controls I avoid perfect colinearity issues when adding lags of these variables.

[21] Note that for all 7 ARDL models $l_3 = 0$.

[22] Choi, 2001 explains how the inverse normal Z statistic presents the best trade-off between size and power for finite and infinite samples. For larger panels, Choi, 2001 recommends the use of the modified chi-squared test.

[23] Additionally, this test proportions exact critical values depending on the size of the panel.

differs from the traditional since it is not necessary to estimate a VAR model and then, derive the IRFs by transforming such a VAR into a moving average representation by appealing to Wold's decomposition theorem (Haug & Smith, 2012). Hence, as stated in Jordà, 2005, this method allows for computing IRFs without the need for the specification and estimation of an underlying multivariate dynamic system. And, contrary to the extrapolation of increasingly distant horizons from a given model required in the VAR, this method simply consists in estimating local projections at each period of interest (Jordà, 2005).

This method has been selected since it is perfectly suitable for the characteristics of our ARDL model. In consonance with Jordà, 2005, the advantages of local projections are several; i) estimation can be conducted by least squares, ii) they provide appropriate inference without the need for asymptotic delta-method approximations or numerical techniques for its calculation,iii) are robust to misspecification of the data generating process and iv) can be easily calculated with available standard regression packages. Additionally, this method is more robust to a small sample size.

Recent works have made use of this method on different topics. Highly related with the fiscal rule model used in this paper, Ramey and Zubairy, 2018 used Jordà's LP method to estimate whether government spending multipliers in the US were higher during periods of economic slack and of near the zero lower bound interest rates or not. With the focus on unemployment, Bernal-Verdugo et al., 2013 studied the influence of banking crisis on unemployment by estimating cumulative impulse responses. Stolbov and Shchepeleva, 2020 studied macrofinancial linkages for a set of European countries although applying a quintile approach by introducing a transformation of the LPs method by Barnichon and Brownlees, 2019. Differently, Hwa et al., 2018 introduces quadratic and cubic terms in the local projections model in a non-linear framework. This work studied the effect of supervisory rating shocks on real economic activity and presented an interesting comparison between IRFs computed by VARs and the LP method. From a theoretical point of view, Plagborg-Møller and Wolf, 2021 developed a deep comparison between the usage of VARs and LPs to compute IRFs. They stated that VARs and LPs should not be thought of as conceptually disparate methods since they are "simply two particular linear projection techniques with a shared estimand". Finally, they demonstrated the similarity in the IRFs obtained by both methods and that both estimates are closely tied together at short horizons.

Before embarking on presenting the LPs model, I will theoretically develop the idea of LPs method by Jordà, 2005 for the proper understanding of this recent methodology. As stated in Jordà, 2005: "Local projections are based on sequential regressions of the endogenous variable shifted several steps ahead and therefore have many points of commonality with direct multi-step forecasting". Following Jordà, 2005, I define the impulse response function at time $t + k$ given the shock in d_i at time t as:

$$IR(t,k,d_i) = \mathbb{E}(y_{t+k}|v_t = d_i; X_t) - \mathbb{E}(y_{t+k}|v_t = Q; X_t), \tag{5.6}$$

where X_t is a vector of lagged values of y_t, the operator $\mathbb{E}(.|.)$ denotes the best, mean squared error predictor, y_t is an $n\times1$ random vector, Q is of dimension $n\times1$, v_t is the vector of reduced-form disturbances and d_i is in an $n\times n$ matrix D that contains the relevant experimental shocks. Thus, the statistical objective here is to obtain "the best, mean squared, multi-step predictions", in line with Jordà, 2005.

Now consider projecting y_{t+k} onto the linear space generated by X_t:

$$y_{t+k} = \alpha^k + B_1^{k+1}y_{t-1} + B_2^{k+1}y_{t-2} + ... + B_p^{k+1}y_{t-p} + e_{t+k}^k, \tag{5.7}$$

where $k = 0,1,2...,h$ (horizon), α^k is an $n\times1$ vector of intercepts and B_i^{k+1} are matrices of coefficients for each lag i and horizon $k+1$. Thus, the collection of h regressions in (5.7) is denoted as *local projections* by Jordà, 2005.

Now if both definitions are tied together, the estimated IRFs from the local-linear projections in (5.7) will be:

$$\widehat{IR}(t,k,d_i) = \hat{B}_1^k d_i \tag{5.8}$$

Hence, I apply this method with the aim of calculating impulse responses with $k = 4$:

$$S_{a,i,t+k} - S_{a,i,t+k-1} = \delta_i^k + \gamma_t^k + \sum_{j=1}^{l_1}\beta_j S_{a,i,t-j} + \varphi^k\hat{\epsilon}_{i,t} + \vartheta^k X_{i,t} + \varepsilon_{i,t}^k, \tag{5.9}$$

where $\varepsilon_{i,t}^k$ is the projection residual, S_a represents the natural logarithm of all income share quintiles and the top 1 share, vector X contains the same controls as in (5.5), $\hat{\epsilon}_{i,t}$ represents the contemporaneous value of discretionary fiscal policy, δ_i^k the country-variant characteristics and γ_t^k the time-variant characteristics. Note that the same number of lags of the dependent variable as in (5.5) is included. Also, φ^k will be interpreted as the estimated response of each income share in each period $t+k$ to an increase of government expenditure due to discretion at time t, compared with the magnitude of the share the previous period. For this reason, the dependent variable is expressed as the difference between $t+k$ and $t+k-1$. This annual variation of the response is named by Jordà, 2005 as the "usual" IRF. The construction of the model follows the adaptations conducted by Stolbov and Shchepeleva, 2020, Gorodnichenko and Lee, 2017 & Furceri and Loungani, 2018.

The estimation method applied will be the Fixed-Effects (FE) estimator to control for country characteristics, which will be clustered at the country level. The choice of FE is due to the recommendations by Jordà, 2005 in the development of the LPs method code.

Additionally, I will estimate and trace out the cumulative responses of the income distribution given a shock of discretion at time t. As personally suggested by Òscar

Jordà, the cumulative response gives the approximate percentage change from the period of the shock to period $t + h$, since the set of dependent variables are transformed into natural logarithms. The transformation required for this estimation is simple. Using model (5.9) as reference, only the difference of the dependent variable will be transformed. In this case, the goal is to show the durability of the discretion effects on income distribution. The time horizon will be increased until $k = 7$ in order to present the long-term effects and therefore, I will achieve information on the degree of persistence of the shock. Thus, the cumulative impulse response functions with $k = 7$ will be the following:

$$S_{a,i,t+k} - S_{a,i,t-1} = \delta_i^k + \gamma_t^k + \sum_{j=1}^{l_1} \beta_j S_{a,i,t-j} + \varphi^k \hat{\epsilon}_{i,t} + \vartheta^k X_{i,t} + \varepsilon_{i,t}^k, \tag{5.10}$$

where the only element that differs from model (5.9) is the second part of the dependent difference which does not follow the horizon. To provide a more comprehensive link between both approaches, theoretically both dependent variables can be expressed by the following equation:

$$S_{a,i,t+k} - S_{a,i,t-1} = S_{a,i,t+k} - S_{a,i,t+k-1} + \ldots + S_{a,i,t} - S_{a,i,t-1}. \tag{5.11}$$

Hence, the cumulative can be calculated as the sum of the non-cumulative response (also named "usual").

These estimations will offer a complete image of the events occurring on the income distribution following a change in fiscal discretion. Depending on the significance and magnitude of the estimated coefficients in each horizon k, the response of each income share to discretion variations will be persistent or transitory. Ideally, although inequality reduction and income redistribution are not the main purposes of discretion actions, positive and persistent effects on the lowest quintiles given a discretion event would be pursued. Simultaneously, opposite and significance events should occurred for the highest quintiles and the top 1 share, giving rise to a complete income redistributive effect of discretion. On the contrary, transitory effects on the lowest quintiles would mean weak performance of discretion. Thus, the LP method application will complement the ARDL estimation results by shedding some light on the potential persistent effects of discretion on income inequality.

6. EMPIRICAL RESULTS

6.1. Fiscal persistence, cyclicality and discretion

Table 6.2 presents the estimates of fiscal persistence, cyclicality and discretion. Additionally, Table 6.1 presents the first stage estimation results, which refer to the estimation of equation (5.2). The joint significance of the instruments is represented by the $F-tests$. Column 1 refers to the OLS estimations and Column 2 to Fixed-Effects estimations in order to control for country differences. Ultimately, the two lags of output growth and one lag of inflation growth are valid instruments at any significance level. Also, the results do not differ much between estimators, except the stronger acceptance of the joint significance of the instruments when using OLS. Note that the estimation results of the controls of the model are not included due to the lack of interest in this case.

	Dependent variable: $\Delta y_{i,t}$	
	OLS	FE
	(1)	(2)
$\Delta y_{i,t-1}$	.505***	.459***
	(7.97)	(7.88)
$\Delta y_{i,t-2}$	-.111**	-.138***
	(-2.20)	(-4.02)
$\Delta lnInf_{i,t-1}$	-.004***	-.004***
	(-2.68)	(-2.80)
$constant$	.007	-.059
	(0.18)	(-0.53)
$obs.$	593	593
F	30.83	23.03
R^2	0.31	0.26

Note: T-statistics based on robust standard errors in parenthesis, except for FE estimations. ***,**,* denote significance at 1 percent, 5 percent and 10 percent, respectively. $F-test$ for the joint validity of the instruments.

Table 6.1. Fiscal rule model: First stage results.

Now, I will briefly discuss the results with regard to the estimation of equation (5.1) represented in Table 6.2. At first glance, it is clear the opposite effects of real GDP growth and lagged expenditure growth on expenditure growth; meaning contrary effects of persistence and cyclicality. Using the entire sample, government expenditure seems to react in a counter-cyclicality manner to real GDP growth. These results are presented in Columns 2 and 3, when OLS and FE are chosen as estimators. Albeit, when endogeneity issues are addressed, the TSLS estimation results point again counter-cyclicality of government expenditure although lacking of significance. Hence, it has been shown that once real GDP growth is instrumented, counter-cyclicality of expenditures dissapears in terms of significance. Thus, it seems that reverse causality upwardly bias the magnitude and significance of the results regarding cyclicality. These results are consistent with the results from Fatás and Mihov, 2010 and Bénétrix and Lane, 2013, and with, as stated in Larch et al., 2021, the fiscal decisions made after the financial crisis episode with the European Economic Recovery Plan of 2009.

	Dependent variable: $\Delta g_{i,t}$		
			IV
	OLS	FE	TSLS
	(1)	(2)	(3)
$\Delta y_{i,t}$	-.271***	-.305***	-.119
	(-3.87)	(-3.56)	(-0.99)
$\Delta g_{i,t-1}$	.174	.132***	.052
	(1.42)	(3.24)	(0.79)
$Inf_{i,t}$	.000	.000	.000
	(0.65)	(0.84)	(0.17)
$Inf_{i,t}^2$	.000	.000	.000
	(-1.00)	(-1.07)	(-0.47)
$Gini_{i,t}$	.007	.092	.022
	(0.38)	(0.96)	(1.12)
$StateDebt_{i,t}$	.000	-.010	.002
	(-0.14)	(-1.67)	(0.47)
$Trend_{i,t}$	.000	-.001	.000
	(0.65)	(-1.15)	(-0.83)
$constant$	-.006	-.254	-.069
	(-0.10)	(-0.77)	(-1.08)
$obs.$	677	677	593
H	–	–	5.39
R^2	0.08	0.05	0.02

Note: T-statistics based on robust standard errors in parenthesis, except for FE estimations. ***,**,* denote significance at 1 percent, 5 percent and 10 percent, respectively. $H-test$ for the endogeneity of instrumented regressors using χ^2.

Table 6.2. Fiscal policy persistence and cyclicality.

With regard to fiscal policy persistency, all estimations suggest a positive persistent character of government expenditure, albeit, not always significant. Only when estimating by Fixed-Effects, contemporaneous government expenditure growth seems to be significantly affected by lagged expenditure growth, denoting clear positive persistency. Controls do not affect significantly in any case. This lack of influence is consistent with Agnello et al., 2013's results, albeit, for the case of state debt. Finally, note the rejection of the existence of endogeneity in the variable instrumented (real GDP growth). The magnitude of the χ^2 obtained by the Hausman test indicates the true exogeneity of real GDP growth after being instrumented at 99% of significance level.

Hence, after addressing endogeneity issues, discretion will be extracted from the estimations in Column 3 of Table 6.2 as the estimated residuals of the model. The evolution of the estimated discretion component is presented in Figure 7.3 in the annex as the mean by year. High government expenditure due to discretion occurred right after the crisis followed by compensatory discretion. In general, the volatile character of discretion is notorious. The next section will show the results obtained from the application of the extracted discretion on the ARDL model.

6.2. Evidence of dynamic effects

In this section I will discuss the results of the baseline ARDL models (5.5) using the full sample. Table 6.3 presents the summary of these findings. Columns (1)-(5) show the parameter estimates for the income share quintiles, Column (6) for the top 1 share of the income distribution and Column (7) for the Gini coefficient. The estimated coefficient of the controls are included in Table 6.3, as well as the autoregressive character of the dependent variable of each ARDL model estimation.

I start analyzing the effects of discretion on income distribution. Interestingly, there is an overall opposite effect of discretion. Contemporaneously, discretion slightly affects the lowest quintile shares positively, being significant for the 1^{st} and 2^{nd} quintiles. Whilst, the contemporaneous effect of discretion on the top 1 share is negative and statistically significant (-.265). The short-term effect of discretion gains significance and follows the same opposite rule; helping the poor and the middle class [24], and harming the rich. Although, the magnitude of the detrimental effect on the top 1 share declines in absolute value. The medium-term effect (2^{nd} lag of discretion) maintains this pattern even presenting greater significance. Also, two extra patterns arise; the medium-term effect alleviates in magnitude for the 2^{nd} and

[24] To define middle class I use the income approach. In this context, the dominant criteria is to define the middle class as the income share going to the middle of the income distribution, from decile 3 to 8 (Vaughan-Whitehead, 2016). Similarly, as stated in OECD, 2008, the middle class is defined as as the distribution of real income in the middle three quintiles. Alternatively, Atkinson and Brandolini, 2013 identify the middle class at higher levels of the income distribution. Additionally, Table 7.2 in the annex also gives a hint on that; these 3 middle quintile hoard, on average, almost half of income share in the EU-27.

3^{rd} quintiles and for the top 1 share, whilst part of the middle class (4^{rd} quintile) and the richest quintile present exacerbated effects in both directions. Note how the significance disappears in the effect of the 3^{rd} and 4^{rd} lags of discretion, whilst the reverse pattern persists only for the 3^{rd} lag.

	Dependent variable:						
	$S_{0-20,i,t}$ (1)	$S_{20-40,i,t}$ (2)	$S_{40-60,i,t}$ (3)	$S_{60-80,i,t}$ (4)	$S_{80-100,i,t}$ (5)	$S_{99-100,i,t}$ (6)	$lnGini_{i,t}$ (7)
$Dep_{i,t-1}$	.603***	.729***	.706***	.629***	.648***	.592***	1.407***
	(6.30)	(10.27)	(10.59)	(9.31)	(9.53)	(9.41)	(29.85)
$Dep_{i,t-2}$	.122**	.066	.055	.073	.086	.062	-.504***
	(2.16)	(0.76)	(0.75)	(1.06)	(1.36)	(1.17)	(-7.55)
$Dep_{i,t-3}$	.029	.025	.074	.115	.119**	.165**	.065
	(0.41)	(0.37)	(1.09)	(1.91)	(2.04)	(2.48)	(0.99)
$Dep_{i,t-4}$	.006	.013	-.052	-.089	-.056	-.072	-.031
	(0.30)	(0.35)	(-1.08)	(-1.79)	(-1.19)	-(1.38)	(-0.79)
$\hat{\epsilon}_{i,t}$	.120**	.072*	.037	.031	-.047	-.265**	-.001
	(2.08)	(1.84)	(1.13)	(1.10)	(-1.54)	(-2.18)	(-0.26)
$\hat{\epsilon}_{i,t-1}$	.021	.023*	.021**	.016***	-.016*	-.158***	-.029***
	(1.13)	(1.68)	(2.00)	(2.90)	(-1.84)	(-9.16)	(-2.66)
$\hat{\epsilon}_{i,t-2}$	.029*	.018**	.016***	.020***	-.020***	-.087**	.005
	(1.87)	(2.23)	(2.60)	(3.19)	(-3.10)	(-2.50)	(1.51)
$\hat{\epsilon}_{i,t-3}$	.012	.005	.008	.003	-.004	-.015	.001
	(0.51)	(0.49)	(0.77)	(0.31)	(-0.41)	(-0.35)	(0.26)
$\hat{\epsilon}_{i,t-4}$	-.016	-.017	-.019	-.007	.011	.018	.003
	(-0.38)	(-0.50)	(-0.64)	(-0.48)	(0.46)	(0.40)	(1.09)
$Pop_{i,t}$	-.884*	-.290	.151	.130	.059	.219	.139
	(-1.71)	(-0.71)	(0.46)	(0.45)	(0.21)	(0.22)	(1.62)
$Trade_{i,t}$	-.034	-.002	-.007	.006	.007	.006	-.005
	(-0.51)	(-0.09)	(-0.31)	(0.30)	(0.32)	(0.08)	(-0.93)
$Inf_{i,t}$	.005*	-.001	-.001	-.001	.001	.002	-.001
	(1.95)	(-0.32)	(-0.87)	(-0.51)	(0.56)	(0.29)	(-1.50)
$obs.$	533	533	533	533	533	533	533
R^2	0.90	0.95	0.91	0.82	0.93	0.85	0.99

Note: T-statistics in parenthesis. ***,**,* denote significance at 1 percent, 5 percent and 10 percent, respectively.

Table 6.3. The income distribution impact of discretionary fiscal policy: ARDL estimations by Fixed-Effects.

Interestingly, the trend shifts when observing the effect of the 4^{rd} lag; detrimental effects on the poorest quintiles including the middle class (Columns (1)-(4)) and positive on the richest. This event indicates a loss of the income redistributive power and simultaneously, a transitory character of the effects on income distribution of discretion.

Hence, overall, an income redistributive pattern arises that alleviates through time; the poorest quintile together with the middle class are favored by discretion, whilst the contrary happens for the richest. Albeit, this alleviation effect weakens two years after the discretion shock for the highest quintile of the middle class and the richest quintile, in opposite directions.

For what concerns the overall effect on inequality, the Gini coefficient, I find a clear concordance with previous results. Stronger and positive effects, in terms of inequality alleviation, appear one year after the shock (-.029). And contrary to previous results, this effect rapidly disappears after two years. Yet, in overall, the income redistributive force presented when analyzing the unbundled income distribution seems to persist when analyzing aggregated inequality, albeit slightly alleviated.

With respect to the autoregressive character of the dependent variables, a clear persistent pattern arises. All dependent variables present a positive and significant 1^{st} order autoregressive component, meaning that the past of the income share highly determines the contemporaneous value. Thus, the introduction of lagged values of the dependent variable controls for the own dynamics of the variable and in some way instruments for potential biases due to endogeneity. This autoregressive effect quickly disappears after the 2^{nd} order, and even turning negative in case of the Gini coefficient and remaining positive in case of the lowest quintile.

Finally, I will briefly discuss the influence of the controls in the estimations. Only the poorest quintile seems to be positively and significantly affected by the growth rate of population (-.884) and the contrary by the natural logarithm of inflation. The control that overall present higher and more significant effects is the growth rate of population, affecting negatively the poorest and positively from the 3^{rd} quintile to the Gini coefficient.

6.3. IRFs results and visual responses

6.3.1. Non-cumulative responses and medium-term dynamics

Table 6.4 reports the estimations of parameter φ^k of model (5.9). Each reported estimation represents the percentage change of each dependent variable compared with the value of the last period given a discretion shock in time t. Thus, each row of Table 6.4 presents the dynamics of the following 4 years ($k = 4$) of income distribution and inequality after an increase of discretion. In order to complement these results and provide visual dynamics, I trace them out in Figures 6.1 and 6.2.

These results show a clear pattern which is consistent with the ARDL results. The lowest quintile and the middle class are positively affected by the shock, whilst the highest quintile and the top 1 share are detrimentally affected. However, reverse effects occur 4 periods after the shock, albeit not significant. Additionally, the estimates on the Gini coefficient present evidence on inequality alleviation after the second period. Panel (c) of Figure 6.2 perfectly shows how inequality ends close to 0 after 4 years.

Also, there is a common trend among all estimations, excepting the case of the 1^{st} quintile; the greatest impact in terms of magnitude occurs 2 years after the shock. This peak rapidly alleviates in every case showing a lack of persistence of the effects. The sharpest effects are suffered by the top 1 share (.145 percentage of decline), although rapidly returns to 0. Hence, from both Figures 6.1 and 6.2, a clear income redistributive power arises that seems to disappear 4 years after the shock.

	Shock: $\hat{\epsilon}_{i,t}$			
	$k = 1$	$k = 2$	$k = 3$	$k = 4$
$S_{0-20,i,t}$	.025	.013	.022	.001
	(0.89)	(0.77)	(1.51)	(0.05)
$S_{20-40,i,t}$	.009	.029	.014*	-.005
	(0.47)	(1.55)	(1.84)	(-0.35)
$S_{40-60,i,t}$	.004	.017**	.009	.004
	(0.259	(2.07)	(1.58)	(0.28)
$S_{60-80,i,t}$	.004	.014***	.011*	-.006
	(0.31)	(3.33)	(1.77)	(-0.48)
$S_{80-100,i,t}$	-.003	-.016**	-.012**	.004
	(-0.19)	(-2.45)	(-2.28)	(0.33)
$S_{99-100,i,t}$	-.031	-.145***	.003	.049
	(-0.47)	(-5.09)	(0.10)	(1.06)
$lnGini_{i,t}$	.017**	-.023***	-.008**	-.001
	(2.00)	(-2.98)	(-2.44)	(-0.41)

Note: T-statistics in parenthesis. ***,**,* denote significance at 1 percent, 5 percent and 10 percent, respectively. Estimates based on equation (6.9). $K = 1, .., 4$ denotes the year following the fiscal discretion shock. All equations estimated by Fixed-Effects estimator.

Table 6.4. The effect of fiscal discretion on inequality (1990–2017): non-cumulative estimation of φ^k by local projections method (Jordà, 2005).

These estimations provide a short- and medium-term image of the events occurred after the shock of discretion; a positive impulse response on the poorest and the middle class, a contrary response for the richest and an after 2 periods inequality alleviation. However an eye needs to be put on the long-term view in order to find whether the income redistributive power persists or not.

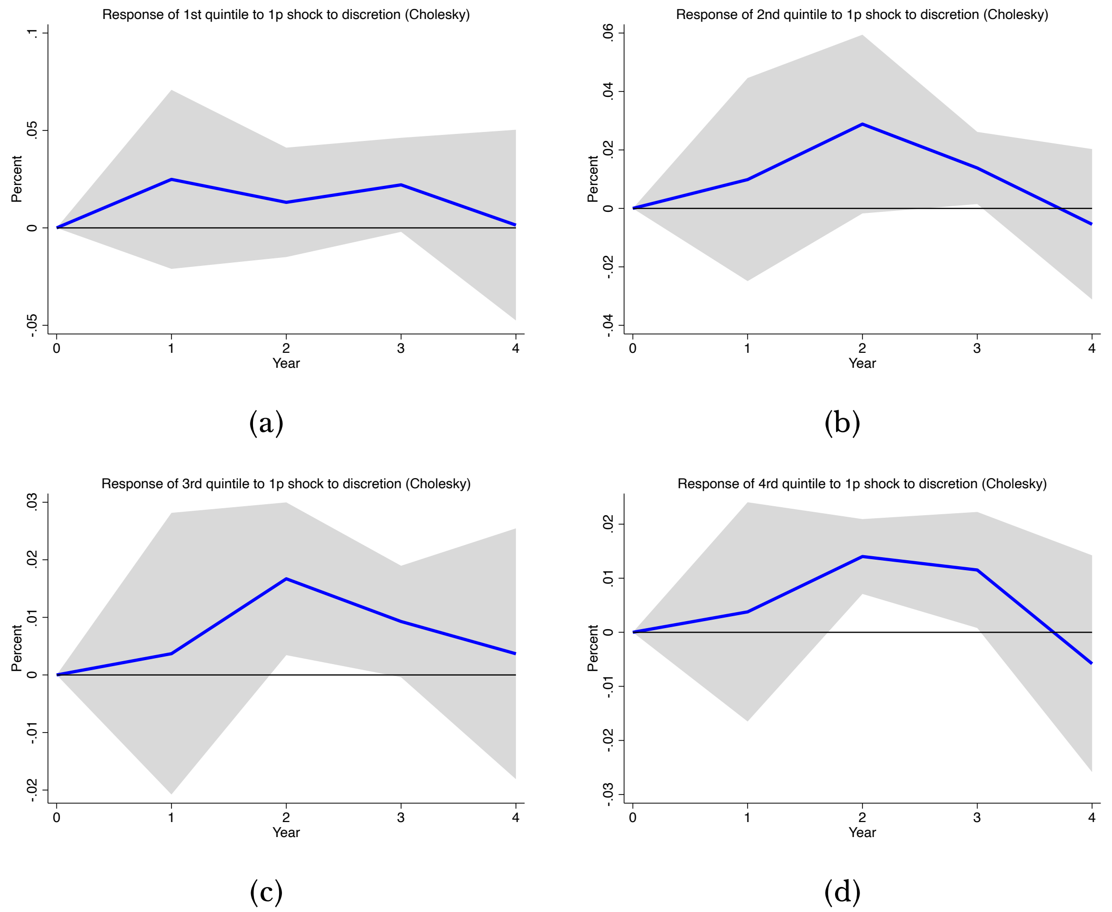
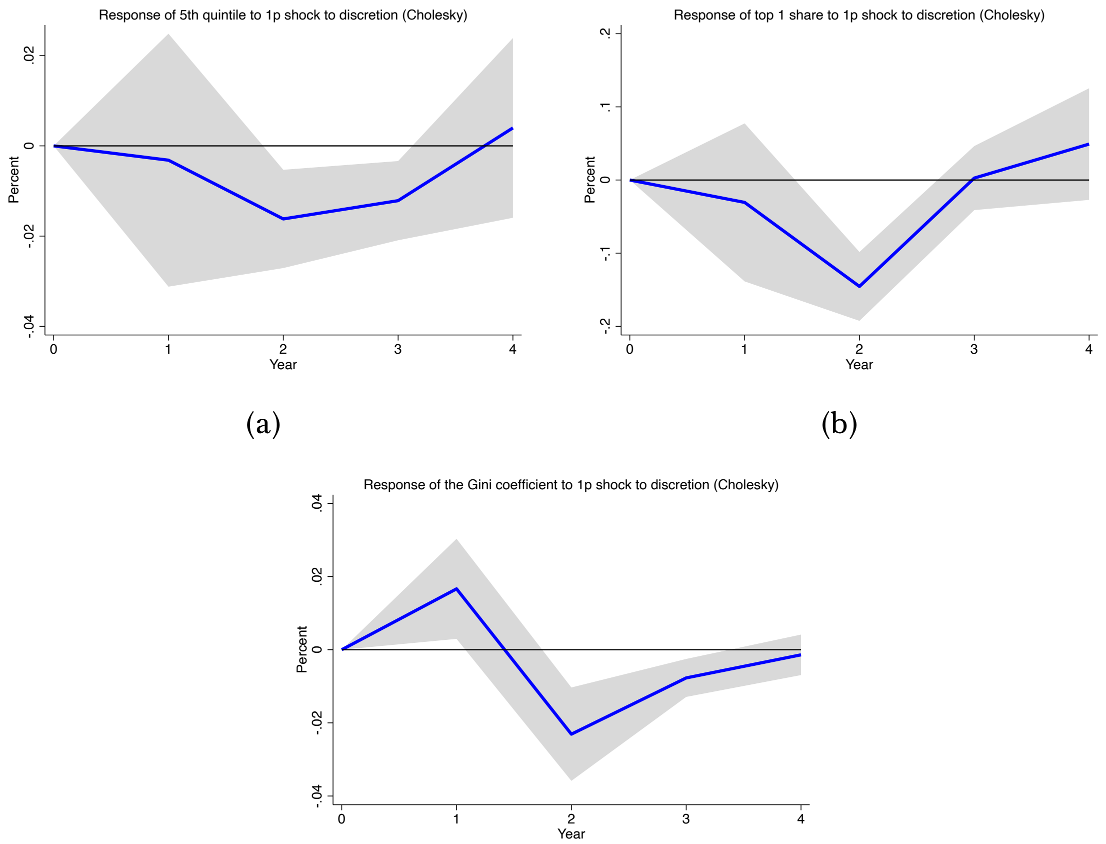


Figure 6.1. Impulse response functions estimated from model (6.9): The dynamic responses from 1^{st} to 4^{th} income quintiles.

Note: the solid blue line corresponds to the IRF (φ^k estimated coefficients) and limits of the grey area correspond to 90 percent confidence bands. The x-axis denotes time: $t = 0$ is the year of the discretionary fiscal policy 1 p. shock (increase). And time horizon is $k = 4$. Panel (a) to (d) correspond from the 1^{st} quintile to the 4^{th}, in that specific order.

Finally, from a comparison view, given this positive discretionary redistributive power, these results complement the work by Anderson et al., 2016 and De Giorgi and Gambetti, 2012. Their positive effects of unexpected fiscal policy shocks, constructed by using Ramey, 2011's identification of newspaper news as exogenous episodes of government spending, on consumption inequality reduction show an additional proof of this power. After an unexpected increase in government expenditure, consumption of the wealthiest tends to decrease, whilst the contrary occurs for the poorest. Thus, this income transfer, although transitory, from the richest to the bottom part, would play the role of an intermediary between the effects of unexpected fiscal policy on consumption. Logically, the marginal income increase of the poorest, would automatically mean consumption growth. However, this two-steps effect is not as evident for the highest share of the distribution. This segment would be playing the role of "sender", instead of suffering clear detrimental effects in terms of consumption given an income fall.



(a) (b)

(c)

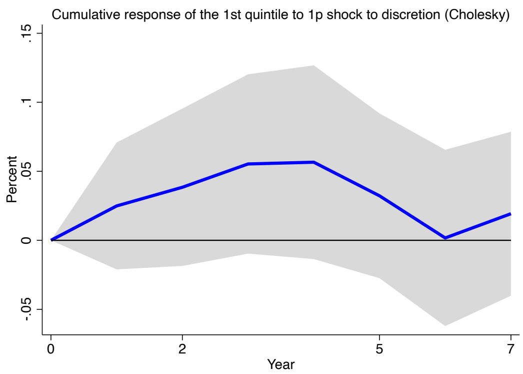
Figure 6.2. Impulse response functions estimated from model (6.9): The dynamic responses of 5^{th} quintile, top 1 share and the Gini coefficient.

Note: the solid blue line corresponds to the IRF (φ^k estimated coefficients) and limits of the grey area correspond to 90 percent confidence bands. The x-axis denotes time: $t = 0$ is the year of the discretionary fiscal policy 1 p. shock (increase). And time horizon is $k = 4$. Panel (a) corresponds to the dynamic responses of the 5^{th} quintile, (b) to the top 1 share and (c) to the Gini coefficient.

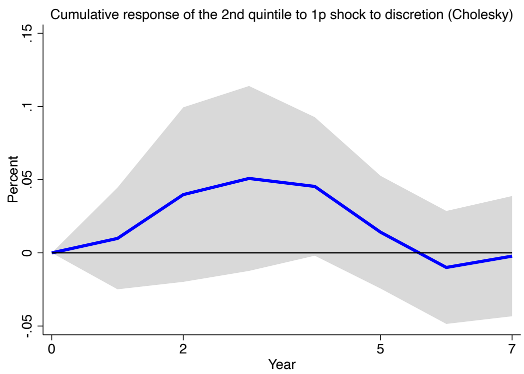
6.3.2. Cumulative responses and long-term persistency

To complement the previous results, I estimate cumulative IRFs based on model (5.10). In this case, I directly trace out the results in Figures 6.3 and 6.4 since some significance is lost in this exercise. Theoretically, the cumulative response after 7 years will be transitory if the magnitude is close to 0 in $k = 7$. Otherwise, the shock of discretion on income distribution and inequality will be persistent.

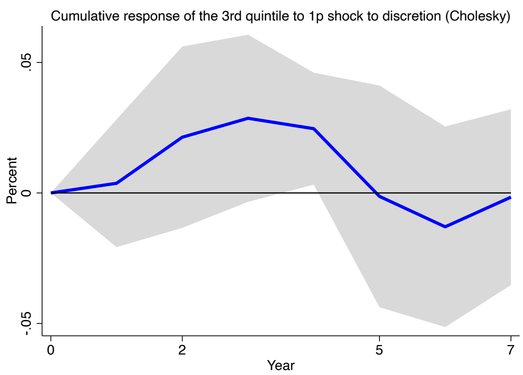
These two figures provide evidence that complement the previous; 7 years after the shock the positive effect on the poorest and the middle class totally disappears since the cumulative effect is close to 0. Only, slightly persistent effects occur for the 4^{th} quintile. And, complementary, the negative effect on the highest quintile completely disappears, showing again evidence on the transitory power of discretion. However, two promising phenomena arise from looking at panels (b) and (c) from Figure 6.4. The cumulative negative effect on the top 1 share persists after 7 years and simultaneously, the cumulative effects on the Gini coefficient present evidence in favor of persistent inequality alleviation 7 years after the increase of discretion. Hence, a cumulative negative effect on these 2 variables persists in the long-run.



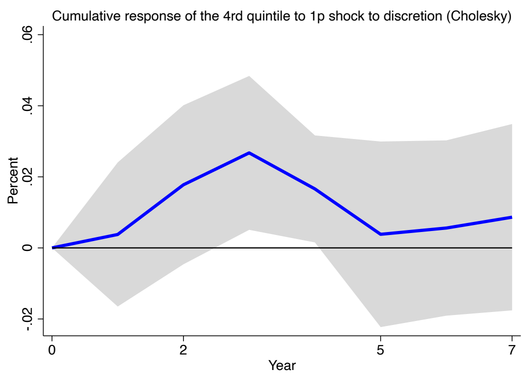
(a)



(b)



(c)

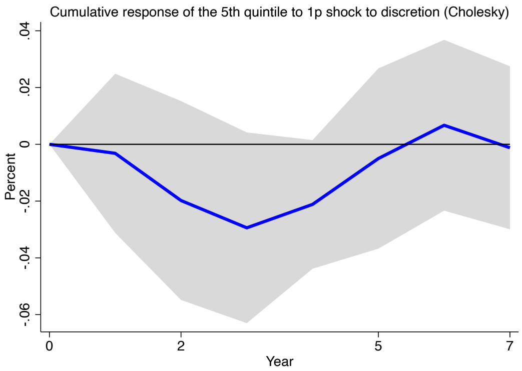


(d)

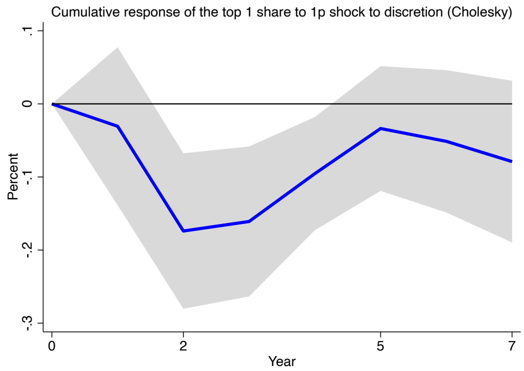
Figure 6.3. Cumulative impulse response functions estimated from model (6.10): The persistent character of the dynamic responses from 1^{st} to 4^{th} income quintiles.

Note: the solid blue line corresponds to the cumulative IRF (φ^k estimated coefficients) and limits of the grey area correspond to 90 percent confidence bands. The x-axis denotes time: $t = 0$ is the year of the discretionary fiscal policy 1 p. shock (increase). And time horizon is $k = 7$. Panel (a) to (d) correspond from the 1^{st} quintile to the 4^{th}, in that specific order.

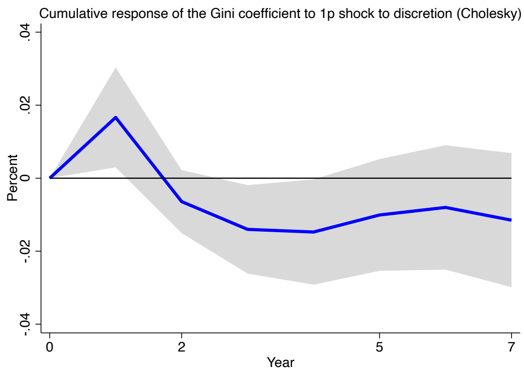
In sum, these two exercises provide supportive evidence that discretionary fiscal policy: i) has a transitory income redistributive power, ii) provokes persistent inequality alleviation in the long-term, and iii) persistently harms the top 1 share of the income distribution. Hence, since great part of the effects on the poorest and the middle class are transitory, discretionary fiscal policy weakly performs in terms of income redistribution.



(a)



(b)



(c)

Figure 6.4. Cumulative impulse response functions estimated from model (6.10): The persistent character of the dynamic responses of 5^{th} quintile, top 1 share and the Gini coefficient.

Note: the solid blue line corresponds to the cumulative IRF (φ^k estimated coefficients) and limits of the grey area correspond to 90 percent confidence bands. The x-axis denotes time: $t = 0$ is the year of the discretionary fiscal policy 1 p. shock (increase). And time horizon is $k = 7$. Panel (a) corresponds to the dynamic responses of the 5^{th} quintile, (b) to the top 1 share and (c) to the Gini coefficient.

6.4. Robustness checks

6.4.1. ARDL's lag parameterizations

The lag selection criteria dictated that every ARDL model should count with 4 lags of the dependent variable and 4 lags of discretion. However, the magnitude and direction of the dynamic effects of income distribution can be sensitive to the choice of the number of lags, conforming to Teulings and Zubanov, 2014 and Bernal-Verdugo et al., 2013. Additionally, they state how sensitive the IRFs obtained from ARDL estimations are to the lags' choice. As a way of checking my ARDL results, I will re-estimate model (5.5) applying 2 extra lag parameterizations; one under the selected criteria $(l_1, l_2) = (2, 2)$ and the second over $(l_1, l_2) = (6, 6)$.

Table 7.4 in the annex reports these results, Panel A for the first lag parameterization and Panel B for the second. In general, both lag's choices results provide the same conclusions as the baseline results in Table 6.3. In terms of magnitude, Panel B results are closer, which was to be expected. However, results from Panel B slightly differ. Also, the higher significance tends to occur in both experiments in the second lag of discretion, as in Table 6.3.

6.4.2. Local projections' lag parameterizations

Following personal recommendations from Òscar Jordà, I will test the robustness of both non-cumulative and cumulative estimation model results, (5.9) and (5.10), using different number of lags of the dependent variable. Initially, the selected number of lags, concurring with the information criteria from ARDL estimations, was equal to 4. Now, I will estimate models (5.9) and (5.10) with 2 and 6 lags of the dependent variable.

Table 7.5 in the annex reports the results from using different lags in the estimation of the non-cumulative version of the LP method. Panel A refers to the usage of 2 lags of the dependent variable and Panel B to 6 lags. Note that only the estimation of the impulse response (φ^k) until $k = 4$ is reported. Again, the conclusions are similar to ones from the main results in Table 6.4. In terms of magnitude, Panel A presents closer results, and Panel B results slightly differ whilst presenting overall greater impulses in absolute value. In the latter case, the inclusion of extra lags of the dependent variable seems to exacerbate the effects of discretion.

With regard to persistence and the long-term view, I trace out the cumulative responses with $k = 7$ in Figures 7.4 and 7.5 in the annex counting with 2 lags of the dependent. Comparing with the main results in Figure 6.3, the results for the poorest quintile and the middle class presented in Figure 7.4 are virtually identical, as well as the transitory effect concluded. Figure 7.5 confirms that the richest are also detrimentally affected by discretion and the persistent effect on the top 1 share remains even with 2 lags of the dependent variable. However, Panel (c) from Figure 7.5 shows how the effect on inequality is completely transitory in this particular lag choice. In overall, the reduction of 2 lags of the dependent variable remains conclusions quite invariant.

Finally, Figures 7.6 and 7.7 in the annex report the cumulative IRFs with $k = 7$

with 6 lags of the dependent. The first shows similar transitory effects of discretion on the poorest quintile and the middle class, although a slight cumulative negative effect arises 5 years after the shock that is rapidly overcame after 2 periods. Figure 7.7 presents how the negative effect on the richest remains when including 2 extra lags of the dependent variable. Yet, the persistent character of the top 1 share response disappears in this case. And, the positive persistent effect on inequality remains. Hence, the positive income redistributive and inequality alleviation powers of discretion remain even with changes in the lag choice of the dependent variable.

6.4.3. Time fixed-effects estimation

An extra recommendation by Òscar Jordà was to include time fixed effects as a way to test for robustness. This test is highly necessary in this paper due to the potential influence of the great variations in discretion after the Great Recession. I include time dummies in the Fixed-Effects estimation and estimate the non-cumulative model (5.9) with the same lag selection. The aim here is to control that part of the variation of the series is influenced by specific periods of time. Thus, I will expect similar magnitude of the dynamic responses with slight changes in terms of significance due to the entrance of these time dummies. Table 7.6 in the annex reports these results.

Conducting an exercise of comparison between Tables 6.4 and 7.6, the results are highly similar in terms of magnitude and sign. The same redistributive pattern remains and also, the greater effect of discretion two years after the shock. Additionally, inequality alleviation maintains in these new results. Although, as it was expected, part of the significance is lost; especially for the middle class. However, part of the significance of the top 1 share and for the Gini coefficient keep constant.

6.4.4. Sign non-linearities (asymmetry)

Ultimately, Òscar Jordà recommended me to estimate the specifications with non-linearities. Thus, I will estimate the non-cumulative [25] version of the LP model (5.9) modified by introducing a sign non-linearity based on indicating discretion consolidations (negative values) and discretion expansions (positive value). Hence, I do not ignore the non-linearity of the impulse responses, as part of the literature in the application of LP estimator do (Barnichon et al., 2018; Tenreyro & Thwaites, 2016), and I will theoretically follow the construction of the LP by Gonçalves et al., 2020 [26] and its application in the study of the exchange rate pass-through correlation

[25] The conclusions obtained from the cumulative version are identical.

[26] Gonçalves et al., 2020 evaluate the power of LP to capture non-linear responses by linear models that include transformed regressors; censored or non-linear transformations. Thus, they present the theoretical introduction of asymmetries, thresholds and other non-linearities in the responses of variables.

between domestic price levels and the nominal exchange rate by Colavecchio and Rubene, 2019.

The non-linear character is introduced by an indicator variable $\omega_{i,t}$ in equation (5.9), which takes value 1 if in period t for country i discretion is positive ($\omega_{i,t} = 1|_{\hat{\epsilon}_{i,t}>0}$) and 0 if it is negative ($\omega_{i,t} = 0|_{\hat{\epsilon}_{i,t}<0}$), thus introducing a sing non-linearity, also named asymmetry, in the model. Hence, the non-linear LP is obtained by estimating the following regression for each forecast horizon $k = 1...4$:

$$S_{a,i,t+k} - S_{a,i,t+k-1} = \delta_i^k + \gamma_t^k + \sum_{j=1}^{l_1} \beta_j S_{a,i,t-j} + \varphi_1^k [1 - \omega_{i,t}] \hat{\epsilon}_{i,t} + \varphi_2^k [\omega_{i,t}] \hat{\epsilon}_{i,t} + \vartheta^k X_{i,t} + \varepsilon_{i,t}^k, \quad (6.1)$$

where φ_1^k measures the effect of negative discretion on income distribution at horizon k and φ_2^k the effect of positive discretion. Theoretically, the presence of asymmetry or sign non-linearity can be tested using a simple $F - test$ of the hypothesis $\varphi_1^k = \varphi_2^k$ at any projected horizon k. In particular, if φ_1^k and φ_2^k are not significantly different, then the effect of discretion on income distribution is linear [27]. In other words, a non-rejection of the null will imply an adequate usage of the linear LP in this paper.

Table 7.7 in the annex reports the $F - tests$ for all k and for all income quintiles, the top 1 share and the Gini coefficient. Without exception and at any significance level, the null hypothesis based on the linearity of the effect of discretion fails to be rejected. Hence, models (5.9) and (5.10) linear LP specifications are adequately constructed and robust to asymmetry specifications.

[27]Note that there are different ways to implement non-linearities. For instance, by establishing a threshold of discretion in the estimated sample and also including net changes of the variable. In this paper, due to space limitations and concrete recommendations by Òscar Jordà, I only apply this non-linear specification to the model. Further research on this topic would need to include extra non-linear specifications. Thus, the initial linear LP model would be robust to all the potential causes of non-linearity.

7. CONCLUDING REMARKS

After the launch of the EMU, the EU adopted a more assertive stance on fiscal policy as a macroeconomic stabilization instrument. With it, automatic stabilizers became the preferred component of fiscal policy against discretionary policy making to cushion the business cycle and to stabilize the economic stance (Brunila et al., 2003). Before the Great Recession, the literature chose automatic stabilizers as an efficient stabilizing tool, albeit, the implementation of rescue and stimulus packages granted to discretionary fiscal policy the leading role after the crisis (Paulus & Tasseva, 2020).

Ex-post, the academia put emphasis, apart from the effects on output stabilization and volatility, on the effects on inequality and income distribution of fiscal policy. The studies on the firsts found a positive effect of fiscal policy (Anderson et al., 2017; Coady et al., 2012; Sidek, 2021) and contrary effect of fiscal consolidation episodes (Agnello & Sousa, 2014; Mulas-Granados et al., 2005). The studies on the seconds, from an aggregate perspective, limited to interpret effects on inequality indexes as income distribution indicators (Agnello et al., 2013; Balseven & Tugcu, 2017; Martinez-Vazquez et al., 2012; Mulas-Granados et al., 2005), and from a microeconomic focused on direct tax-benefit transfers without adding dynamic frameworks (Bargain et al., 2017; De Agostini et al., 2016; Hills et al., 2019; Paulus et al., 2020).

The aim of this paper was to fill these gaps through a comprehensive study of the income distributional impacts of exogenous and discretionary government expenditure changes in the EU-27. By the application of dynamic models and the development of impulse response functions (ARDLs and IRFs via local projections method by Jordà, 2005, respectively), I complement the existing literature with an aggregate study that combines the estimation of lagged and future responses of income distribution given unexpected fiscal policy shocks, along with a study on the long-run persistence of the effects of discretion.

In overall, I find supportive evidence on the heterogeneity in the response of income distribution to discretionary changes in government spending. Such heterogeneity is shown as i) a positive yet transitory income redistributive power represented by a transitory positive effect on the share of the bottom quintile and the middle class and ii) a persistent detrimental impact on the top 1 share of the income distribution. These results are successfully complemented with a persistent inequality alleviation in the long-run. Hence, given this transitory impact, discretionary fiscal policy weakly performs in terms of income redistribution durability, although without this being the main objective of discretion.

These results complement Anderson et al., 2016 and De Giorgi and Gambetti, 2012's evidence of consumption inequality alleviation due to unexpected government spending. Furthermore, the results coincide with those of the microeconomic approaches that evaluate the effects of discretion on income distribution: (Bargain et al., 2017; De Agostini et al., 2016; Hills et al., 2019; Paulus et al., 2020).

Ideally, an extra measure of exogenous changes in government expenditures should be applied. The most reliable measure is, as mentioned during this paper, the narrative approach by Ramey, 2011. The main issue is the need for its construction adapted to a European context. Once created, its implementation as a test for robustness would be straight-forward. Additionally, it would correct any potential reverse causality issue in this inequality-discretion context, although as argued before it seems to be practically nonexistent.

In addition, further research on this paper and the implementation of new methodologies would be required. Including multivariate systems like VARs to introduce the interaction between income shares, for instance. From a more specific perspective, the focus on case studies of determined discretionary policy actions on a certain country and period of time, complemented with higher frequency data would provide more detailed results. Also, the application of this framework to the study of different fiscal or political events and their effects on income distribution from a dynamic perspective. And finally, the inclusion of extra non-linearities to check for the robustness of the linearity of the discretion-income nexus.

In sort, theoretically without seeking it, discretion action in the EU-27 seems to have successfully helped the poorest of the income distribution, albeit in a transitory manner, leading to a medium-term non-existent redistributive effect. Simultaneously, the top 1 share appears to have been persistently and detrimentally affected, supporting the persistent inequality alleviation in the long-run in the EU-27 countries. Possibly, reinforcing discretion could lead to persistent redistributive effects on the bottom of the distribution, although this role is assigned to automatic stabilizers due to their rapid capability to come into operation.

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ANNEXES

Austria	Belgium	Bulgaria	Croatia
Cyprus	Czech Republic	Denmark	Estonia
Finland	France	Germany	Greece
Hungary	Ireland	Italy	Latvia
Lithuania	Luxembourg	Malta	Netherlands
Poland	Portugal	Romania	Slovak Republic
Slovenia	Spain	Sweden	

Table 7.1. List of countries: EU-27.

Variable	Mean	Stdv.	Obs	Source
Real GDP 2011 US$ (growth rate)	.024	.046	729	MPD 2020
Gov. expenditure %GDP (growth rate)	.004	.096	710	WDI & IMF
Inf. (GDP deflator)	7.969	39.702	725	WDI
Inf. squared	1635.367	31245.440	725	WDI
Gini coefficient (ln)	3.347	.131	756	SWIID
State Debt (ln)	3.679	.909	732	WDI & EU**
1^{st} quintile share	.028	.005	756	WIID
2^{nd} quintile share	.108	.015	756	WIID
3^{rd} quintile share	.157	.014	756	WIID
4^{rd} quintile share	.221	.011	756	WIID
5^{th} quintile share	.481	.042	756	WIID
Top 1 share	.100	.024	756	WIID
Population (growth rate)	.002	.008	729	WDI
Trade openness (growth rate)	.020	.114	729	WDI

Note: ** denotes that central state debt data was also extracted from OECD data and the IMF Historical Public Debt Database, as it is explained in the Data chapter. Due to space issues these two sources are not directly included in the Table.

Table 7.2. Descriptive statistics

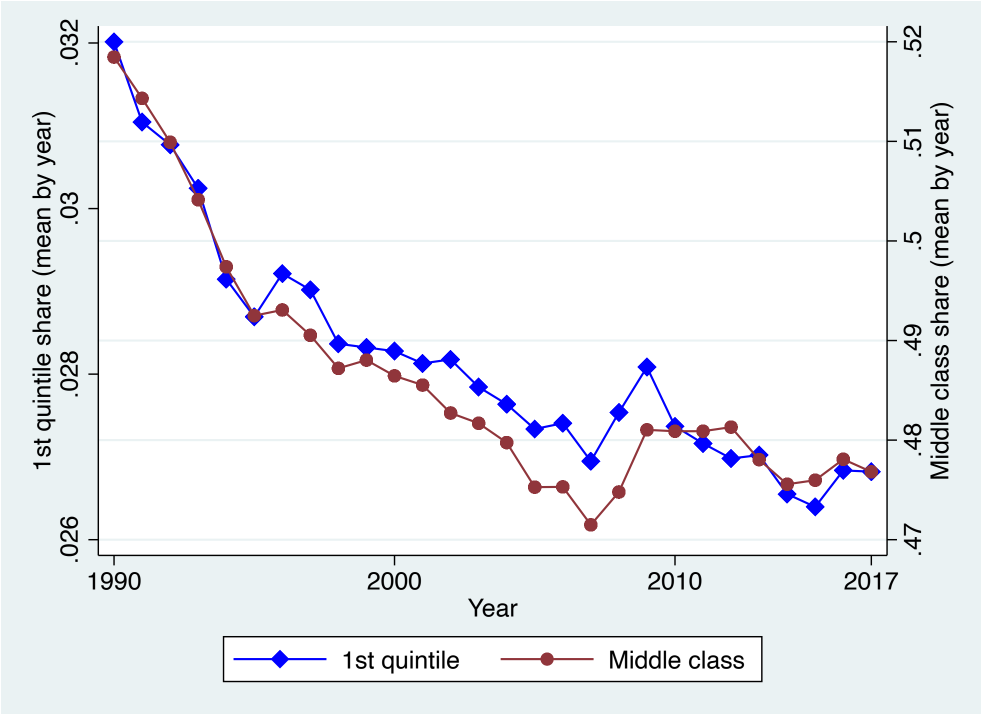


Figure 7.1. Evolution of the share of middle class and the share of the 1^{st} quintile from 1990 to 2017 measured as the mean per year among all EU-27 countries.

Note: Middle class share refers to the sum of the shares from the 2^{nd} to the 4^{th} quintile.

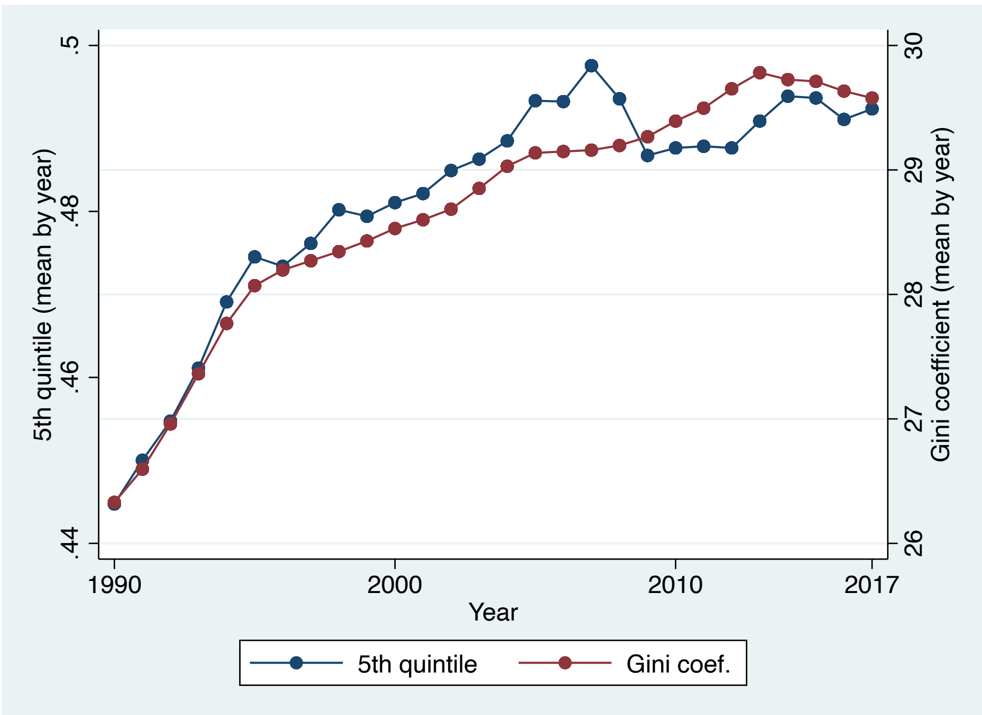


Figure 7.2. Evolution of the share of the 5^{th} quintile and the Gini coefficient from 1990 to 2017 measured as the mean per year among all EU-27 countries.

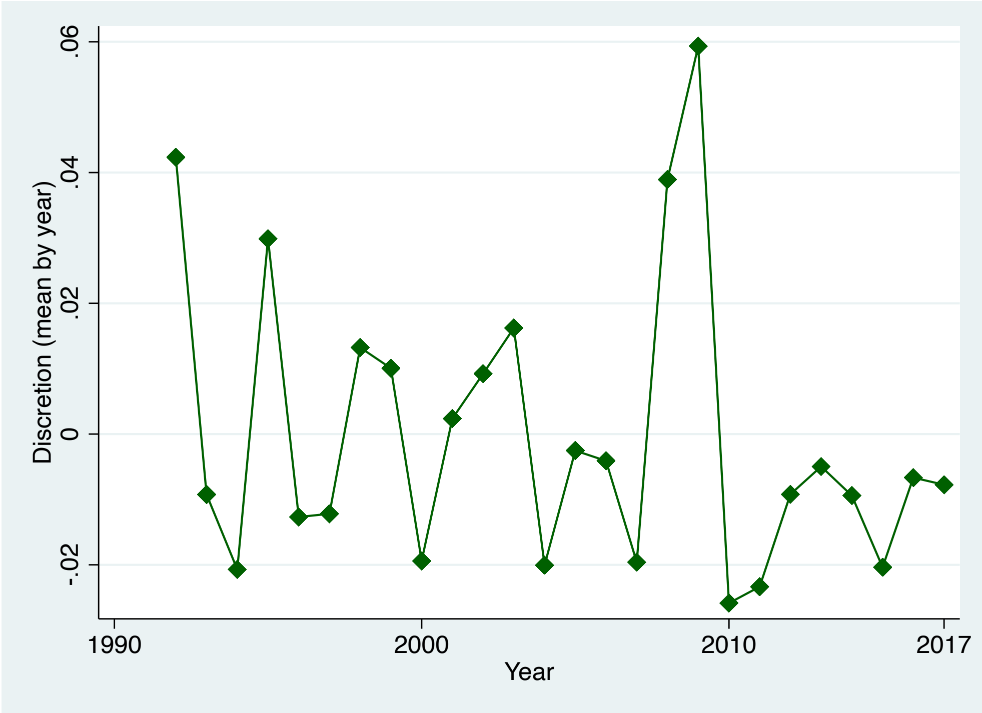


Figure 7.3. Evolution of discretionary government expenditure from 1990 to 2017 measured as the mean by year among all EU-27 countries.

Variable	ADF	IPS	Order of integration
$ln(p0-20)$	-2.039**	-2.203***	I(0)
$ln(p20-40)$	-2.700***	-2.038***	I(0)
$ln(p40-60)$	-2.505***	-2.026***	I(0)
$ln(p60-80)$	-3.158***	-2.077***	I(0)
$ln(p80-100)$	-4.055***	-2.057***	I(0)
$ln(p99-100)$	-4.354***	-2.355***	I(0)
$lnGini$	-2.535***	-1.985***	I(0)
$\hat{\epsilon}$	-15.013***	-4.540***	I(0)
$\Delta lnPop$	-6.656***	-1.852***	I(1)
ΔlnT	-19.346***	-5.445***	I(1)
$lnInf$	-3.557***	-2.548***	I(0)

Note: ***,**,* denote significance at 1%, 5% and 10%, respectively. For the ADF test, p-values are provided and for the IPS exact critical values for the size of the panel: -1.820 at 1%, -1.730 at 5% and -1.690 at 10%.

Table 7.3. Integration order properties of ARDL variables: ADF & IPS tests.

	Dependent variable:						
	$S_{0-20,i,t}$	$S_{20-40,i,t}$	$S_{40-60,i,t}$	$S_{60-80,i,t}$	$S_{80-100,i,t}$	$S_{99-100,i,t}$	$lnGini_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
$\hat{\epsilon}_{i,t}$	.032	.015	.008	.006	-.008	-.042	.017**
	(0.98)	(0.65)	(0.48)	(0.50)	(-0.41)	(-0.60)	(2.36)
$\hat{\epsilon}_{i,t-1}$	.005	.016	.017	.017***	-.014*	-.145***	-.030***
	(0.29)	(1.22)	(1.60)	(2.78)	(-1.65)	(-8.01)	(-2.79)
$\hat{\epsilon}_{i,t-2}$	.028*	.013*	.015***	.018***	-.016***	-.059*	.009***
	(1.65)	(1.80)	(2.91)	(2.94)	(-2.90)	(-1.94)	(3.14)
$obs.$	586	586	586	586	586	586	586
R^2	0.90	0.95	0.92	0.82	0.93	0.85	0.99
Panel B							
$\hat{\epsilon}_{i,t}$	.143**	.085*	.044	.036	-.055	-.293**	-.005
	(2.14)	(1.80)	(1.21)	(1.07)	(-1.58)	(-2.04)	(-0.86)
$\hat{\epsilon}_{i,t-1}$	.123**	.080**	.065**	.042***	-.058***	-.279***	-.004
	(2.26)	(2.28)	(2.31)	(2.84)	(-3.02)	(-4.25)	(-0.56)
$\hat{\epsilon}_{i,t-2}$	.113**	.066**	.059***	.060***	-.066***	-.317***	.006
	(2.17)	(2.08)	(2.47)	(2.65)	(-2.73)	(-3.19)	(1.27)
$\hat{\epsilon}_{i,t-3}$	.037	.017	.019	.008	-.014	-.052	-.001
	(1.55)	(1.38)	(1.57)	(0.71)	(-1.23)	(-1.02)	(-0.30)
$\hat{\epsilon}_{i,t-4}$	-.002	-.008	-.012	-.001	.003	-.009	.007***
	(-0.05)	(-0.26)	(-0.43)	(-0.14)	(0.16)	(-0.23)	(2.50)
$\hat{\epsilon}_{i,t-5}$	-.010	-.010	-.002	.007	.003	-.062*	.001
	(-0.67)	(-1.05)	(-0.29)	(1.00)	(0.50)	(-1.80)	(0.34)
$\hat{\epsilon}_{i,t-6}$	-.006	-.001	-.002	.002	.001	-.048	.000
	(-0.33)	(-0.13)	(-0.19)	(0.30)	(0.18)	(-1.54)	(-0.36)
$obs.$	481	481	481	481	481	481	481
R^2	0.89	0.94	0.91	0.82	0.92	0.84	0.99

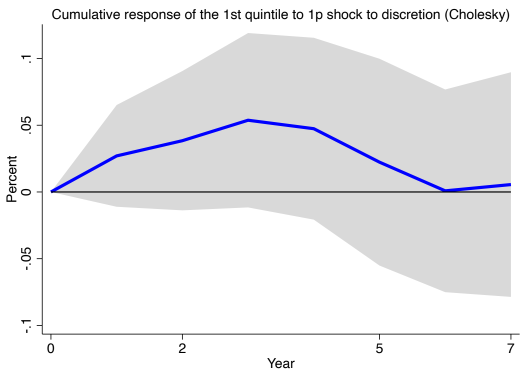
Note: T-statistics in parenthesis. ***,**,* denote significance at 1 percent, 5 percent and 10 percent, respectively. Panel A refers to ARDL estimations (model (6.5)) with $(l_1, l_2) = (2, 2)$ and Panel B to $(l_1, l_2) = (6, 6)$. Note as well that only discretion estimations are included due to presentation clarity.

Table 7.4. The income distribution impact of discretionary fiscal policy: Different lag parameterizations of ARDL estimations by Fixed-Effects.

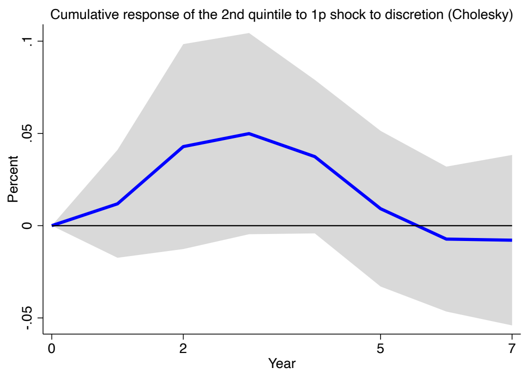
Shock: $\hat{\epsilon}_{i,t}$								
	Panel A				Panel B			
	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 1$	$k = 2$	$k = 3$	$k = 4$
$S_{0-20,i,t}$	.027	.0107	.019	-.006	.069	.063	.063	-.002
	(1.17)	(0.55)	(1.30)	(-0.25)	(1.08)	(1.24)	(1.33)	(-0.03)
$S_{20-40,i,t}$	.011	.030	.009	-.012	.047	.092**	.047*	-.054
	(0.67)	(1.58)	(1.27)	(-0.83)	(1.29)	(1.97)	(1.75)	(-1.49)
$S_{40-60,i,t}$	.003	.022**	.006	-.003	.018	.050*	.032*	-.006
	(0.27)	(2.03)	(0.98)	(-0.30)	(0.62)	(1.95)	(1.83)	(-0.21)
$S_{60-80,i,t}$	.003	.019***	.006	-.008	.017	.024	.041*	-.032
	(0.38)	(3.16)	(1.16)	(-0.76)	(0.67)	(1.33)	(1.94)	(-1.19)
$S_{80-100,i,t}$	-.005	-.020***	-.008	.010	-.029	-.042**	-.036*	.033
	(-0.39)	(-2.28)	(-1.45)	(0.88)	(-0.99)	(-2.10)	(-1.92)	(1.30)
$S_{99-100,i,t}$	-.026	-.148***	.017	.067	-.176	-.184*	-.127	.191**
	(-0.40)	(-5.24)	(0.80)	(1.50)	(-1.53)	(-1.92)	(-1.41)	(2.05)
$lnGini_{i,t}$	.020**	-.019***	-.004	.007***	.001	-.008	-.007	-.0008
	(2.32)	(-2.69)	(-1.46)	(3.21)	(0.15)	(-1.32)	(-1.42)	(-0.13)

Note: T-statistics in parenthesis. ***,**,* denote significance at 1 percent, 5 percent and 10 percent, respectively. Estimates based on equation (6.9). $K = 1, .., 4$ denotes the year following the fiscal discretion shock. Panel A refers to the usage of 2 lags of the dependent variable and Panel B to the usage of 6.

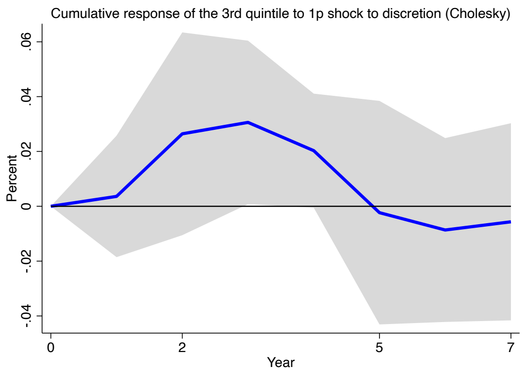
Table 7.5. The effect of fiscal discretion on inequality (1990–2017): non-cumulative estimation of φ^k by local projections method (Jordà, 2005) and using different lag selections.



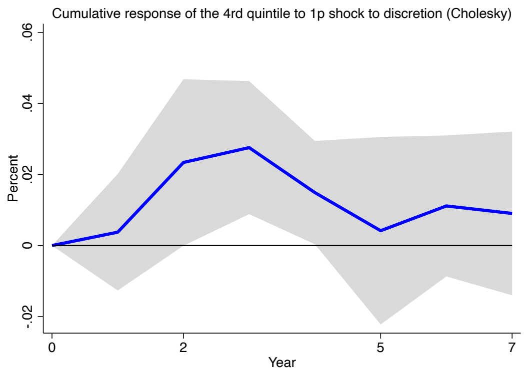
(a)



(b)



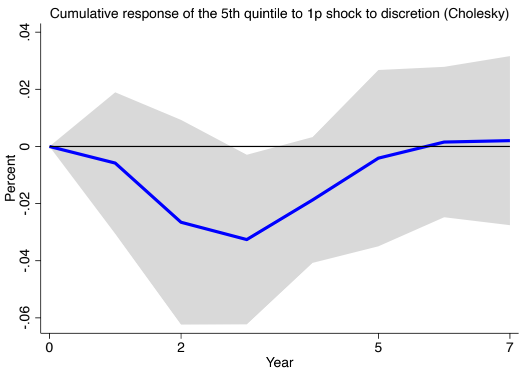
(c)



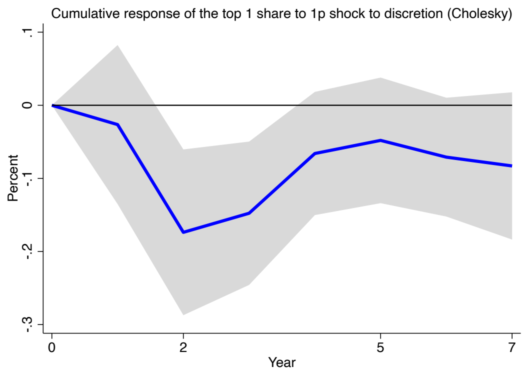
(d)

Figure 7.4. Cumulative impulse response functions estimated from model (6.10): The persistent character of the dynamic responses from 1^{st} to 4^{th} income quintiles with 2 lags of the dependent variable.

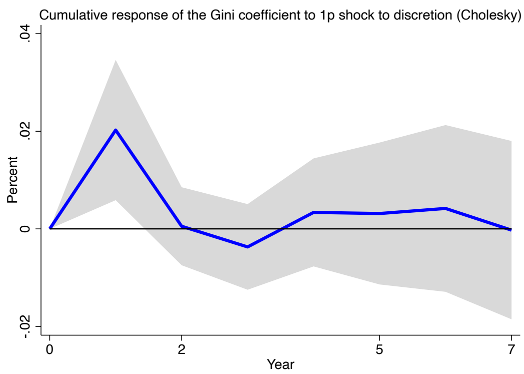
Note: the solid blue line corresponds to the cumulative IRF (φ^k estimated coefficients) and limits of the grey area correspond to 90 percent confidence bands. The x-axis denotes time: $t = 0$ is the year of the discretionary fiscal policy 1 p. shock (increase). And time horizon is $k = 7$. Panel (a) to (d) correspond from the 1^{st} quintile to the 4^{th}, in that specific order.



(a)



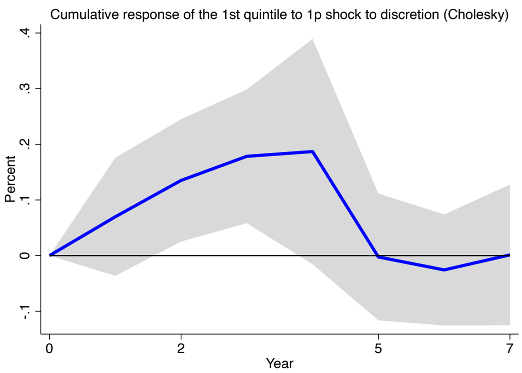
(b)



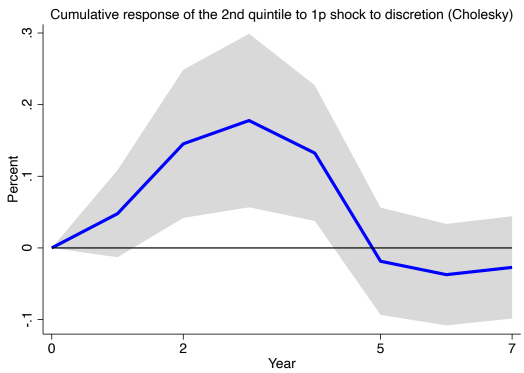
(c)

Figure 7.5. Cumulative impulse response functions estimated from model (6.10): The persistent character of the dynamic responses of 5^{th} quintile, top 1 share and the Gini coefficient with 2 lags of the dependent variable.

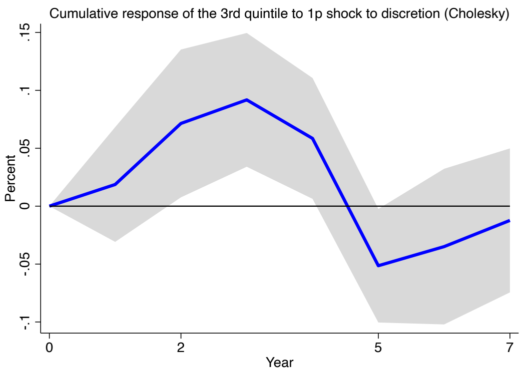
Note: the solid blue line corresponds to the cumulative IRF (φ^k estimated coefficients) and limits of the grey area correspond to 90 percent confidence bands. The x-axis denotes time: $t = 0$ is the year of the discretionary fiscal policy 1 p. shock (increase). And time horizon is $k = 7$. Panel (a) corresponds to the dynamic responses of the 5^{th} quintile, (b) to the top 1 share and (c) to the Gini coefficient.



(a)



(b)



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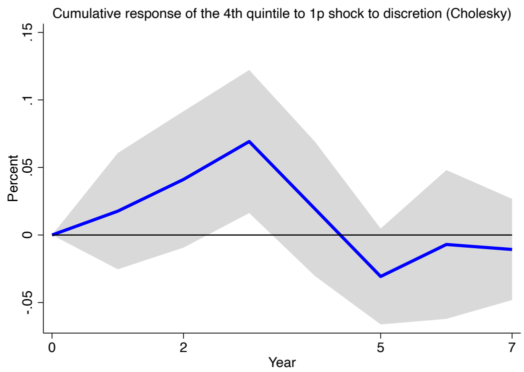
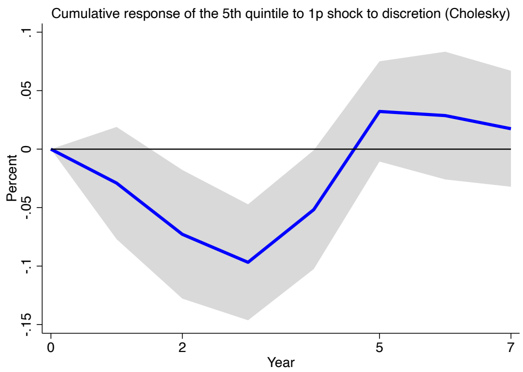


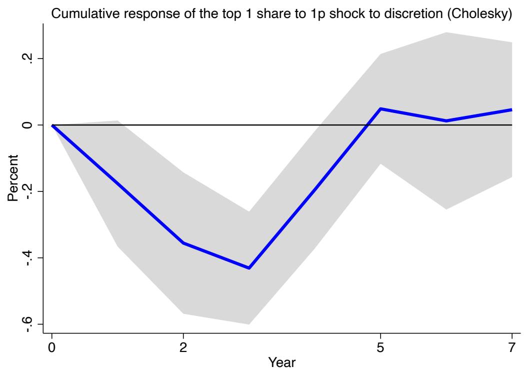
(d)

Figure 7.6. Cumulative impulse response functions estimated from model (6.10): The persistent character of the dynamic responses from 1^{st} to 4^{th} income quintiles with 6 lags of the dependent variable.

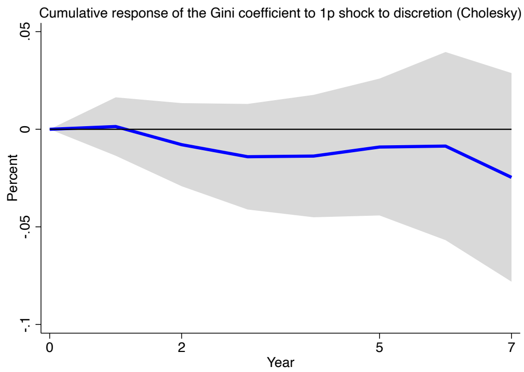
Note: the solid blue line corresponds to the cumulative IRF (φ^k estimated coefficients) and limits of the grey area correspond to 90 percent confidence bands. The x-axis denotes time: $t = 0$ is the year of the discretionary fiscal policy 1 p. shock (increase). And time horizon is $k = 7$. Panel (a) to (d) correspond from the 1^{st} quintile to the 4^{th}, in that specific order.



(a)



(b)



(c)

Figure 7.7. Cumulative impulse response functions estimated from model (6.10): The persistent character of the dynamic responses of 5^{th} quintile, top 1 share and the Gini coefficient with 6 lags of the dependent variable.

Note: the solid blue line corresponds to the cumulative IRF (φ^k estimated coefficients) and limits of the grey area correspond to 90 percent confidence bands. The x-axis denotes time: $t = 0$ is the year of the discretionary fiscal policy 1 p. shock (increase). And time horizon is $k = 7$. Panel (a) corresponds to the dynamic responses of the 5^{th} quintile, (b) to the top 1 share and (c) to the Gini coefficient.

Shock: $\hat{\epsilon}_{i,t}$				
	$k=1$	$k=2$	$k=3$	$k=4$
$S_{0-20,i,t}$	.016	.009	.040	.001
	(0.48)	(0.25)	(1.13)	(0.04)
$S_{20-40,i,t}$	.001	.022	.0208	-.0024
	(0.04)	(1.30)	(1.21)	(-0.14)
$S_{40-60,i,t}$	.000	.014	.012	.006
	(0.01)	(0.99)	(0.82)	(0.39)
$S_{60-80,i,t}$	.004	.011	.011	-.003
	(0.35)	(0.96)	(0.97)	(-0.24)
$S_{80-100,i,t}$	.001	-.012	-.016	.002
	(0.08)	(-1.01)	(-1.26)	(0.19)
$S_{99-100,i,t}$	-.016	-.127***	-.015	.039
	(-0.36)	(-2.69)	(-0.30)	(0.769)
$lnGini_{i,t}$	.017***	-.025***	-.010**	-.003
	(3.68)	(-5.19)	(-2.06)	(-0.70)

Note: T-statistics in parenthesis. ***,**,* denote significance at 1 percent, 5 percent and 10 percent, respectively. Estimates based on equation (6.9). $K = 1, .., 4$ denotes the year following the fiscal discretion shock. All equations estimated by Fixed-Effects estimator controlling for time fixed-effects.

Table 7.6. The effect of fiscal discretion on inequality (1990–2017): non-cumulative estimation of φ^k by local projections method (Jordà, 2005) with time fixed-effects.

$F - tests; \quad H_0 : \varphi_1^k = \varphi_2^k$				
	$k = 1$	$k = 2$	$k = 3$	$k = 4$
$S_{0-20,i,t}$	0.01	0.77	0.66	0.18
	(0.937)	(0.388)	(0.424)	(0.676)
$S_{20-40,i,t}$	1.98	0.08	0.00	1.15
	(0.172)	(0.776)	(0.973)	(0.293)
$S_{40-60,i,t}$	1.24	0.30	0.44	2.01
	(0.275)	(0.589)	(0.512)	(0.168)
$S_{60-80,i,t}$	0.32	0.03	0.27	0.45
	(0.575)	(0.865)	(0.606)	(0.510)
$S_{80-100,i,t}$	0.34	0.01	0.51	1.10
	(0.566)	(0.927)	(0.480)	(0.304)
$S_{99-100,i,t}$	0.22	0.10	0.01	0.65
	(0.641)	(0.752)	(0.935)	(0.428)
$lnGini_{i,t}$	1.71	2.79	0.06	1.05
	(0.202)	(0.107)	(0.809)	(0.314)

Note: p-values in parenthesis. $F - tests$ based on equation (7.1). $K = 1, .., 4$ denotes the year following the fiscal discretion shock. All equations estimated by Fixed-Effects estimator.

Table 7.7. The effect of fiscal discretion on inequality (1990–2017): asymmetry or sign non-linearity $F - tests$ of local projections method (Jordà, 2005).