The Role of Income Inequality on Fiscal Multipliers

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Abstract

This paper investigates the role of income inequality on the size of fiscal multipliers during the recent crisis. Using various measures of income inequality, the empirical strategy developed suggests a positive and statistically significant impact of inequality on the size of fiscal multipliers of European economies during 2010-11. The results are robust after controlling for the role of outliers, by adding controls that could be driving the results, testing for different forecast vintages, and using a different source of standardized income inequality data.

Theoretical arguments that may explain the results are presented. Namely the existence of credit constraints to relatively poor households, and the lower propensity to consume of relatively wealthier households.

Keywords: Fiscal policy, forecasting, income inequality, government expenditure, output fluctuations.

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1 Introduction

After the 2008 crisis, a significant number of advanced economies were forced to undertake measures of fiscal consolidation. The high levels of government debt were the main driving force for such necessity. However, the short-term effects of those government spending cuts or tax hikes on economic activity (the so-called *fiscal multipliers*) were highly uncertain.

A large body of literature has been devoted to study the size of the fiscal multiplier, using different techniques for the fiscal policy identification. Seminal contributions include Blanchard and Perotti (2002), Mountford and Uhlig (2009), and Ramey (2011). However, different model classes, identification strategies, and specifications yield far from consensual results.[1]

More recently, the literature on fiscal multipliers has evolved to allow for state-dependent multipliers, thus rejecting the hypothesis of a permanent, time-invariant multiplier. In fact, the economic context during the crisis was particularly complex. This, in turn, added to the uncertainty surrounding the consequences of fiscal consolidation measures. For that contributed the binding zero lower bound on nominal interest rates, the presence of increased financial frictions, and a greater deal of slack in the economy, with a greater degree of underutilized resources.

In an influential paper published by the International Monetary Fund (IMF), Blanchard and Leigh (2013) conclude that real GDP growth forecast errors for 26 European economies were systematically correlated with fiscal consolidation forecasts during the recent crisis. Specifically, countries with higher levels of fiscal consolidation forecasts registered, on average, more negative growth forecast errors. These results imply that professional forecasters systematically underestimated the impact of fiscal consolidation measures on growth, and suggest multipliers well above 1 earlier in the crisis. Robustness tests were performed and their baseline results still hold after the control of outliers, the inclusion of additional variables that are likely correlated with both growth forecast errors and fiscal consolidation forecasts, and for different forecast vintages.

The main goal of this paper is to investigate the relation between income inequality and the size of the fiscal multiplier. The methodology follows closely Blanchard and Leigh (2013) by interpreting growth forecast errors as higher-than-normal fiscal multipliers. Such a framework suggests that higher-than-expected fiscal multipliers caused higher growth forecast errors during 2010-11. Using the European Union Statistics on Income and Living Conditions (EU-SILC) dataset, we construct various measures of income inequality for the same 26 European economies.

[1] See Gechert et al. (2012) for a meta regression analysis of various studies on multiplier effects.

The empirical strategy used suggests that the countries with higher pre-crisis levels of income inequality registered, on average, higher growth forecast errors during their fiscal consolidation efforts for the period 2010-11. According to the framework developed, these results provide evidence of larger-than-expected multipliers. The obtained coefficients have relevant sizes and are statistically significant. We also test for a non-linear relation between income inequality and the fiscal multiplier. The results suggest that income inequality has a higher marginal impact on fiscal multipliers for higher inequality levels. The baseline results are robust after controlling for the influence of outlier observations, after adding controls that could cause higher-than-expected growth downfalls and be related with our regressors, after checking that the relation does not hold for more normal times (1997-2008), and using a different source of standardized income inequality.

Our estimation results also suggest that the relation between income inequality and the fiscal multiplier depends on the income definition used to measure inequality. Specifically, the results provide evidence that the distribution of income among European economies only affected the fiscal multiplier in 2010-11 if measured by household disposable income. The relation does not seem to hold if one accounts for the market (rather than disposable) distribution of income, where market income is calculated gross of income taxes and social security employee contributions. These results have very interesting implications by suggesting that European governments' redistributive policies actually ended up increasing the impact of fiscal policy on real growth.

In section 2 theoretical insights are presented regarding the relation between income inequality and the size of fiscal multipliers. Specifically, it is possible that countries with higher levels of inequality had a higher share of liquidity constrained households, and/or a higher share of agents with a higher marginal propensity to consume. As long as there is a mapping between income inequality and any of these channels, it is possible that income inequality may affect how contractionary fiscal consolidation policies are. This section also provides a brief literature review on state-dependent fiscal multipliers.

Thus, complementary to Blanchard and Leigh (2013) findings, our results suggest that forecasters did not underestimate the impact on growth of fiscal consolidation *per se*. Instead, they suggest that forecasters underestimated the consequences of heterogeneity of agents during fiscal austerity.

The remainder of this paper is organized as follows. Section 3 includes an overview of Blanchard and Leigh's (2013) work, and describes the empirical procedure developed to test if income inequality had an impact on fiscal multipliers during 2010-11. The section finalizes with additional testing on the non-linear relationship between them. In section 4 we produce various robustness tests along various dimensions: by using different economies and controlling for the impact of possible outliers, by including additional controls, by assessing whether the relationship holds for more normal times (1997-2008), and using a different source of standardized income inequality data. Section 5 shows evidence regarding liquidity constrained households for some euro area countries during 2010, and relates with the measures of inequality used in our baseline estimation results. The final section concludes.

2 Theoretical Background

Fiscal multipliers are defined as the effect that a fiscal shock (either positive or negative) has on output. It represents the percentage change in real GDP (or real GDP growth) that follows a fiscal shock totaling 1 percent of GDP. Despite playing a central role in fiscal policy analysis, there remains an enormous range of views on its characteristics, namely its size.

Recent literature suggests that fiscal multipliers depend on economies' circumstances as well as underlying economic structures and policy regimes (beyond any variation related to the specific fiscal measure at hand) (Corsetti et al., 2012). Spilimbergo et al. (2009) list a number of conditions under which multipliers in general (and fiscal multipliers in particular) are larger. Specifically, fiscal multipliers are larger if a) the fiscal consolidation impacts especially on consumption (rather than on savings) or mainly reduces the consumption of domestically produced goods (rather than imported ones), and b) the monetary conditions cannot adapt to offset the negative short-term effects of fiscal consolidation (e.g., interest rates cannot decrease due to a binding zero lower bound on nominal interest rates).

An additional circumstance prone to influence the size of the fiscal multiplier, but with the opposite effect, is the state of public finances. Fiscal multipliers are generally assumed to be lower when consolidation is implemented during a rapid deterioration in public finances given the increased credibility and confidence in sovereign health. The reduction in fiscal multipliers can be achieved through lower sovereign spreads required by the market.[2]

The way income is distributed within an economy can, in turn, affect most of the aforementioned conditions. Specifically, countries with a more unequal distribution of income (i.e., higher income inequality) will have a higher share of lower income households. Consequently, this group of households

[2]Consumers' expectations towards lower future taxation may also increase consumption in the short-run, thus reducing the contractionary impact of fiscal consolidation. As explained in Blanchard (1990), "... by taking measures today, the government eliminates the need for larger, maybe much more disruptive adjustments in the future and this may in turn increase consumption" (pp. 111). However, this channel may not work if households face a binding liquidity constraint.

is likely to have a higher marginal propensity to consume *vis-à-vis* higher income households.[3] In the context of fiscal consolidation, this factor increases the size of the fiscal multiplier. The reason is that a higher proportion of agents experience a reduction in their disposable income that was otherwise targeted to consumption. Thus, the fiscal consolidation episode becomes more contractionary.

Dynan et al. (2004) consistently find that higher-lifetime income households save a larger fraction of their income than lower-income households using three different sources of micro-data. This result suggests that the rich do consume a smaller proportion of their income than the poor. Jappelli et al. (2014) also find a substantial heterogeneity of marginal propensities to consume across income groups. The authors use the 2010 Italian Survey of Household Income and Wealth and ask consumers how much of an unexpected transitory income change they would consume. They find that the average marginal propensity to consume declines sharply with cash-on-hand,[4] from around 65 percent in the lowest cash-on-hand percentile to 30 percent for the richest households.

Additional evidence is provided by Mian et al. (2013) for the U.S. economy after the housing collapse of 2006 to 2009. They find that after a housing net worth shock, the marginal propensity to consume varies significantly with income and debt levels. As the authors mention, the results suggest that the aggregate impact of wealth shocks depends not only on the total wealth lost but also on how these losses are distributed across the population.

Countries with higher income inequality are also prone to have a higher share of liquidity constrained households. By having a higher share of lower income agents, it is likely that a higher proportion of the households either do not possess enough wealth to resort during a negative income shock, or do not possess enough collateral to borrow from financial institutions (Furman and Stiglitz, 1998). Thus, during a fiscal consolidation episode, the negative income shock will force liquidity constrained families to reduce their consumption levels, given their inability to borrow funds and smooth their consumption path.[5]

Coenen et al. (2012) find a multiplier between 1 and 1.5 in various policy models that include liquidity constrained households if monetary policy remains accommodative for 2 years. These results are roughly twice as large as under normal conditions. Galí et al. (2007) extend the standard new Keynesian model to allow for the presence of liquidity constrained households. The addition of this

[3]Differences in the marginal propensity to consume can arise for a number of reasons. Modigliani (1986) suggests that life-cycle motives are the source of differences in saving behavior across households. Other economists have focused on the role of time preferences, characterizing a class of agents as "impatient" (Iacoviello, 2005, and Eggertsson and Krugman, 2010).

[4]Cash-on-hand is defined as the sum of household disposable income and financial wealth, net of consumer debt.

[5]The inability to smooth consumption may also occur if households' wealth is held in illiquid assets, together with imperfect financial markets.

non-Ricardian element to the model increases the sensitivity of current consumption to current income levels. Thus, the authors find a larger fiscal multiplier in the presence of liquidity constrained households.

Using a panel of nineteen OECD countries from 1970-2002, Tagkalakis (2008) also finds that fiscal policy impacts more on consumption during economic recessions. The author purposes that liquidity constraints are the driving force behind the asymmetric effects of fiscal policy on consumption over the business cycle.

To the extent that income inequality affects either of the aforementioned channels, income distribution may affect the size of the multiplier. Furthermore, the economic situation in Europe early in the crisis was particularly complex, increasing the uncertainty regarding the impact of fiscal consolidation measures. One particular element to be considered was the binding zero lower bound on nominal interest rates that rendered the European Central Bank with no (conventional) monetary policy. Evidence from Christiano et al. (2011) show that, using a dynamic stochastic general equilibrium (DSGE) model, an economy in a liquidity trap can have multipliers above 3. Further evidence is provided by Woodford (2011) using a new Keynesian DSGE model. The author found that, in the presence of a zero lower bound,[6] multipliers can rise well above 1.

Thus, not only the economic context in general was prone to higher-than-normal multipliers, but also countries faced different levels of income inequality. Then, it becomes important to investigate whether those differences in income inequality, in the context of fiscal consolidation, played any role on the size of the fiscal multiplier.

3 Inequality and Growth Forecast Errors

In this section, we present our model, explain the estimation procedure, describe the inequality measures used, and present our results. To do that, we start by presenting Blanchard and Leigh's (2013) model and their results. After that, we focus on a model that explicitly includes income inequality as a regressor, and present our baseline estimation results while exploring different relations between income inequality and the fiscal multiplier.

3.1 Model Specification and Data

Our work investigates whether countries with higher levels of income inequality before the crisis,

[6] In fact, as mentioned in Woodford (2011), it only matters that the policy rate be at a level that the central bank is unwilling to go below. The "effective lower bound" need not be zero.

jointly with fiscal consolidation measures, had higher-than-forecasted real GDP growth disappointments. We interpret growth forecast errors as higher-than-expected fiscal multipliers.

In order to study these relations empirically, we start by presenting the parsimonious model developed in Blanchard and Leigh (2013). We decompose the model in question in order to fully comprehend its meaning. Furthermore, when performing empirical analysis, this will make coefficient interpretation clearer, thus allowing us to better understand what the data describes.

The model tries to capture the essence of the forecasting models used by forecasters. It starts by assuming that real GDP growth can be expressed as the following equation:

$$\triangle Y_{i,t:t+1} = m_{i,t:t+1} \cdot \text{Forecast of } \triangle F_{i,t:t+1|t} + \delta_{i,t:t+1} \cdot X_{i,t-2|t} + u_{i,t:t+1}, \tag{1}$$

where $\Delta Y_{i,t:t+1}$ denotes cumulative (year-over-year) growth of real GDP in economy i - i.e., $(Y_{i,t+1}/Y_{i,t-1}-1)$. $\Delta F_{i,t:t+1|t}$ denotes the change in the general government structural fiscal balance in percent of potential GDP, and is used as a measure of discretionary fiscal policy.[7] Positive values of $\Delta F_{i,t:t+1|t}$ indicate fiscal consolidation, and negative values indicate fiscal stimulus. The resulting forecast is defined as f$\{F_{i,t+1} - F_{i,t-1}|\Omega_t\}$, where f denotes the forecast conditional on Ω_t, the information set available early in year t. $X_{i,t-2|t}$ represents other exogenous variables that could affect the real GDP growth during period t to t+1, such as government debt, structural fiscal balance, etc.[8] It is assumed that fiscal consolidation forecasts during period t to t+1 affect real growth through the fiscal multiplier $m_{i,t:t+1}$, and the exogenous controls affect it via $\delta_{i,t:t+1}$. The last term, $u_{i,t:t+1}$, is considered to be a zero mean random disturbance.

If forecasters assumed an economy represented by the model in equation (1) to perform their forecasts, their forecast in period t can be represented as the expected value of that equation, given the information available until that moment, Ω_t,

$$E_t[\triangle Y_{i,t:t+1}|\ \Omega_t] = \hat{m}_{i,t:t+1} \cdot \text{Forecast of } \triangle F_{i,t:t+1|t} + \hat{\delta}_{i,t:t+1} \cdot X_{i,t-2|t}, \tag{2}$$

where $\hat{m}_{i,t:t+1}$ and $\hat{\delta}_{i,t:t+1}$ are the estimated multipliers. Thus, by computing the difference between the observed and the forecasted real GDP growth, $\triangle Y^{obs}_{i,t:t+1} - E_t[\triangle Y_{i,t:t+1}|\ \Omega_t]$, Blanchard and Leigh

[7]As explained in the World Economic Outlook data appendix, "The structural budget balance refers to the general government cyclically adjusted balance adjusted for nonstructural elements beyond the economic cycle. These include temporary financial sector and asset price movements as well as one-off, or temporary, revenue or expenditure items. The cyclically adjusted balance is the fiscal balance adjusted for the effects of the economic cycle; see, for example, Fedelino et al. (2009).

[8]For the complete list of controls included in the empirical analysis of Blanchard and Leigh (2013), see footnote 11.

(2013) obtain the forecast error of real GDP growth. That is,

$$\begin{aligned}\text{Forecast Error of } \Delta Y_{i,t:t+1} \quad &= \quad m_{i,t:t+1} \cdot \text{Forecast of } \triangle F_{i,t:t+1|t} + \delta_{i,t:t+1} \cdot X_{i,t-2|t} + u_{i,t:t+1} \\ &\quad -(\hat{m}_{i,t:t+1} \cdot \text{Forecast of } \triangle F_{i,t:t+1|t} + \hat{\delta}_{i,t:t+1} \cdot X_{i,t-2|t}). \qquad (3)\end{aligned}$$

Rearranging the terms in (3) shows that the forecast error of real GDP growth can be represented as the difference between the actual multipliers and the estimated ones, plus a random disturbance,

$$\begin{aligned}\text{Forecast Error of } \Delta Y_{i,t:t+1} \quad &= \quad (m_{i,t:t+1} - \hat{m}_{i,t:t+1}) \cdot \text{Forecast of } \triangle F_{i,t:t+1|t} \\ &\quad +(\delta_{i,t:t+1} - \hat{\delta}_{i,t:t+1}) \cdot X_{i,t-2|t} + u_{i,t:t+1}. \qquad (4)\end{aligned}$$

Thus, aiming to investigate whether European countries registered higher-than-expected multipliers during the beginning of the crisis, Blanchard and Leigh (2013) test if forecasters systematically misspecified the impact of fiscal consolidation forecasts and other additional controls impacts' on real growth. They interpret systematic forecast errors made by professional forecasters as an indicator of higher- or lower-than-expected multipliers. The authors propose the following empirical strategy:

$$\text{Forecast Error of } \Delta Y_{i,t:t+1} = \alpha + \beta \text{ Forecast of } \triangle F_{i,t:t+1|t} + \gamma\, X_{i,t-2|t} + \varepsilon_{i,t:t+1}. \qquad (5)$$

This equation relates growth forecast errors with fiscal consolidation forecasts and other lagged controls, plus a random disturbance. The coefficients of fiscal consolidation forecasts and other controls indicate the average growth forecast error associated with each additional unit of fiscal consolidation forecasts and other lagged controls, respectively. The β and γ coefficients allow to investigate, for a given period of time, if countries with higher levels of fiscal consolidation forecasts or other controls, respectively, were systematically related with positive or negative growth forecast errors

In order to test the above relationship in the beginning of the crisis, growth forecast errors are calculated for the period 2010-11 as the difference between actual cumulative real GDP (year-over-year) growth, based on the latest (October 2014 WEO) data, minus the forecast prepared early in the crisis (April 2010 WEO). The forecast of the change in the structural fiscal balance as a percentage of potential GDP is also during 2010-11, taken from the April 2010 WEO. The results are obtained using all European Union's 27 member states, plus Iceland, Norway, and Switzerland. However, since WEO forecasts of the structural fiscal balance are not available for Estonia, Latvia, Lithuania, and Luxembourg, the sample only includes the remaining 26 European economies.[9]

If the model was correctly specified and assuming rational expectations, estimation of equation (5) should yield coefficients not statistically different from zero of fiscal consolidation forecasts and other lagged controls. The zero coefficients would indicate that forecasters did not consistently over- or underestimated the value of their forecast during the period 2010-11, which suggest forecast efficiency. On the other hand, if the obtained coefficients were higher or lower than zero, this would suggest that forecasters systematically over- or underestimated the contractionary effect of the regressors included, respectively. This, in turn, would suggest that forecasters did not efficiently incorporate past information into their information set (Nordhaus, 1987).

In fact, Blanchard and Leigh (2013) did find statistically significant estimates of β around -1.2 during 2010-11, and no significant estimates of γ irrespectively of the control used.[10] Thus, according to equation (4), the results provided evidence that the real impact of each additional percentage point of GDP of fiscal consolidation forecasts on real growth, $\triangle Y_{i,t:t+1}$, was underestimated by forecasters, on average, by -1.2 points. I.e., the actual fiscal multiplier of the 26 European economies included in the sample during the early years of the crisis, $m_{2010-11}$, can be expressed as the sum of the estimated multiplier, $\hat{m}_{2010-11}$, and the average underestimation,

$$m_{2010-11} = \hat{m}_{2010-11} + 1.2. \tag{6}$$

One should notice that the actual values of the fiscal multiplier, $m_{2010-11}$ (as well as the ones estimated by forecasters, $\hat{m}_{2010-11}$), cannot be obtained with the framework developed above. In order to calculate the value of $m_{2010-11}$, one needs to obtain a measure of a fiscal shock that is uncorrelated with other economic developments. This ensures that the estimated coefficient reflects solely the causal effect of the fiscal policy on growth, and not the response of growth on fiscal policy (through, for example, automatic stabilizers). In the multipliers literature, this is called the identification problem of

[9]The 26 European economies included are Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Iceland, Italy, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom.

[10]In fact, the work of Blanchard and Leigh (2013) reports an estimate of β of -1.095 (t-statistic $= -4.29$) when no additional controls are included (i.e., excluding $X_{i,t-2|t}$ from (5), since all of these yield non-significant coefficients, and their inclusion has no sizable impact on the estimation of coefficients). However, their estimates are computed relative to October 2012 WEO data, the last database available at the time of their publication. When we perform the same exercise using the most up-to-date database (October 2014 WEO), we find an estimate of β of -1.191 (t-statistic $= -3.85$), i.e., a slightly greater estimate of that coefficient.

fiscal policy. The framework does, however, provide evidence of systematic miscalculation of forecasted fiscal multipliers versus actual multipliers.

As mentioned, the authors investigated the possibility of having other variables - plausibly related to fiscal consolidation forecasts and lower-than-expected growth - driving the results. The omission of such variables could bias the analysis toward finding that multipliers were larger than assumed. The variables in question are the countries' debt ratio, their fiscal balance, their current account balance, etc.[11] However, given that the authors were interested in the causal effect of each of those variables on growth forecast errors, and the variables are most likely endogenous in the above specification, the authors included lagged (i.e., pre-crisis) values in equation (5). Nevertheless, none of the variables included produced a statistically significant coefficient, nor they virtually changed the fiscal consolidation estimation results.

There is, however, a group of controls that could potentially affect the growth forecast errors that was not considered by Blanchard and Leigh (2013) - measures of income distribution among the European economies. As mentioned in section 2, there are various channels through which countries with higher levels of income heterogeneity can have higher multipliers. Specifically, given the multiyear fiscal consolidation plans undertaken in 2010, it is possible that countries with higher levels of income inequality registered higher growth forecast errors (in absolute terms) due to its impact on the fiscal multiplier.

Thus, we now investigate if, in fact, income inequality affected the size of the fiscal multiplier of European countries during the beginning of the crisis.

3.2 The Role of Inequality on Fiscal Multipliers

We start by describing the income inequality measures used, and then we present the estimation results of a model that explicitly accounts for income inequality.

3.2.1 Income Inequality Measures and Data

We use the European Union Statistics on Income and Living Conditions (EU-SILC) data in order to compute various measures of income inequality for the baseline results.[12] This dataset contains

[11] The complete list of variables included as controls by Blanchard and Leigh (2013) is: pre-crisis (2009) debt ratio, fiscal balance, structural fiscal balance, sovereign CDS, bank CDS, and a dummy for banking crisis as in Laeven and Valencia (2012). Additionally, the authors included the pre-crisis (2009) initial growth forecast, potential growth forecast, and for the 2007 current account balance, net foreign liabilities, household debt, and trading partners fiscal consolidation.

[12] We only use the EU-SILC dataset in this section because of unavailability of comparable data from other sources, and/or for the period we are interested in. For example, the World Bank calculates the Gini index and the Quantile ratios using both income and consumption inequality in their calculations. This renders inequality measures not comparable

comparative statistics on income distribution in the European Union, collected via a harmonized framework among the various member states. This ensures the comparability of inequality measures across countries. The EU-SILC is also the most complete dataset available for European economies for the economies and years studied.

In order to have a clear picture about the income distribution, and tackle the inherently difficult task of measuring inequality, we create diverse measures of income inequality using EU-SILC dataset. Namely we construct the Quartile ratio (share of top quartile to the first quartile), Quintile ratio, Decile ratio, 5^{th} Percentile ratio, Palma ratio[13], and the Gini coefficient of equivalised disposable income.[14]

The various measures of income inequality aim to provide a better description of the income distribution among the European countries analyzed. Listings 1 and 2 provide the lists of inequality measures used for years 2008 and 2009, respectively. It also includes the values of other variables used in the estimation of the baseline results.

3.2.2 The Model With Income Inequality

In order to investigate if inequality affected the size of the fiscal multiplier, we turn to the model specified in subsection 3.1, and change the specification of the fiscal multiplier to be related with inequality. After the fiscal multiplier being specified, we modify equation (5) in order to have a framework that allows us to obtain testable hypothesis about the role of inequality on fiscal multipliers.

We start by specifying a fiscal multiplier, $m_{i,t:t+1}$, linearly related to inequality. For concreteness, consider

$$m_{i,t:t+1} = \nu_{i,t:t+1} + \rho_{i,t:t+1}\text{Income Inequality}y_{i,t-2|t}, \tag{7}$$

where both $\nu_{i,t:t+1}$ and $\rho_{i,t:t+1}$ are constants. This specification for the fiscal multiplier implies that fis-

across countries. Additionally, the dataset only includes 11 inequality observations for the year 2008, and 5 observations for the year 2009 for the sample of countries we are analyzing. Similarly, the Luxembourg Income Study Database (LIS), despite using a harmonized framework that ensures cross country comparability of inequality measures, is only available for a very limited number of economies and years. We do, however, perform a robustness test in section 4 using the Standardized World Income Inequality Database.

[13] The Palma ratio, named after the work of the economist Gabriel Palma (2011), consists of the ratio of the top decile to the four bottom deciles. This measures was created after Palma's observation that while the deciles 5 to 9 (the "middle class") tend to capture about 50% of national income on a cross countries basis, the other half of national income varies considerably across countries between the richest 10% (top decile) and the poorest 40% (four bottom deciles).

[14] Unless otherwise specified, Gini measures always refer to the Gini coefficient of equivalised disposable income (i.e., obtained using after taxes and transfers data).

In order to calculate the households' disposable income, the EU-SILC takes into account that the needs of a household grow less than proportionally with each additional member. This happens because of economies of scale in consumption of housing space, electricity, etc. Thus all disposable income measures are equivalised using the "OECD-modified scale", which gives a weight of 1.0 to the first adult, a weight of 0.5 to other household members aged 14 or over, and a weight 0.3 to other household members aged 13 or less.

cal policy affects real growth through an autonomous component, $\nu_{i,t:t+1}$, plus a component dependent on the income inequality level, $\rho_{i,t:t+1}$. Using this specification, we change equation (4) accordingly to obtain:[15]

$$\begin{aligned} \text{Forecast Error of } \Delta Y_{i,t:t+1} \quad = \quad & (\nu - \hat{\nu}) \cdot \text{Forecast of } \triangle F_{i,t:t+1|t} + (\delta - \hat{\delta}) \cdot \text{Income Inequality}_{i,t-2|t} \\ & +(\rho - \hat{\rho}) \cdot \text{Forecast of } \triangle F_{i,t:t+1|t} \cdot \text{Income Inequality}_{i,t-2|t} \\ & +\varepsilon_{i,t:t+1.} \end{aligned} \tag{8}$$

Note that the fiscal multiplier is assumed to be related with pre-crisis levels of income inequality, rather than contemporaneous levels. The reason is that income inequality is most likely an endogenous variable in equation (8). On the one hand, higher income inequality can be the *result* of lower-than-expected growth via, for example, lower redistributive policies. On the other hand, higher income inequality can be the *cause* of lower growth through, for example, one of the channels previously mentioned, such as a higher share of liquidity constrained households. Thus, we follow Blanchard and Leigh (2013) and deal with this potential endogeneity by lagging the variables. Specifically, we use both 2008 and 2009 as pre-crisis years of income inequality.[16]

In order to test whether income inequality had any effect on the size of fiscal multipliers during the crisis, and following the spirit of the empirical model presented on (5), we perform the following OLS regression:

$$\begin{aligned} \text{Forecast Error of } \Delta Y_{i,t:t+1} \quad = \quad & \alpha + \beta \text{ Forecast of } \Delta F_{i,t:t+1|t} + \gamma \text{ Income Inequality}_{i,t-2|t} \\ & +\eta \text{ Forecast of } \Delta F_{i,t:t+1|t} \cdot \text{Income Inequality}_{i,t-2|t} \\ & +\upsilon_{i,t:t+1}. \end{aligned} \tag{9}$$

This model consists of the estimation of equation (5) using pre-crisis income inequality as a control, augmented with the interaction between fiscal consolidation and lagged income inequality. The resulting estimates of β can be interpreted as the average forecast error caused by each additional

[15] The included controls, $X_{i,t-2|t}$, are pre-crisis levels of income inequality. Also, the indexes on ν and ρ are suppressed in order to make the equations more easily readable.

[16] In practice, using both 2008 and 2009 for pre-crisis years of inequality translates into using income inequality for both years $t-2$ and $t-1$. However, for simplicity and consistency, we only write income inequality for year $t-2$.

percentage point of GDP of fiscal consolidation *when* Income $\text{Inequality}_{i,t-2|t}$ *is zero.* This coefficient is not very illustrative since episodes of perfect income equality are very atypical.

On the other hand, γ is an estimate of the average forecast error caused by each additional point of pre-crisis inequality *when* Forecast of $\Delta F_{i,t:t+1|t}$ *is zero.*[17] This coefficient allows to investigate if countries with higher levels of income inequality registered higher-than-expected multipliers during 2010-11 other than through the fiscal multiplier.

Finally, estimates of η measure the average forecast error caused by each additional point of pre-crisis income inequality *and* fiscal consolidation. This is the most interesting coefficient in our specification since it allows us to test whether countries with higher inequality had, in fact, higher growth downfalls during their fiscal austerity plans. Negative values of η provide evidence that forecasters underestimated the impact of inequality on fiscal multipliers.

Given the specification of the fiscal multiplier in equation (7), we can write an expression for the (average) true fiscal multiplier as:

$$m_{2010-11} = (\hat{\nu}_{2010-11} - \beta) + (\hat{\rho}_{2010-11} - \eta) \cdot \text{Income Inequality}_{i,t-2|t}. \tag{10}$$

The multiplier can thus be expressed as the sum of the forecasted components, minus their average estimation "error". Specifically, the true fiscal multiplier during 2010-11 can be expressed as the sum of two components: the forecast of the autonomous component of the fiscal multiplier, $\hat{\nu}_{2010-11}$, minus the β coefficient estimated in equation (9), and the estimated inequality-dependent component, $\hat{\rho}_{2010-11}$, minus the estimated η coefficient, adjusted for the country-specific level of inequality.

Recall that, according to equation (7), we are assuming a fiscal multiplier that depends on income inequality. I.e., we are assuming that the impact of fiscal policy on real growth may be affected by the level of income inequality. Thus, the above equation is an extension of equation (6) that separates the effects that influence the size of the fiscal multiplier into two components. One component, $(\hat{\nu}_{2010-11} - \beta)$, captures the impact of fiscal policy on real growth that does not depend on inequality (i.e., when income inequality is equal to zero). The other component, $(\hat{\rho}_{2010-11} - \eta)$, captures the impact of fiscal

[17] In order to understand this point, one should take the partial derivative of Forecast Error of $\Delta Y_{i,t:t+1}$ with respect to Forecast of $\Delta F_{i,t:t+1|t}$ and Income $\text{Inequality}_{i,t-2|t}$, respectively. Since the partial effect of the Forecast of $\Delta F_{i,t:t+1|t}$ on the Forecast Error of $\Delta Y_{i,t:t+1}$ (while holding income inequality constant) is given by

$$\frac{\partial E(\text{Forecast Error of } \Delta Y_{i,t:t+1})}{\partial \text{Forecast of } \Delta F_{i,t:t+1|t}} = \beta + \eta \text{ Income Inequality}_{i,t-2|t},$$

the value of β can be interpreted as the partial effect of fiscal consolidation on the Forecast Error of $\Delta Y_{i,t:t+1}$ *when* Income $\text{Inequality}_{i,t-2|t}$ *is zero.* The same reasoning applies to the partial effect of income inequality on the Forecast Error of $\Delta Y_{i,t:t+1}$.

policy on real growth that is dependent on income inequality. Consequently, since this component is assumed to depend on inequality, we need to adjust for the country-specific level of inequality. Hence, we multiply it for the level of inequality.

3.3 Baseline Results

The OLS estimation results for the period 2010-11 are presented in Tables 1 and 2.[18] Our empirical model suggests a statistically significant negative relation between the interaction term (Forecast of $\Delta F_{i,t:t+1|t} \cdot \text{Income Inequality}_{i,t-2|t}$) and growth forecast errors. The results hold for various measures of income inequality, with the interaction coefficient varying considerably in size, depending on the inequality measure used. Regarding statistical significance, the results obtained are highly significant for most inequality measures used for the pre-crisis year 2008, with most p-values below 1 percent.

However, before proceeding, it is important to review the meaning of the t-statistics and resulting p-values of the interaction term. Contrary to the coefficients obtained with Forecast of $\Delta F_{i,t:t+1|t}$ and Income $\text{Inequality}_{i,t-2|t}$ individually, one cannot infer about its statistical relevance using its individual significance. Because income inequality enters the model via an interaction term, its marginal effect on growth forecast errors are conditional on the fiscal consolidation forecasts. As a result, the marginal effect of income inequality on growth forecast errors can be significant for substantially relevant values of fiscal consolidation forecast, even if the coefficient on the interaction term is insignificant.[19] Thus, in order to infer about the relevance of including the interaction term in the model, one should first calculate the standard error of the marginal impact of income inequality on growth forecast errors. Alternatively, one could also plot the marginal effect of inequality on growth forecast errors for different values of fiscal consolidation forecast. This way, it is possible to visually check if the estimated confidence intervals are above or below zero at any region of the graph. If they are, that provides evidence that under such values of fiscal consolidation, the marginal impact of inequality on growth forecast errors is statistically significant at the given confidence level.

As mentioned, the coefficients vary considerably in size, depending on the inequality measure used. The highest values of the interaction coefficient are obtained using the Palma Ratio, with a coefficient of -3.020 and -3.282 for the pre-crisis years of 2008 and 2009, respectively. The lowest values of

[18] Throughout the paper, all forecast errors are computed relative to the latest (October 2014 WEO) dataset. Also, the reported statistical inference is based on heteroskedasticity-robust standard errors. All the confidence intervals are calculated using the conventional 95% confidence level.

[19] For a deeper discussion about the interpretation of interaction terms on econometric models, see Brambor et al. (2006).

interaction are obtained with the Gini coefficient for the year 2008 (with an estimate of -0.165), and with the Decile ratio for the year 2009 (estimate of -0.087).

The estimated coefficients of Income Inequality$_{i,t-2|t}$, γ, are not significantly different from zero. These results hold for all the measures of income inequality included, and for both pre-crisis years. As explained before, the zero coefficient of pre-crisis income inequality on growth forecast errors provides evidence that its impact on growth *when there are no fiscal policy* was not misspecified. I.e., excluding the impact via the fiscal multiplier, pre-crisis income inequality does not impact on growth beyond forecasted.

The coefficients of Forecast of $\Delta F_{i,t:t+1|t}$ display positive but mostly insignificant results. The statistical significance is dependent on the inequality measure used, and it varies from the 2008 to the 2009 specification. One must, however, recall that this coefficient measures the average forecast error caused by each additional percentage point of GDP of fiscal consolidation *when* Income Inequality$_{i,t-2|t}$ *is zero.* Thus, given that episodes of complete absence of income inequality are logically irrelevant, we find this coefficient very little informative.

Since the marginal impact of income inequality on fiscal multipliers varies with the amount of fiscal consolidation, we use a graph to depict how much that impact changes for different values of fiscal consolidation forecasts. Figures 1 and 2 present the marginal effect of pre-crisis income inequality using both pre-crisis years (2008 and 2009), where the dashed lines represent the 95% confidence interval. From the graphs it is possible to assert that the marginal impact of pre-crisis income inequality increases (in absolute terms) the forecast error of real growth the higher the fiscal consolidation measures. Thus, higher levels of fiscal consolidation are associated with more negative growth forecast errors via the impact of higher income inequality. According to the framework developed above, this provides evidence that pre-crisis income inequality increased the size of the fiscal multiplier during 2010-11.

Complementary to Blanchard and Leigh's (2013) conclusions, by obtaining simultaneously a negative estimate of the interaction term and a zero coefficient of income inequality, our results suggest that forecasters did not underestimate the impact on growth of fiscal consolidation *per se.* Instead, they suggest that forecasters underestimated the consequences of heterogeneity of agents during fiscal austerity. In conclusion, the obtained results provide evidence that, in fact, the distribution of income within each European country played an important role on how contractionary were the fiscal consolidation measures during the recent crisis.

Thus, once the level of heterogeneity of agents - which in our reduced form model is represented by inequality - is taken into account, the source of misspecification becomes clearer. Economies with more heterogeneous agents suffered higher growth forecast errors during their fiscal consolidation efforts. This, according to our specification, provides evidence of higher fiscal multipliers as a result of income inequality.

3.4 Is the Relation Between Inequality and Fiscal Multipliers Linear?

We now turn to the specific relation between income inequality and the fiscal multiplier. Until now we have assumed a linear relation between inequality and the multiplier. This was clear by the specification presented on equation (7). But is the marginal impact of inequality on the size of the multiplier really constant (as a result of a linear relationship), or does the marginal impact of income inequality on the multiplier increase/decrease with the amount of inequality?

In order to test this hypothesis, we start by defining a multiplier related to inequality in a non-linear fashion, specifically in a quadratic form:

$$m_{i,t:t+1} = \nu_{i,t:t+1} + \rho_{i,t:t+1}\text{Income Inequality}_{i,t-2|t} + \sigma_{i,t:t+1}\text{Income Inequality}^2_{i,t-2|t}. \tag{11}$$

where $\nu_{i,t:t+1}$, $\rho_{i,t:t+1}$, and $\sigma_{i,t:t+1}$ are constants. This particular specification relates fiscal policy with real growth via an autonomous component, a component dependent on inequality, and a newly added component dependent on squared inequality, aiming to capture its non-linear behavior.

After modifying equation (4) to include this multiplier specification, and still using lagged inequality as a control, it is possible to empirically test this model according to the following framework:

$$\begin{aligned}
\text{Forecast Error of } \Delta Y_{i,t:t+1} \quad = \quad & \alpha + \beta \text{ Forecast of } \Delta F_{i,t:t+1|t} + \gamma \text{ Income Inequality}_{i,t-2|t} \\
& + \eta \text{ Forecast of } \Delta F_{i,t:t+1|t} \cdot \text{Income Inequality}_{i,t-2|t} \\
& + \kappa \text{ Forecast of } \Delta F_{i,t:t+1|t} \cdot \text{Income Inequality}^2_{i,t-2|t} \\
& + \upsilon_{i,t:t+1}.
\end{aligned} \tag{12}$$

The additional interaction term with squared inequality aims to capture decreasing or increasing marginal effects of inequality on growth forecast errors. Values of the κ coefficient different from zero suggest the existence of non-linear forces between inequality and its impact on the size of the fiscal multiplier. Specifically, negative values of the κ coefficient indicate that forecasters, on average, underestimated more than proportionally the impact of higher levels of income inequality on growth forecast errors. This, in turn, suggests that the marginal effect of income inequality on the size of the fiscal multiplier increases with the level of inequality. The opposite goes for positive values of the κ coefficient.

Given this specification, we present how to calculate the marginal impact of income inequality:

$$\begin{aligned}\frac{\partial E(\text{Forecast Error of } \Delta Y_{i,t:t+1})}{\partial \text{Income Inequality}_{i,t-2|t}} \quad = \quad & \gamma + \eta \text{ Forecast of } \Delta F_{i,t:t+1|t} \\ & +2\ \kappa \text{ Forecast of } \Delta F_{i,t:t+1|t} \cdot \text{Income Inequality}_{i,t-2|t}. \quad (13)\end{aligned}$$

The results of the OLS estimation of equation (12) are presented in Tables 3 and 4. The coefficient that includes the squared inequality, κ, has a negative sign for the majority of income inequality measures used. The negative sign provides evidence that income inequality causes marginally higher-than-expected growth downfalls for higher levels of income inequality. The results, however, display different levels of statistical significance, depending on the income inequality measure used and, mostly, on the pre-crisis year of inequality. Nevertheless, recall that one cannot infer about the relevance of the interaction terms simply by looking at the significance of the coefficients on the interaction terms.

Since, according to our specification, the marginal effect of income inequality on growth forecast errors - and, thus, on the fiscal multiplier - is dependent upon the levels of income inequality itself and fiscal consolidation, we present a three-dimensional graph to analyze the obtained results. Figures 3 and 4 present the graphs for the different measures of income inequality and for both pre-crisis years.[20]

As the graphs depict, higher levels of income inequality jointly with higher levels of fiscal consolidation forecasts increase the size of the marginal impact of inequality on growth forecast errors. The marginal impact of income inequality varies considerably with the inequality measure used. The results are robust to most income inequality measures used,[21] and for both pre-crisis years of income inequality. In conclusion, these results provide evidence that an increase of one unit of pre-crisis income

[20] The graphs are constructed to display the marginal effect of income inequality on the growth forecast error according to *reasonable* values of fiscal consolidation forecast and income inequality. Those *reasonable* values are constrained between the maximum and minimum values of both fiscal consolidation forecasts and income inequality among the 26 European economies studied, and for the years analyzed.

[21] The exception being the 5^{th} Percentile ratio and Decile ratio for the pre-crisis years 2008 and 2009, respectively. The results obtained exceptionally suggest that the marginal impact of income inequality on growth forecast errors actually decreases with inequality.

inequality had a stronger marginal impact on the size of fiscal multipliers the higher the initial value of income inequality.

But which of the models considered (linear versus non-linear) explains better the data? The R-squared does not answer this question since the linear model of equation (9) is nested on the non-linear model of equation (12). This implies that the R-squared of the non-linear model will be necessarily higher than the R-squared obtained with model (9) given the extra regression term. This way, we look at the Adjusted R-squared, which penalizes the extra number of regressors, to compare both models.

The Adjusted R-squared between the linear and non-linear models are not very different for both pre-crisis years of income inequality. Even though it is higher for non-linear models using most income inequality specifications, the difference cannot be considered very significant. These results, in turn, suggest that the non-linear component of income inequality adds little information explaining the data.

4 Robustness Tests

We now determine the validity of the obtained results by performing some robustness tests. The results reported by Blanchard and Leigh (2013) suggest that countries with larger planned fiscal consolidation had, on average, larger growth disappointments during 2010-11. These results hold after a) controlling for different groups of economies and limiting the influence of potential outlier observations, and b) adding control variables to the equation that could plausibly have both affected the growth forecast error and been correlated with fiscal consolidation. The authors also find that the relation does not hold for forecasts made in more normal times (1997-2008), as one would expect.

In our baseline specification developed on subsection 3.2, the results show that countries with higher levels of pre-crisis income inequality in the context of fiscal consolidation reported, on average, higher real GDP growth declines during the crisis. This is, according to the framework presented, evidence that inequality increased the size of the fiscal multiplier during 2010-11. Thus, in order to determine the validity of our results, we now perform some robustness checks. Specifically, we perform the same tests as in Blanchard and Leigh (2013), plus an additional test with a different source of income inequality measures.[22]

[22]Ideally, one extra robustness test would be performed - estimation of equation (9) with wealth and consumption (rather than income) inequality data. Those different inequality definitions measure different aspects of inequality. Thus it would be interesting to study whether the baseline results still hold when we define inequality in a different manner. However, to our knowledge, there are no standardized source of consumption inequality measures among European economies, and the only source of comparable wealth inequality is provided by the Luxembourg Income Study Database (LIS). But given the very reduced number of observations available for European economies (only Austria, Cyprus, Finland, Germany, Italy, Norway, Sweden, and the United Kingdom), we do not present the results.

4.1 Using Different Economies and Their Sensitivity to Outliers

We start by investigating whether the obtained results change if the countries included in the sample also change. As mentioned earlier, the WEO dataset did not have available forecasts for the structural fiscal balance available of four EU member states - Estonia, Latvia, Lithuania, and Luxembourg. Thus we first re-estimate our results replacing those four missing observations with European Commission forecasts. The results are presented in Tables 5 and 6.

The estimated coefficients are virtually unchanged, and yield the same conclusions as the baseline model specified in equation (9). More specifically, the interaction term between pre-crisis income inequality and fiscal consolidation forecasts is still negative, irrespectively of the income inequality measure used, and the coefficient of income inequality on growth forecast errors is still statistically non different from zero. These results provide additional evidence that income inequality affected growth forecast errors through its impact on the fiscal multiplier.

Then, we test the sensitivity of the results to countries with the largest interaction (in absolute terms) of fiscal policy change forecast and income inequality. The two countries with the highest absolute values of both fiscal policy change and income inequality are Germany and Greece, irrespectively of the inequality measure used and the pre-crisis year (2008 or 2009).[23] The results are presented in Tables 7 and 8. As expected, the obtained coefficients of interaction decrease in size. However, the obtained results still conserve the negative sign of interaction, and the zero coefficient of income inequality when there are no fiscal consolidation forecasts. The income inequality measure that yield the highest impact on growth forecast errors (in absolute terms) is still the Palma ratio, with an interaction coefficient of -1.764 and -1.908 for the pre-crisis years of 2008 and 2009, respectively. The lowest interaction coefficients are obtained with the Gini measure of inequality. Its estimated coefficients are -0.094 for 2008 and -0.090 for 2009.

As an additional test, we check the sensitivity of the results by excluding the economies under IMF assistance programs during 2010-11. Given the nature of IMF assistance programs to lend money to countries in severe financial trouble, it is likely that those countries had a relatively high fiscal consolidation forecasts and, perhaps, high levels of income inequality. The countries in question are Portugal, Greece, Ireland, Iceland, and Romania. In fact, this group of countries registered relatively higher levels of both fiscal consolidation forecasts and inequality in the beginning of the crisis.

[23]Denmark is an exception by standing as the country with a higher interaction of forecast of fiscal policy change forecast and income inequality measured by the Decile ratio during 2009, with a value of -22.32 (the negative result is caused by the negative fiscal consolidation - i.e., positive fiscal stimulus - incurred by Denmark during 2010-11). Nevertheless, Germany registered a close value for the interaction measured by the Decile ratio during 2009 of -18.75.

The resulting OLS estimations are presented in Tables 9 and 10. The results hold for all 2008 measures of income inequality, with a negative estimated interaction coefficient, and a zero coefficient for income inequality individually. However, the estimated coefficients produce positive interaction coefficients when we include 2009 measures of income inequality. These results suggest that income inequality levels in European economies (excluding the ones under IMF assistance programs during 2010-11) changed from 2008 to 2009 in a way that rendered its relationship with fiscal multipliers less clear.

We also re-estimate our results excluding from the sample the four economies classified as "emerging" in the WEO database. Those economies are Bulgaria, Hungary, Poland, and Romania. See Tables 11 and 12 for the results. Once again, our baseline results are robust to the exclusion of the four emerging economies of our dataset.

Next, we apply different estimation strategies constructed to resist the influence of potential outliers. The first method employed is a robust regression, which down-weights observations with larger absolute residuals using iterative least squares. By down-weighting influential outliers, this estimation procedure is less influenced by them than ordinary least squares (OLS) estimations. The estimated coefficients are presented in Tables 13 and 14. We can assert that our baseline conclusions were not being driven by outliers, given that the estimated coefficients are very similar to the ones estimated using OLS. Then, the same exercise is performed but using a quantile regression approach. This estimation procedure minimizes the sum of the absolute residuals about the median, rather than about the mean as in OLS. This makes the estimates less affected by outliers. The estimation results are presented in Tables 15 and 16. The results still hold using this estimation procedure, with more sizable coefficients being obtained with pre-crisis year 2008.

As a last robustness check,[24] we re-estimate our results using Cook's distance method. Specifically, we re-estimate our results deleting observations with a Cook's distance greater than $4/N$, where N is the sample size. The results are presented in Tables 17 and 18, and, once again, show that our baseline results were not being driven by the influence of outliers.

[24] Given that there are no harmonized inequality data collected for the additional 10 advanced economies listed in the WEO database that ensures comparability across countries, we cannot investigate whether the inclusion of those additional advanced economies influenced the obtained results. However, as Blanchard and Leigh (2013) mention, most of the additional economies - namely Australia, Hong Kong SAR, Israel, Korea, New Zealand, Singapore, and Taiwan Province of China - did not face a liquidity trap during 2010-11, which reduces the chances of higher-than-expected multipliers.

4.2 Controlling for Other Variables

We now test the robustness of our results in a different dimension. Specifically, we test if the obtained results were being driven by some other factors that could plausibly have affected both the interaction of inequality with fiscal consolidation and lower-than-expected growth.

In order to test for this, we extend our model developed in subsection 3.2 to include an additional control variable. This way, if the obtained results still hold after the inclusion of these additional variables that could possibly affect the interaction of inequality with fiscal consolidation and lower-than-expected growth, we have evidence that those additional factors were not driving the results.

The control variables included in our specification are all pre-crisis levels (2008 and 2009). The reason is that we are interested to know if forecasters underestimated the causal effect of some factors - other than the interaction of inequality with fiscal consolidation forecasts - on growth. However, if we include those variables during 2010-11 in our estimations, the coefficients obtained do not measure such causal effect since the variables suffer from endogeneity - i.e., they can simultaneously be the *cause* and the *result* of lower-than-expected growth. Thus, in order to obtain the causal effect of those controls on growth, we use pre-crisis values. This way, we ensure that the estimation only captures the causal effect of controls on growth.

In order to ensure that the variables were included in the forecasters' information set, we use the same dataset as the fiscal consolidation forecasts - the April 2010 WEO. We start by including backward-looking measures of fiscal accounts, such as the pre-crisis government-debt-to-GDP ratio, pre-crisis fiscal-balance-to-GDP ratio, and the pre-crisis structural fiscal-balance-to-GDP ratio. The results (not shown) are virtually unchanged when those fiscal measures are included as controls. The results hold for pre-crisis years 2008 and 2009 of both inequality and controls. The results are also robust when we include the average five-year sovereign credit default swap (CDS) spread in the first quarter of 2009 and 2010.

Next, we check whether larger-than-expected financial sector stress are driving the results. Thus we control for pre-crisis bank CDS spread, and for a dummy variable indicating a systemic banking crisis, as identified by Laeven and Valencia (2012). The results remain unchanged, thus providing evidence that financial sector developments were not driving the baseline results.

Lastly, we also control for the trade-weighted fiscal consolidation of other countries (scaled by the share of exports in GDP, given that fiscal consolidation by trading partner countries may be driving the results), and the pre-crisis (2006 and 2007) current-account-deficit-to-GDP-ratio, net foreign liabilities in percentage of GDP, and the household-debt-to-disposable-income-ratio. The results to all these robustness checks suggest that our baseline estimations were not being biased by the exclusion of these control variables.

4.3 Using Different Forecast Vintages

The work developed until now focused on forecasts produced in early 2010, when a number of large fiscal consolidation plans were announced. However, as mentioned in Blanchard and Leigh (2013), it is worth analyzing whether the results also hold for forecasts made in other years. Specifically, it is important to test if the results hold for forecasts produced in more normal times (1997-2008). Thus we now investigate whether the interaction term of lagged income inequality and fiscal consolidation forecasts still has a negative impact on growth forecast errors using forecasts made in more normal times. As stated before, forecast efficiency requires forecast errors not to be systematically related to any of the regressors. So, our expectation is that the interaction term coefficient should be around zero for these different forecast vintages.

The empirical strategy now consists in including a set of two-year intervals during the pre-crisis decade (1997-2008) together in a panel. We follow Blanchard and Leigh (2013) and write the equation as:

$$\begin{aligned}\text{Forecast Error of } \Delta Y_{i,t:t+1} \quad = \quad & \alpha + \lambda_t + \beta \text{ Forecast of } \Delta F_{i,t:t+1|t} + \gamma \text{ Income Inequality}_{i,t-2|t} \\ & +\eta \text{ Forecast of } \Delta F_{i,t:t+1|t} \cdot \text{Income Inequality}_{i,t-2|t} \\ & +\upsilon_{i,t:t+1}. \end{aligned} \tag{14}$$

This equation is simply our equation (9) augmented with a vector of time-fixed effects, λ_t, where t = 1997, 1998, ..., and 2008. Since we are using two-year overlapping intervals, we use the Newey-West procedure to correct for MA(1) serial correlation. Once again, the exercise is performed for various measures of income inequality, and the estimation now includes 139 observations for most income inequality specifications. Recall that we are using lagged income inequality in order to ensure that causality runs from inequality to growth forecast errors.

The estimations results are presented in Table 19. As we expected, the coefficient of the interaction term is very close to zero for the panel regression obtained with pre-crisis decade data. These results hold for the various measures of income inequality included in the sample, with coefficients varying from -0.005 using the Quartile ratio to 0.330 using the Palma ratio.

On the one hand, these results suggest that, in fact, during normal times, forecasters did use the correct model specification in their forecasts. As a result, growth forecast errors were not systematically related with the interaction of lagged income inequality and fiscal consolidation forecasts during the pre-crisis decade. One the other hand, given the systematic and consistent growth forecast errors made by forecasters in the beginning of the crisis (2010-11), this test provides an extra robustness check that, in fact, the uncertainty regarding the size of the fiscal multipliers was exceptionally high during that period. As a result, forecasters systematically underestimated the impact of fiscal consolidation measures on real growth. According to our particular framework, the results suggest that one of the channels through which fiscal consolidation measures impacted on growth was via the distribution of income.

4.4 Using a Different Source of Income Inequality Data

We also test the robustness of our results using a different inequality dataset. Specifically, we use data from the Standardized World Income Inequality Database (SWIID) for the same 26 European economies. Even though this dataset relies solely on Gini measures of income inequality, it maximizes the comparability of available data for the broadest possible sample of countries and years (Solt, 2009). Interestingly, this dataset introduces two different Gini measures - one calculated using household disposable income (similarly to the one we used with the EU-SILC dataset), and another using household market income (i.e., pre-tax and pre-transfer).

Thus we re-estimate equation (9), but this time using inequality data from the SWIID dataset. The resulting estimation output is presented in Table 20 for both 2008 and 2009 inequality measures. The graphs depicting the marginal impact of income inequality on growth forecast errors are presented in Figures 5 and 6.

The estimated results showed in the first and third columns in Table 20 display a negative relation between the interaction term and growth forecast errors. These results are obtained with an interaction term composed by the pre-crisis disposable income Gini and fiscal consolidation forecasts. The results hold for both 2008 and 2009 pre-crisis years of income inequality. Additionally, the estimated coefficients are very similar to the ones estimated with the Gini using EU-SILC dataset. Specifically, the obtained estimates using the SWIID dataset are -0.173 and -0.171 for 2008 and 2009, respectively. Recall that the results obtained for the Gini coefficient using the EU-SILC dataset (that are also calculated using disposable income data) are -0.165 and -0.173 for 2008 and 2009, respectively. The similarity between the magnitude of the estimated coefficients is reassuring and gives more confidence to the results obtained.

Also, and similarly to the baseline results, the coefficient of income inequality individually is also not statistically significant for both pre-crisis years of income inequality. Thus, the baseline results are entirely robust to the use of this harmonized dataset.

Figures 5 and 6 also indicate that the relation between the interaction term and growth forecast errors breaks down when income inequality is measured by market (rather than disposable) income. Despite displaying a slightly negative marginal impact of inequality on growth forecast errors for both pre-crisis years, this impact is not statistically significant. From the figures, it is possible to see that the estimated coefficients are not significant independently of the amount of fiscal consolidation forecast. More formal evidence is also presented in the second and fourth columns of Table 20.

In order to better understand the meaning of these results, one needs first to understand how the Gini (pre-tax and pre-transfer) measures are constructed. According to the Luxembourg Income Study (LIS) Harmonization Guidelines,[25] the market income Gini is constructed using amounts gross of income taxes and social security employee contributions (but not employer contributions). By subtracting the overall amount of taxes and contributions to the gross income, one obtains the household disposable income.

On the one hand, our results suggest that the *market* distribution of income of European economies did not affect the fiscal multiplier during 2010-11. That is, the distribution of income accrued to households before government's intervention in the market (through income taxes and social security employee contributions) did not have a mapping with the fiscal multiplier early in the crisis. On the other hand, according to our baseline results and various robustness tests, the way income was distributed after government's intervention (i.e., the distribution of household *disposable* income) did affect the fiscal multiplier. Specifically, European countries with higher levels of household disposable income inequality registered, on average, higher fiscal multipliers during 2010-11.

This is a very important result. It provides evidence that government's redistributive policies

[25] The LIS Harmonization Guidelines are available at http://www.lisdatacenter.org/wp-content/uploads/our-lis-documentation-harmonisation-guidelines.pdf.

Even though, in this section, we are using data from the SWIID, this dataset uses the LIS data as standard. The reason to do so, according to the author, is that the LIS dataset has the most-comparable income inequality statistics currently available. Thus all the data in the SWIID is constructed to be directly comparable with the LIS data. For additional information regarding the standardization process, see Solt (2009).

altered the distribution of income in a manner that increased the fiscal multipliers during 2010-11. I.e., it suggests that fiscal policy itself changed the distribution of income in a way that its impact on the real economy (i.e., the fiscal multiplier) increased. Thus, according to our results, it is not the way income is distributed by the market that affected the size of the fiscal multiplier. It is the way government's redistribute income that actually increased the fiscal multiplier early in the crisis.

5 Extension

So far we have presented evidence that, early in the crisis, European economies with higher pre-crisis levels of income inequality registered higher-than-expected growth downfalls during their fiscal consolidation plans. We interpreted those results as higher levels of income inequality causing higher-than-expected fiscal multipliers. However, we were intentionally silent about the possible channels through which income inequality may materialize into higher fiscal multipliers.

In section 2 we presented some possible channels through which that relation may occur. Those channels included a higher share of households among more unequal countries with a higher marginal propensity to consume and/or with a binding liquidity constraint. In this section, we briefly present some data from the Eurosystem Household Finance and Consumption Survey (HFCS). This dataset contains information about households' assets and liabilities, income, and indicators of consumption and credit constraints for 15 euro area countries. The HFCS survey reports their results having 2010 as base year.

From the microdata available, we constructed the proportion of liquidity constrained households for each country. Following Martin et al. (2014), we defined a liquidity constrained household as one with liquid assets below two months of its total gross income. These measures were created for different subgroups of the population. Specifically, we created the proportion of liquidity constrained households among indebted households, and the total fraction of liquidity constrained in the economy (i.e., that includes both indebted and not indebted households). The type of debt considered can result from mortgages and consumer credit.

In order to investigate if, in fact, countries with higher levels of income inequality registered a higher proportion of liquidity constrained households, we plot various graphs between the two variables. More specifically, we are interested to know if european countries with higher levels of income inequality measured during 2008 and 2009 faced a higher proportion of liquidity constrained households during the beginning of the crisis (2010). Moreover, we also want to investigate whether the relation between both variables depends on the definition of liquidity constraints. I.e., if the results vary when using liquidity constraints restricted to indebted households versus the total fraction of liquidity constrained households.

Figures 7 and 8 present the graphs relating the proportion of indebted households that face a liquidity constraint and income inequality. In order to ensure consistency, we plotted the proportion of indebted liquidity constrained households in 2010 and the various income inequality measures used in the baseline results for both 2008 and 2009. Additionally, we also included the R-squared obtained for each linear regression.

A first look at both figures does not seem to suggest a very strong relation between the percentage of indebted liquidity constrained households and the different measures of income inequality. Consequently, measures of income inequality may not be a good proxy for the share of liquidity constrained households. However, there is a couple of countries that seem to appear as outliers in this analysis: Slovenia and Slovak Republic. One possible explanation for the exceptionally high share of liquidity constrained households in these countries may be their relatively lower financial development.

Hence the fitted line presented, and thus the estimated R-squared, excludes those two countries from the regression. As Figures 7 and 8 show, there is a positive relationship between the income inequality level and the proportion of liquidity constrained households among those that are indebted. The obtained R-squared of around 0.25, nevertheless, suggests that there is a large fraction of liquidity constraints variation among european economies that is not explained by income inequality. However, one also needs to take into account the low sample of countries included (only 13 countries given that we have excluded Slovenia and Slovak Republic).

When the same exercise is performed using the total share of liquidity constrained households (instead of restricting the sample to indebted agents), the above relationship does not seem to hold. However, these results (not showed) are not surprising given our definition of liquidity constraints. Recall that we consider that a household is liquidity constrained if its liquid assets are below two months of its total gross income. Nevertheless, in practice, a liquidity constraint is binding when agents cannot borrow as much as they would optimally do. So, despite a household with liquid assets below two months of its total gross income being considered liquidity constrained in our specification, it does not mean that in practice the agent will not be able to borrow funds. Thus, it is much more plausible that agents that already hold debt will face, on average, much more restrictive borrowing conditions than households with no debt.

In conclusion, the obtained results provide some evidence that, as assumed in our work, income inequality is a valid proxy for the proportion of liquidity constrained households among those that are indebted. Specifically, the evidence suggests that income inequality (measured during 2008 and 2009) may have affected the size of the fiscal multiplier early in the crisis through its impact on the amount of liquidity constrained households. Nevertheless, one must consider both the small sample used and the relatively low R-squared when analyzing the results. Thus, further research must de developed to better understand the channels through which higher income inequality may materialize into higher fiscal multipliers.

6 Conclusion

This paper investigated the role of pre-crisis income inequality on growth forecast errors. The results show that countries with higher levels of income inequality during 2008 and 2009 registered, on average, more negative real growth forecast errors during 2010-11 during their fiscal consolidation episodes. According to our framework, and following the work by Blanchard and Leigh (2013), these results provide evidence of higher-than-expected multipliers during the beginning of the crisis. Specifically, our results suggest that forecasters did not underestimate how contractionary the fiscal consolidation measures *per se* would have been. They do suggest that forecasters underestimated the impact of the distribution of income had on fiscal multipliers via, for example, its impact on liquidity constrained households.

We also showed that the relationship between the marginal impact of income inequality and fiscal multipliers seems to be non-linear. More precisely, our results provide evidence that income inequality has a marginally higher impact on the size of the fiscal multiplier when the level of income inequality is higher. However, given the rather small difference between linear and non-linear models' predictive power, evidence suggests that the non-linear component may not be very strong. Additionally, we also presented various robustness tests, to which our results seem to hold. Those tests consisted of: controlling for the influence of outlier observations, controlling for other factors that could plausibly have affected both the interaction of inequality with fiscal consolidation and lower-than-expected growth, verifying that the results do not hold for more normal times - as one would expect -, and, finally, re-estimating our baseline equation using a different source of income inequality data.

However, our robustness tests also suggest that the role of income inequality on fiscal multipliers change for different definitions of income inequality. Specifically, the distribution of income solely affects the size of the fiscal multiplier if it is based on household disposable (rather than market) income. The income that accrues to households directly from the market (i.e., before government's redistributive policies) does not seem to affect the size of the fiscal multiplier. This is a very important result since it suggests that the way European governments conducted redistributive policies ended up affecting the size of the fiscal multiplier early in the crisis.

In general, the results obtained suggest that countries with more unequal distributions of income suffered more contractionary impacts of the fiscal consolidation measures. It is thus plausible that, for the 26 European economies, the actual multipliers were higher-than-expected by forecasters. Specifically, given the inequality levels of European economies and the results reported in the tables, it is likely that fiscal multipliers were well above 1 during 2010-11. These results oppose to the usually assumed multiplier of 0.5.[26]

This work contributes to the literature on state-dependent multipliers, specifically regarding the impact of income inequality on fiscal multipliers. It provides evidence that the distribution of income may affect the impact of fiscal policy on the real economy. As a consequence, it makes a strong case that the way income is distributed within an economy may have a significant influence on the impact of the fiscal policy. Thus, it suggests that the distribution of income should be taken into consideration when assessing the real impact of fiscal policy. Moreover, the impact of government's redistributive policies should also be considered when measuring fiscal multipliers.

Nevertheless, one should always recall that multipliers are influenced by various characteristics of the economy, with income distribution being only one of those characteristics. That is why multipliers are assumed to vary across countries and periods of time.

[26]As mentioned by Blanchard and Leigh (2013), various empirical studies suggested multipliers around 0.5 for the period before the crisis. Some of those studies are presented on IMF (2008) and IMF (2010). Given these results and the authors' finding between no difference, on average, between actual and estimated multipliers before the crisis, one can reasonably assume that multipliers before the crisis were, indeed, around 0.5.

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Table 1: Baseline results. Year of income inequality measures: 2008.

	Blanchard et al. (2013)	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year		*2008*	*2008*	*2008*	*2008*	*2008*	*2008*
β	-1.191***	2.475**	2.150*	1.308*	1.367	2.325	3.885*
	(0.310)	(1.193)	(1.078)	(0.756)	(0.860)	(1.525)	(2.190)
γ		0.402	0.291	0.089	0.225	1.035	0.060
		(0.573)	(0.437)	(0.174)	(0.306)	(2.338)	(0.131)
η		-0.866***	-0.668***	-0.294***	-0.417***	-3.020**	-0.165**
		(0.268)	(0.203)	(0.080)	(0.140)	(1.281)	(0.070)
Constant	0.809**	-0.521	-0.291	0.342	-0.244	-0.122	-0.760
	(0.379)	(2.371)	(2.143)	(1.489)	(1.860)	(2.661)	(3.969)
Observations	26	26	26	26	26	26	26
R-squared	0.522	0.657	0.663	0.676	0.674	0.620	0.618
Adj. R-squared	0.502	0.611	0.617	0.632	0.629	0.569	0.566

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 2: Baseline results. Year of income inequality measures: 2009.

	Blanchard et al. (2013)	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year		*2009*	*2009*	*2009*	*2009*	*2009*	*2009*
β	-1.191***	2.464*	1.812	-0.349	1.000	2.553	4.082
	(0.310)	(1.412)	(1.213)	(0.815)	(0.591)	(1.687)	(2.593)
γ		0.294	0.099	-0.213	0.130	0.990	0.057
		(0.604)	(0.456)	(0.161)	(0.222)	(2.646)	(0.141)
η		-0.873**	-0.599**	-0.087	-0.314***	-3.282**	-0.173*
		(0.324)	(0.237)	(0.094)	(0.079)	(1.448)	(0.084)
Constant	0.809**	-0.131	0.520	2.443*	0.246	-0.036	-0.663
	(0.379)	(2.477)	(2.193)	(1.267)	(1.478)	(2.913)	(4.213)
Observations	26	26	26	26	26	26	26
R-squared	0.522	0.635	0.635	0.610	0.700	0.622	0.612
Adj. R-squared	0.502	0.586	0.586	0.557	0.659	0.570	0.559

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 3: Results using a non-linear model. Year of income inequality measures: 2008.

	Blanchard et al. (2013)	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year		*2008*	*2008*	*2008*	*2008*	*2008*	*2008*
β	-1.191***	-3.673	-2.869	-2.141	3.432**	-6.938	-24.425**
	(0.310)	(4.283)	(3.565)	(2.159)	(1.594)	(5.070)	(10.441)
γ		0.519	0.377	0.129	0.122	1.710	0.095
		(0.614)	(0.464)	(0.181)	(0.323)	(2.518)	(0.138)
η		2.105	1.397	0.576	-1.046**	13.741	1.756**
		(1.997)	(1.398)	(0.508)	(0.412)	(8.752)	(0.689)
κ		-0.349	-0.205	-0.051*	0.045	-7.402*	-0.032***
		(0.230)	(0.135)	(0.029)	(0.026)	(3.730)	(0.011)
Constant	0.809**	-0.883	-0.588	0.138	0.277	-0.680	-1.552
	(0.379)	(2.498)	(2.237)	(1.505)	(1.955)	(2.820)	(4.145)
Observations	26	26	26	26	26	26	26
R-squared	0.522	0.676	0.680	0.695	0.688	0.653	0.675
Adj. R-squared	0.502	0.615	0.619	0.637	0.629	0.586	0.613

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 4: Results using a non-linear model. Year of income inequality measures: 2009.

	Blanchard et al. (2013)	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year		*2009*	*2009*	*2009*	*2009*	*2009*	*2009*
β	-1.191***	-8.166	-6.032	2.663	0.464	-9.436	-29.636***
	(0.310)	(4.834)	(3.886)	(1.998)	(1.841)	(5.486)	(9.798)
γ		0.414	0.215	-0.193*	0.145	1.567	0.065
		(0.619)	(0.465)	(0.105)	(0.229)	(2.753)	(0.143)
η		4.315*	2.642	-0.784*	-0.144	18.983*	2.131***
		(2.301)	(1.544)	(0.404)	(0.521)	(9.818)	(0.654)
κ		-0.618**	-0.325**	0.037*	-0.012	-10.103**	-0.039***
		(0.270)	(0.150)	(0.020)	(0.035)	(4.342)	(0.011)
Constant	0.809**	-0.425	0.159	2.297**	0.179	-0.465	-0.653
	(0.379)	(2.504)	(2.209)	(1.018)	(1.519)	(3.014)	(4.245)
Observations	26	26	26	26	26	26	26
R-squared	0.522	0.670	0.665	0.642	0.700	0.661	0.681
Adj. R-squared	0.502	0.607	0.601	0.574	0.643	0.596	0.621

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 5: Robustness Test - Filling missing observations with EC forecasts. Year of income inequality measures: 2008.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2008*	*2008*	*2008*	*2008*	*2008*	*2008*
β	2.250**	2.084**	1.413*	1.068	2.241*	4.470**
	(1.087)	(0.987)	(0.700)	(0.657)	(1.246)	(1.854)
γ	0.443	0.376	0.165	0.128	1.483	0.124
	(0.532)	(0.420)	(0.184)	(0.231)	(1.945)	(0.120)
η	-0.800***	-0.647***	-0.307***	-0.353***	-2.911***	-0.184***
	(0.252)	(0.193)	(0.077)	(0.103)	(1.031)	(0.060)
Constant	-0.518	-0.489	0.037	0.427	-0.407	-2.410
	(2.089)	(1.933)	(1.419)	(1.353)	(2.177)	(3.522)
Observations	30	30	30	30	30	30
R-squared	0.567	0.573	0.579	0.573	0.534	0.551

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 6: Robustness Test - Filling missing observations with EC forecasts. Year of income inequality measures: 2009.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2009*	*2009*	*2009*	*2009*	*2009*	*2009*
β	2.174	1.839	0.199	0.981*	2.139	4.493*
	(1.284)	(1.080)	(0.882)	(0.534)	(1.391)	(2.193)
γ	0.470	0.316	-0.039	0.152	1.792	0.139
	(0.593)	(0.434)	(0.186)	(0.204)	(2.314)	(0.132)
η	-0.786**	-0.596***	-0.155	-0.307***	-2.848**	-0.184**
	(0.299)	(0.208)	(0.100)	(0.073)	(1.176)	(0.071)
Constant	-0.688	-0.284	1.470	0.342	-0.780	-2.908
	(2.302)	(1.993)	(1.406)	(1.223)	(2.488)	(3.857)
Observations	30	30	30	30	30	30
R-squared	0.542	0.540	0.481	0.595	0.523	0.536

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 7: Robustness Test - Excluding the two countries with the highest absolute values of both fiscal policy change and income inequality. Year of income inequality measures: 2008.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2008*	*2008*	*2008*	*2008*	*2008*	*2008*
β	1.689	1.485	0.934	0.952	1.215	2.039
	(1.408)	(1.258)	(0.857)	(0.765)	(1.896)	(2.973)
γ	0.096	0.063	0.001	0.025	-0.205	-0.006
	(0.619)	(0.476)	(0.189)	(0.328)	(2.423)	(0.141)
η	-0.616*	-0.483*	-0.225**	-0.294**	-1.764	-0.094
	(0.352)	(0.266)	(0.106)	(0.127)	(1.748)	(0.103)
Constant	0.503	0.588	0.867	0.738	1.029	0.980
	(2.539)	(2.304)	(1.574)	(1.962)	(2.758)	(4.232)
Observations	24	24	24	24	24	24
R-squared	0.342	0.348	0.363	0.411	0.299	0.286

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 8: Robustness Test - Excluding the two countries with the highest absolute values of both fiscal policy change and income inequality. Year of income inequality measures: 2009.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2009*	*2009*	*2009*	*2009*	*2009*	*2009*
β	1.394	0.814	0.849	1.155	1.342	1.922
	(1.911)	(1.673)	(1.067)	(0.852)	(2.270)	(3.636)
γ	-0.109	-0.229	0.118	0.135	-0.434	-0.024
	(0.692)	(0.530)	(0.202)	(0.313)	(2.867)	(0.155)
η	-0.534	-0.325	-0.248*	-0.337**	-1.908	-0.090
	(0.487)	(0.368)	(0.142)	(0.145)	(2.128)	(0.126)
Constant	1.218	1.790	0.329	0.180	1.257	1.455
	(2.805)	(2.509)	(1.557)	(1.893)	(3.146)	(4.598)
Observations	24	24	24	24	24	24
R-squared	0.321	0.327	0.463	0.404	0.298	0.281

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 9: Robustness Test - Excluding the economies under IMF assistance programs during 2010-11. Year of income inequality measures: 2008.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2008*	*2008*	*2008*	*2008*	*2008*	*2008*
β	0.386	0.255	-0.027	0.907	-0.338	0.086
	(2.118)	(1.899)	(1.293)	(1.418)	(2.180)	(3.148)
γ	0.162	0.109	0.031	0.064	-0.050	0.011
	(0.676)	(0.515)	(0.198)	(0.343)	(2.636)	(0.149)
η	-0.332	-0.254	-0.117	-0.324	-0.498	-0.033
	(0.533)	(0.405)	(0.161)	(0.227)	(1.977)	(0.106)
Constant	0.270	0.399	0.661	0.533	0.906	0.538
	(2.753)	(2.477)	(1.651)	(2.090)	(2.984)	(4.466)
Observations	21	21	21	21	21	21
R-squared	0.272	0.272	0.273	0.299	0.264	0.265

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 10: Robustness Test - Excluding the economies under IMF assistance programs during 2010-11. Year of income inequality measures: 2009.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2009*	*2009*	*2009*	*2009*	*2009*	*2009*
β	-2.068	-2.580	-1.743***	0.471	-0.947	-1.716
	(2.053)	(1.877)	(0.518)	(1.429)	(2.449)	(3.271)
γ	-0.384	-0.460	-0.164**	0.138	-0.624	-0.040
	(0.736)	(0.563)	(0.069)	(0.317)	(3.138)	(0.161)
η	0.326	0.395	0.113***	-0.237	0.088	0.030
	(0.549)	(0.435)	(0.038)	(0.234)	(2.317)	(0.113)
Constant	2.262	2.819	2.067**	0.163	1.479	1.984
	(2.939)	(2.627)	(0.851)	(1.963)	(3.420)	(4.769)
Observations	21	21	21	21	21	21
R-squared	0.272	0.287	0.355	0.289	0.264	0.265

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 11: Robustness Test - Excluding the economies classified as "emerging" in the WEO database. Year of income inequality measures: 2008.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2008*	*2008*	*2008*	*2008*	*2008*	*2008*
β	2.601*	2.247*	1.343	1.985*	2.184	3.561
	(1.378)	(1.231)	(0.823)	(0.957)	(1.880)	(2.605)
γ	0.578	0.401	0.123	0.081	1.406	0.074
	(0.729)	(0.555)	(0.217)	(0.361)	(3.166)	(0.168)
η	-0.898**	-0.688***	-0.297***	-0.521***	-2.879*	-0.153*
	(0.319)	(0.239)	(0.089)	(0.154)	(1.656)	(0.086)
Constant	-1.124	-0.718	0.136	0.516	-0.463	-1.118
	(2.964)	(2.669)	(1.818)	(2.150)	(3.490)	(4.991)
Observations	22	22	22	22	22	22
R-squared	0.618	0.624	0.640	0.650	0.577	0.577

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 12: Robustness Test - Excluding the economies classified as "emerging" in the WEO database. Year of income inequality measures: 2009.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2009*	*2009*	*2009*	*2009*	*2009*	*2009*
β	2.361	1.700	-0.446	0.960	2.283	3.596
	(1.679)	(1.456)	(0.869)	(0.583)	(1.960)	(3.004)
γ	0.318	0.087	-0.211	0.144	0.979	0.053
	(0.717)	(0.557)	(0.163)	(0.231)	(3.149)	(0.167)
η	-0.842**	-0.571*	-0.070	-0.304***	-3.007	-0.155
	(0.401)	(0.297)	(0.106)	(0.076)	(1.746)	(0.100)
Constant	-0.191	0.587	2.431*	0.200	0.012	-0.511
	(2.901)	(2.611)	(1.300)	(1.567)	(3.414)	(4.929)
Observations	22	22	22	22	22	22
R-squared	0.591	0.591	0.574	0.669	0.582	0.573

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 13: Robustness Test - Robust regression. Year of income inequality measures: 2008.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2008*	*2008*	*2008*	*2008*	*2008*	*2008*
β	2.908**	2.577**	1.590*	1.789**	2.891*	4.757**
	(1.163)	(1.043)	(0.782)	(0.787)	(1.435)	(2.030)
γ	0.868*	0.652	0.221	0.482*	2.914	0.167
	(0.500)	(0.386)	(0.184)	(0.261)	(1.915)	(0.104)
η	-0.979***	-0.760***	-0.328***	-0.485***	-3.556***	-0.195***
	(0.278)	(0.211)	(0.094)	(0.130)	(1.243)	(0.066)
Constant	-2.571	-2.170	-0.886	-1.966	-2.360	-4.092
	(1.887)	(1.701)	(1.332)	(1.423)	(2.010)	(2.964)
Observations	26	26	26	26	26	26
R-squared	0.719	0.720	0.712	0.724	0.671	0.681

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 14: Robustness Test - Robust regression. Year of income inequality measures: 2009.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2009*	*2009*	*2009*	*2009*	*2009*	*2009*
β	2.877*	2.254	1.174	1.332**	3.079*	4.871*
	(1.552)	(1.376)	(0.874)	(0.603)	(1.634)	(2.471)
γ	0.659	0.428	0.219	0.312	2.758	0.143
	(0.655)	(0.502)	(0.190)	(0.213)	(2.359)	(0.130)
η	-0.978**	-0.697**	-0.295**	-0.362***	-3.782**	-0.200**
	(0.378)	(0.282)	(0.107)	(0.090)	(1.452)	(0.082)
Constant	-1.702	-1.132	-0.566	-1.068	-2.059	-3.318
	(2.451)	(2.201)	(1.344)	(1.189)	(2.418)	(3.671)
Observations	26	26	25	26	26	26
R-squared	0.651	0.644	0.704	0.754	0.641	0.632

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 15: Robustness Test - Quantile regression. Year of income inequality measures: 2008.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2008*	*2008*	*2008*	*2008*	*2008*	*2008*
β	2.684	2.337	1.463	1.950*	2.737	5.064
	(1.825)	(1.653)	(1.089)	(1.124)	(2.231)	(3.337)
γ	0.865	0.666	0.306	0.672*	3.591	0.186
	(0.785)	(0.612)	(0.257)	(0.373)	(2.978)	(0.171)
η	-0.948**	-0.730**	-0.323**	-0.507**	-3.597*	-0.210*
	(0.436)	(0.335)	(0.130)	(0.186)	(1.933)	(0.109)
Constant	-2.579	-2.256	-1.541	-3.178	-3.027	-4.589
	(2.962)	(2.698)	(1.856)	(2.032)	(3.126)	(4.872)
Observations	26	26	26	26	26	26
R-squared	0.370	0.372	0.374	0.396	0.320	0.325

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 16: Robustness Test - Quantile regression. Year of income inequality measures: 2009.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2009*	*2009*	*2009*	*2009*	*2009*	*2009*
β	3.800*	3.178*	-1.175	1.079	1.610	3.248
	(2.200)	(1.850)	(0.989)	(0.865)	(2.272)	(3.549)
γ	1.105	0.821	-0.038	0.337	3.904	0.194
	(0.929)	(0.675)	(0.175)	(0.306)	(3.280)	(0.187)
η	-1.215**	-0.895**	0.036	-0.321**	-2.787	-0.157
	(0.536)	(0.379)	(0.108)	(0.129)	(2.019)	(0.118)
Constant	-3.391	-2.872	0.689	-1.442	-3.271	-4.744
	(3.476)	(2.960)	(1.409)	(1.707)	(3.362)	(5.272)
Observations	26	26	26	26	26	26
R-squared	0.317	0.315	0.243	0.415	0.300	0.295

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 17: Robustness Test - Cook's distance. Year of income inequality measures: 2008.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2008*	*2008*	*2008*	*2008*	*2008*	*2008*
β	2.568**	2.284**	1.560**	1.444	2.049	3.716*
	(1.170)	(1.064)	(0.720)	(0.937)	(1.304)	(1.890)
γ	0.697	0.528	0.202	0.318	2.428	0.147
	(0.490)	(0.376)	(0.148)	(0.225)	(1.667)	(0.086)
η	-0.867***	-0.679***	-0.324***	-0.393**	-2.821**	-0.162**
	(0.288)	(0.220)	(0.076)	(0.157)	(1.177)	(0.064)
Constant	-1.881	-1.577	-0.690	-0.991	-1.911	-3.589
	(1.876)	(1.700)	(1.171)	(1.321)	(1.778)	(2.474)
Observations	24	24	25	23	23	23
R-squared	0.561	0.568	0.780	0.448	0.616	0.623

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 18: Robustness Test - Cook's distance. Year of income inequality measures: 2009.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2009*	*2009*	*2009*	*2009*	*2009*	*2009*
β	1.699	0.958	0.244	1.275**	2.466	4.223
	(1.469)	(1.329)	(0.917)	(0.519)	(1.884)	(3.070)
γ	0.482	0.194	0.005	0.290*	2.090	0.113
	(0.506)	(0.398)	(0.225)	(0.151)	(2.102)	(0.113)
η	-0.692*	-0.422	-0.187	-0.356***	-3.196*	-0.177
	(0.369)	(0.291)	(0.119)	(0.068)	(1.722)	(0.103)
Constant	-1.164	-0.224	0.997	-0.860	-1.420	-2.503
	(1.946)	(1.771)	(1.736)	(0.972)	(2.204)	(3.244)
Observations	23	23	22	25	22	22
R-squared	0.576	0.562	0.515	0.813	0.577	0.570

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 19: Robustness Test - Using different forecast vintages. Year of income inequality measures: 2008.

	Quartile ratio	Quintile ratio	Decile ratio	Percentile 95/5	Palma ratio	Gini
Inequality Year	*2008*	*2008*	*2008*	*2008*	*2008*	*2008*
β	-0.114	-0.278	-0.246	0.708	-0.518	-0.323
	(0.700)	(0.596)	(0.532)	(1.599)	(0.787)	(0.880)
γ	0.274	0.186	0.033	-0.010	1.031	0.043
	(0.255)	(0.190)	(0.080)	(0.006)	(1.028)	(0.046)
η	-0.005	0.029	0.018	-0.001	0.330	0.007
	(0.167)	(0.119)	(0.054)	(0.006)	(0.735)	(0.031)
Constant	-0.229	-0.015	0.590	3.677**	-0.286	-0.414
	(1.133)	(1.011)	(0.806)	(1.774)	(1.202)	(1.386)
Observations	139	139	139	56	139	158
R-squared	0.698	0.698	0.696	0.745	0.700	0.705

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level).

Table 20: Robustness Test - Using a different source of income inequality data. Years of income inequality measures: 2008 and 2009. Source: WEO and SWIID database.

	Gini	Gini (pre-tax and transfers)	Gini	Gini (pre-tax and transfers)
Inequality Year	*2008*	*2008*	*2009*	*2009*
β	4.020*	-0.131	3.966*	-0.231
	(2.287)	(3.016)	(2.167)	(3.256)
γ	0.057	0.095	0.050	0.105
	(0.136)	(0.070)	(0.133)	(0.081)
η	-0.173**	-0.022	-0.171**	-0.020
	(0.076)	(0.064)	(0.071)	(0.068)
Constant	-0.672	-3.588	-0.463	-4.061
	(1.133)	(3.258)	(3.948)	(3.836)
Observations	26	26	26	26
Imputations	100	100	100	100

Note: Table reports point estimates and heteroskedasticity-robust standard errors in parentheses. Asterisks denote statistical significance, with *** (1% level), ** (5% level), and * (10% level). Multiple-imputations model estimated using 100 imputations. The differences across imputations capture the uncertainty in the inequality estimate (Solt, 2014).

Figure 1: The marginal effect of income inequality (2008) on the real GDP growth forecast error. 95% confidence intervals are presented. Source: WEO and EU-SILC database.

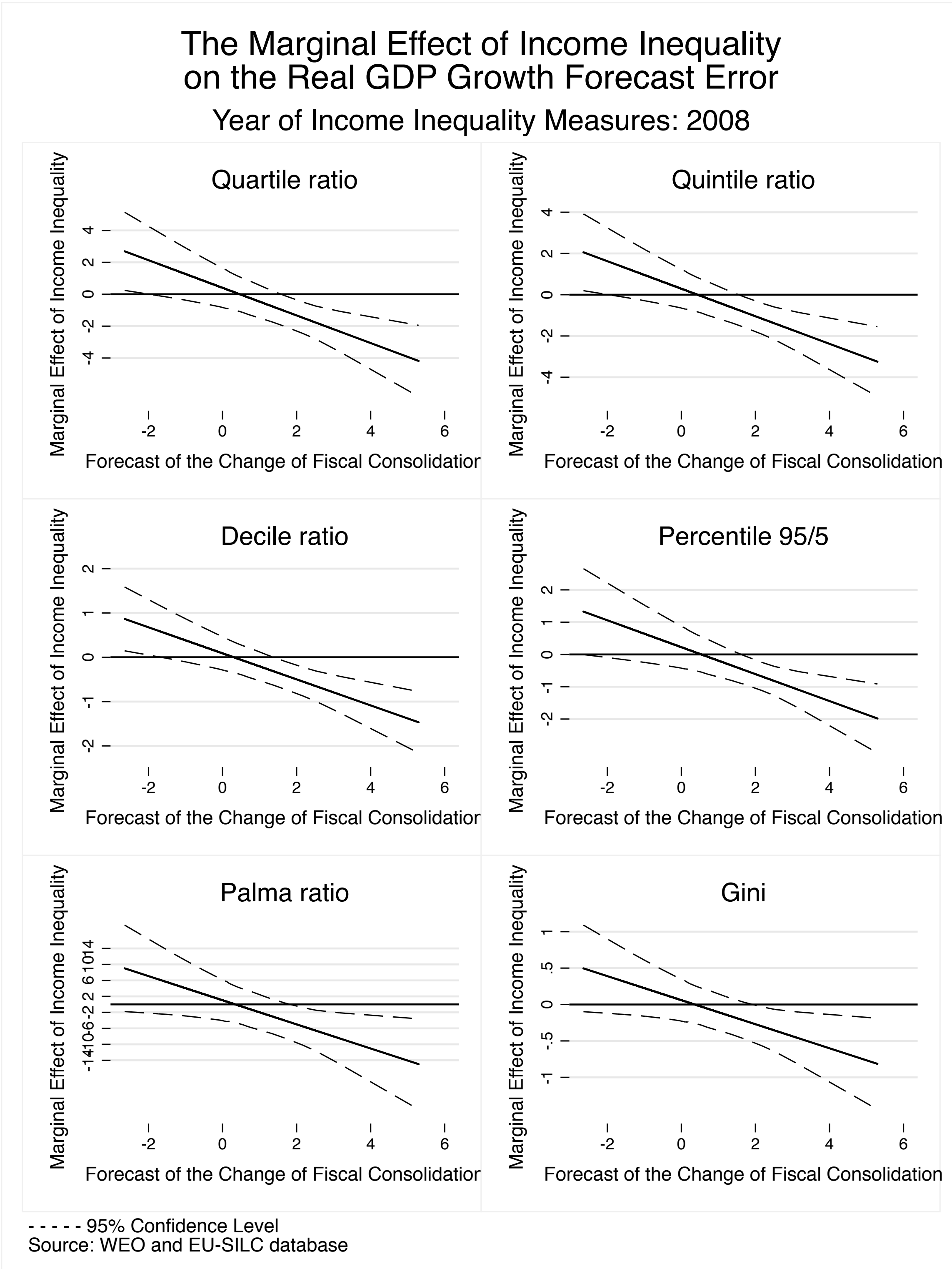


Figure 2: The marginal effect of income inequality (2009) on the real GDP growth forecast error. 95% confidence intervals are presented. Source: WEO and EU-SILC database.

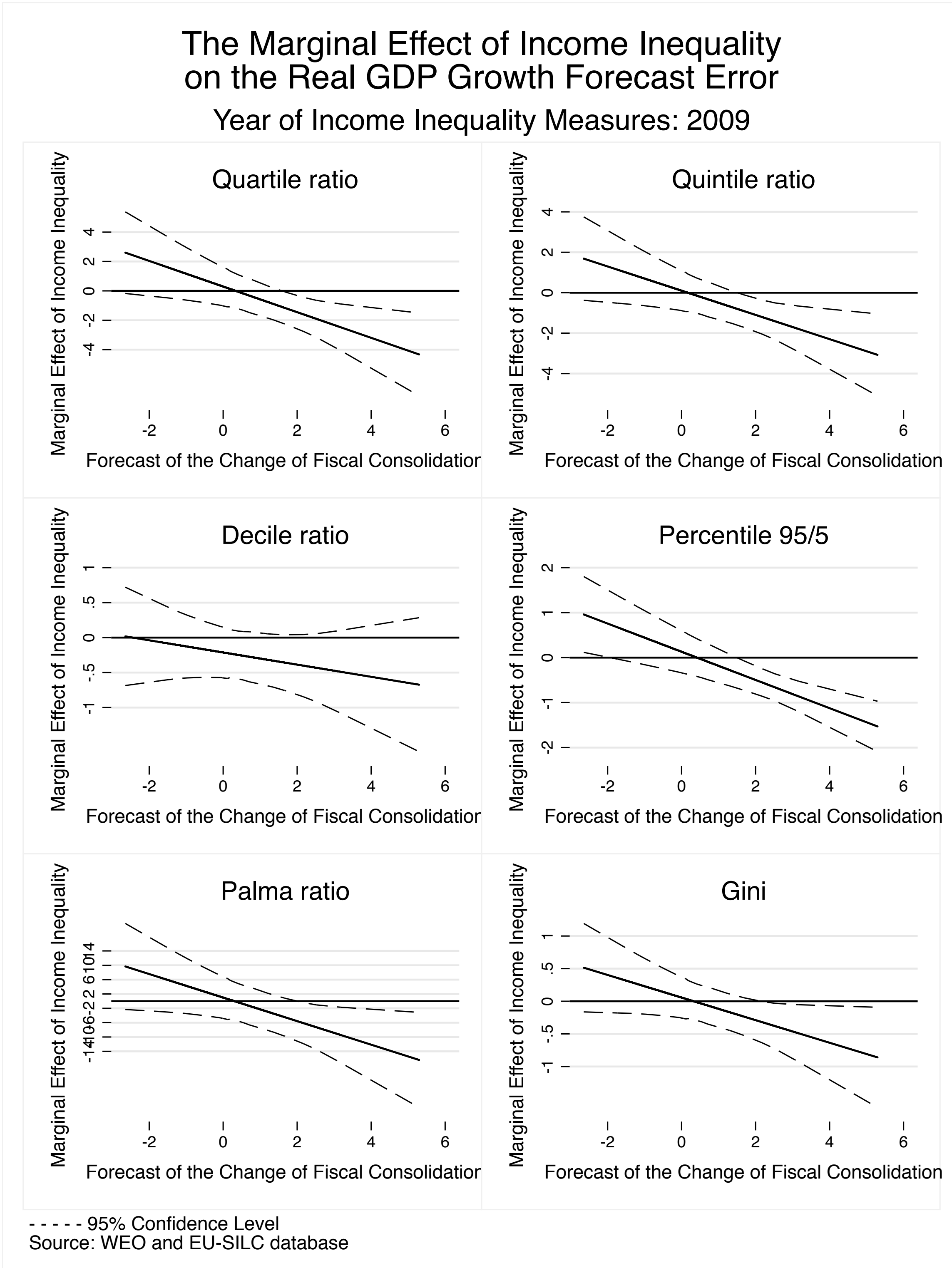


Figure 3: The non-linear marginal effect of income inequality (2008) on the real GDP growth forecast error. Source: WEO and EU-SILC database.

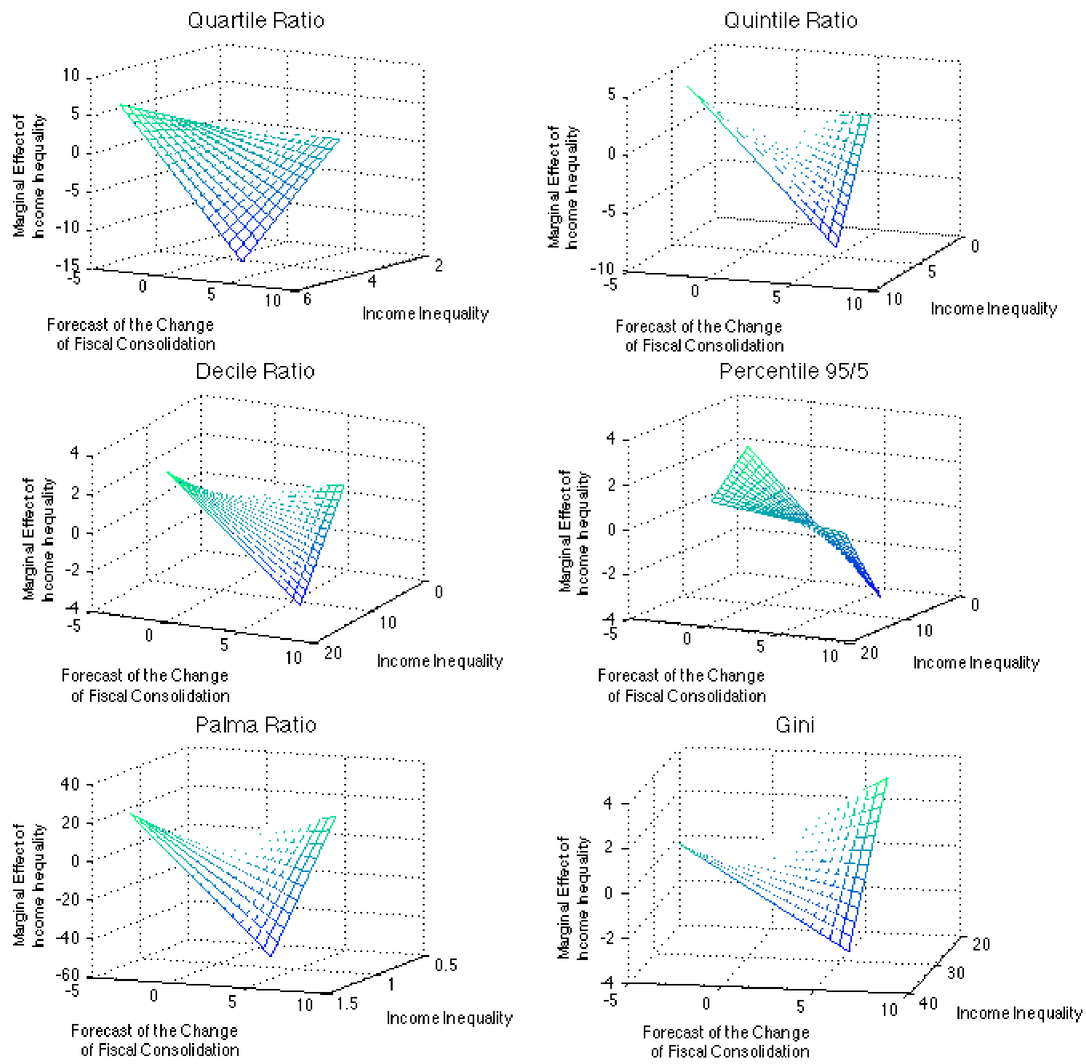


Figure 4: The non-linear marginal effect of income inequality (2009) on the real GDP growth forecast error. Source: WEO and EU-SILC database.

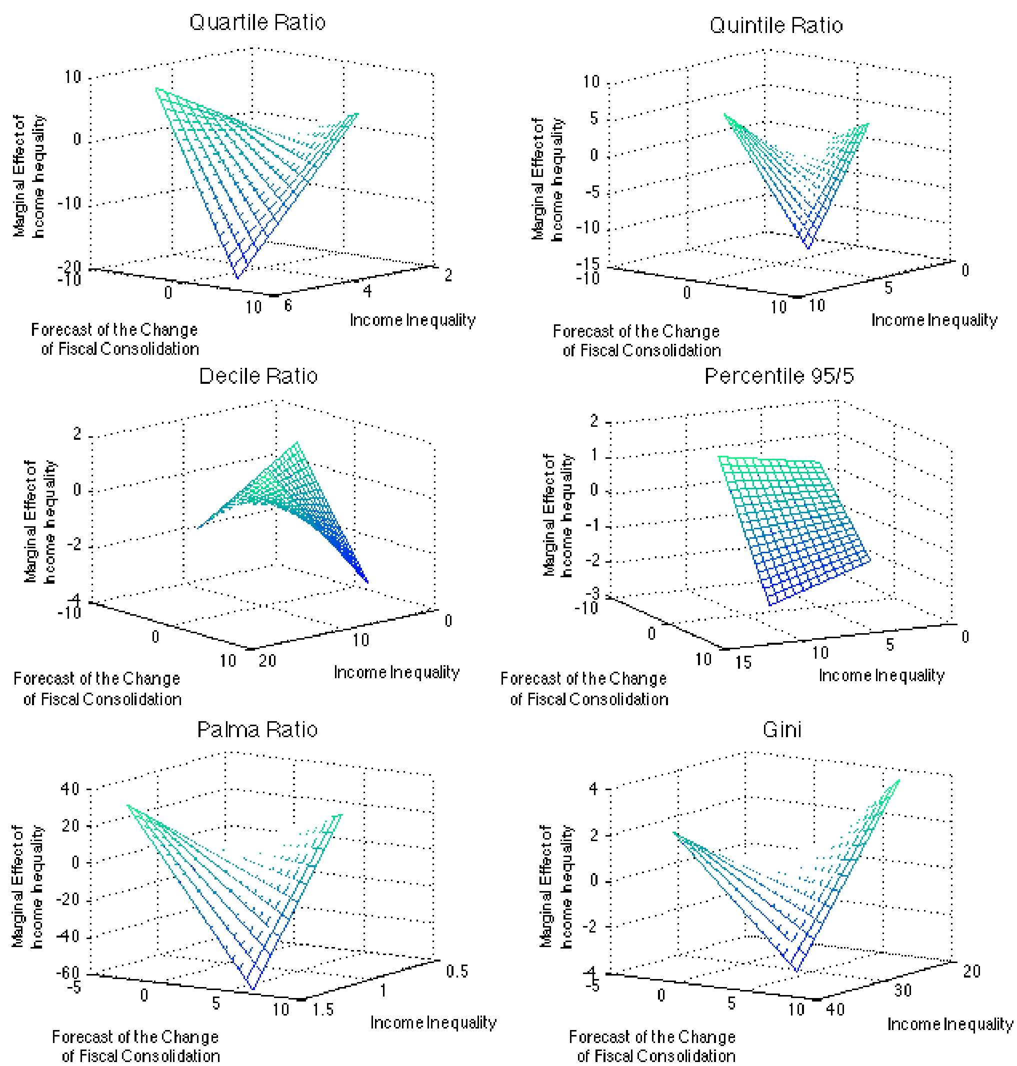


Figure 5: Robustness Test - Using a different source of income inequality data. The marginal effect of income inequality (2008) on the real GDP growth forecast error. 95% confidence intervals are presented. Source: WEO and SWIID database.

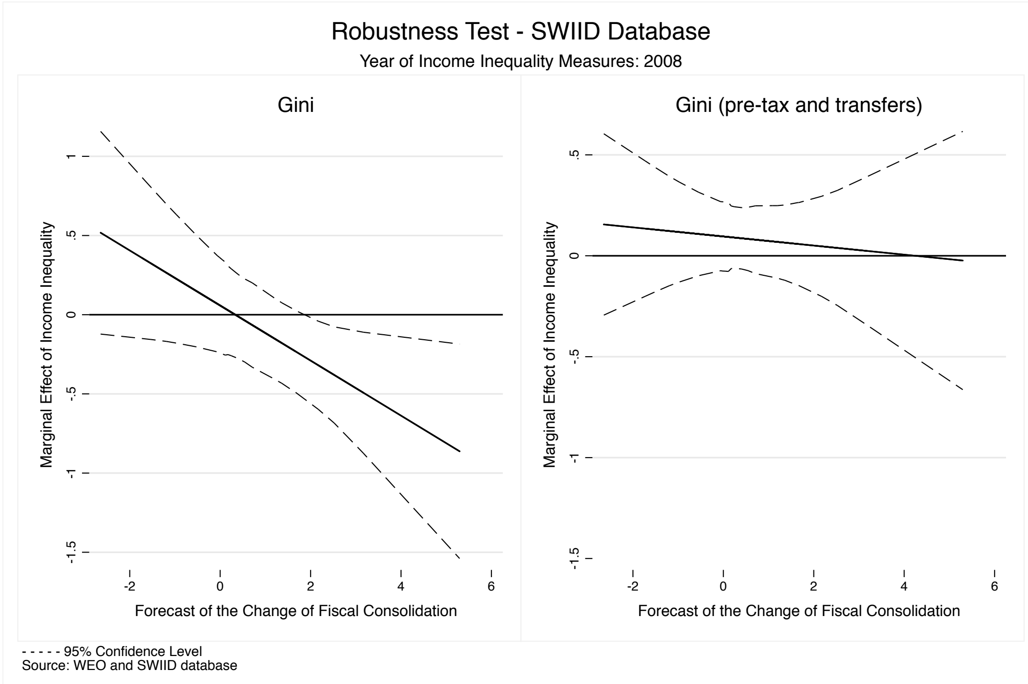


Figure 6: Robustness Test - Using a different source of income inequality data. The marginal effect of income inequality (2009) on the real GDP growth forecast error. 95% confidence intervals are presented. Source: WEO and SWIID database.

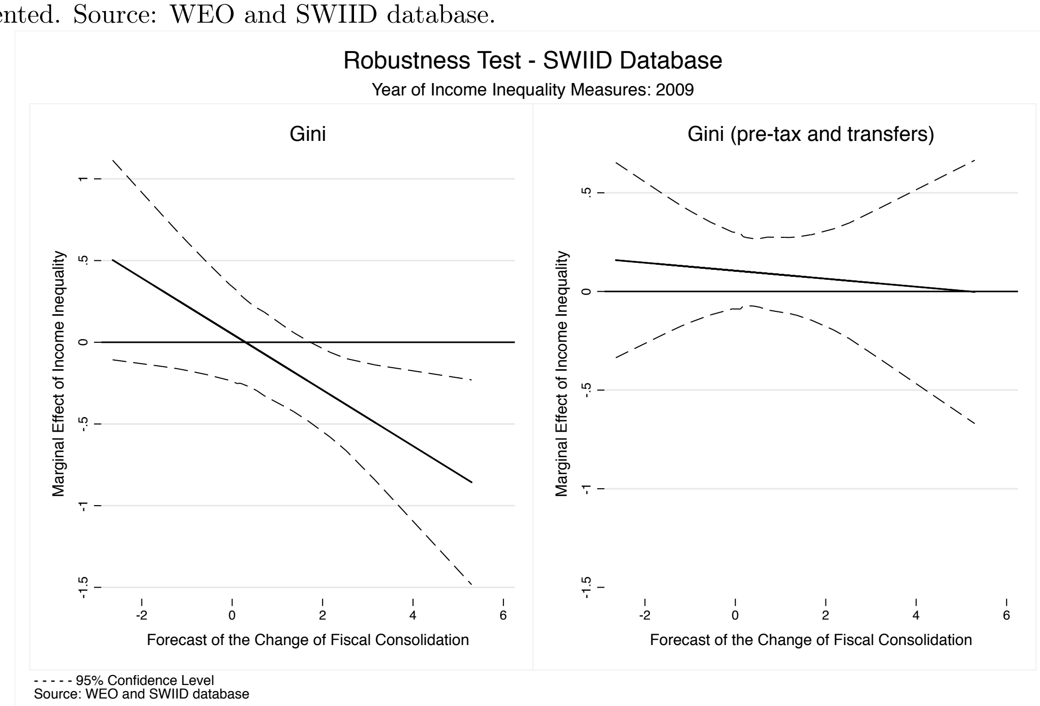
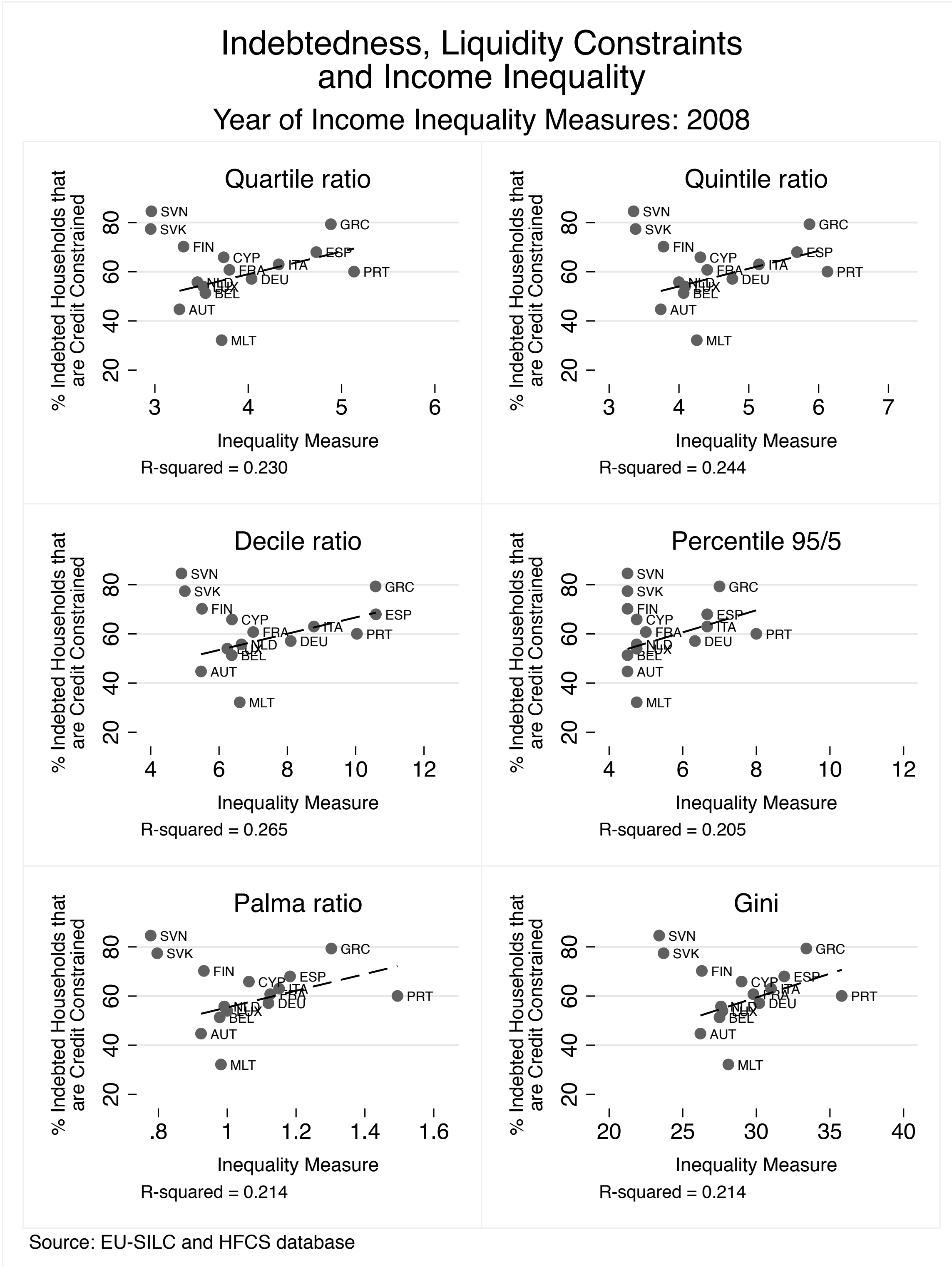
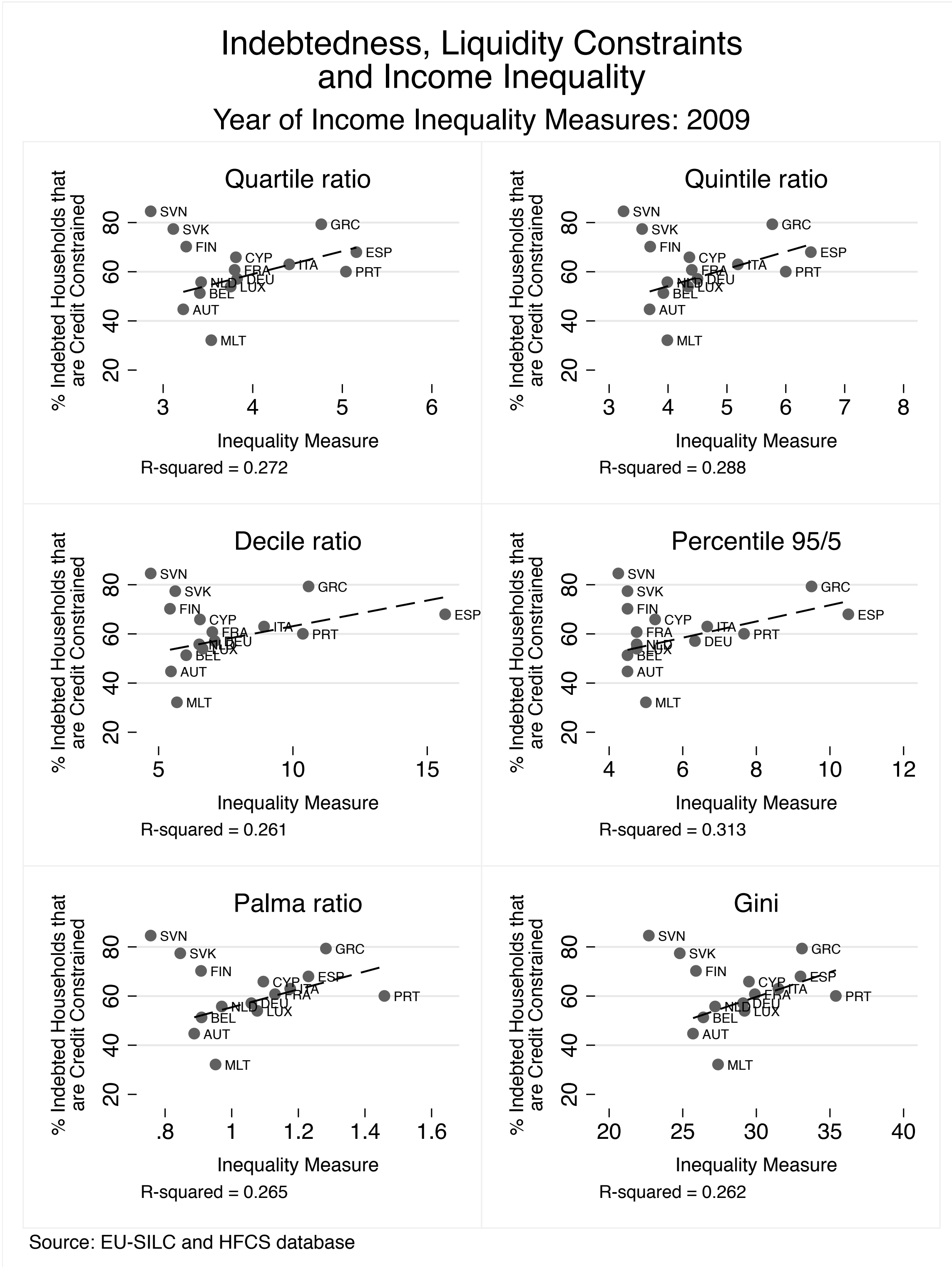


Figure 7: Extension - Indebtedness, liquidity constraints and income inequality (2008). Source: EU-SILC and HFCS database.



Note: Slovenia and Slovak Republic are excluded from the regression line sample.

Figure 8: Extension - Indebtedness, liquidity constraints and income inequality (2009). Source: EU-SILC and HFCS database.



Note: Slovenia and Slovak Republic are excluded from the regression line sample.

Listing 1 Countries and variables used in the estimation of baseline results. Year of income inequality measures: 2008.

Country	Code	△GDP (%)	Forecast △GDP (%)	Forecast Error (%)	△*Fiscal* Cons. (%)	Quartile ratio	Quintile ratio	Decile ratio	Percentile *95/5*	Palma ratio	Gini
Year		*2010-11*	*2010-11*	*2010-11*	*2010-11*	*2008*	*2008*	*2008*	*2008*	*2008*	*2008*
Austria	AUT	4.653	3.059	1.594	-1.133	3.264	3.740	5.475	4.500	0.924	26.200
Belgium	BEL	4.133	2.505	1.628	1.362	3.542	4.067	6.371	4.500	0.978	27.500
Bulgaria	BGR	2.241	2.204	0.037	0.173	5.385	6.439	11.458	7.333	1.511	35.900
Cyprus	CYP	1.757	1.216	0.541	-1.732	3.737	4.307	6.378	4.750	1.063	29.000
Czech Republic	CZE	4.333	4.348	-0.015	0.245	3.015	3.427	5.143	4.500	0.864	24.700
Denmark	DNK	2.473	2.776	-0.303	-1.532	3.155	3.642	5.861	4.250	0.865	25.100
Finland	FIN	6.283	3.478	2.805	-0.970	3.307	3.779	5.500	4.500	0.932	26.300
France	FRA	3.787	3.302	0.485	0.403	3.798	4.404	7.000	5.000	1.125	29.800
Germany	DEU	7.387	2.979	4.409	-2.644	4.036	4.765	8.100	6.333	1.120	30.200
Greece	GRC	-11.697	-3.029	-8.668	5.296	4.885	5.870	10.583	7.000	1.303	33.400
Hungary	HUN	2.642	3.030	-0.389	0.708	3.177	3.592	5.300	4.500	0.869	25.200
Iceland	ISL	-1.529	-0.811	-0.718	2.171	3.323	3.845	5.950	4.500	0.996	27.300
Ireland	IRL	1.083	0.361	0.722	3.166	3.871	4.425	6.639	4.750	1.106	29.900
Italy	ITA	2.181	2.011	0.169	0.546	4.327	5.147	8.778	6.667	1.150	31.000
Malta	MLT	5.111	1.938	3.173	-0.544	3.716	4.256	6.606	4.750	0.982	28.100
Netherlands	NLD	2.487	2.667	-0.180	-0.018	3.456	4.000	6.657	4.750	0.991	27.600
Norway	NOR	1.674	2.914	-1.240	0.047	3.197	3.710	6.594	4.250	0.858	25.100
Poland	POL	8.571	6.074	2.497	0.111	4.336	5.141	8.433	7.000	1.228	32.000
Portugal	PRT	0.662	0.948	-0.286	1.298	5.134	6.127	10.036	8.000	1.495	35.800
Romania	ROM	0.984	5.915	-4.931	2.522	5.798	7.017	12.619	11.000	1.489	36.000
Slovak Republic	SVK	7.540	8.785	-1.245	1.094	2.956	3.380	5.000	4.500	0.797	23.700
Slovenia	SVN	1.976	3.189	-1.213	1.659	2.963	3.350	4.900	4.500	0.778	23.400
Spain	ESP	-0.151	0.488	-0.640	1.195	4.729	5.691	10.591	6.667	1.183	31.900
Sweden	SWE	9.682	3.761	5.921	-0.061	3.085	3.526	5.657	4.250	0.805	24.000
Switzerland	CHE	4.796	3.317	1.479	-1.196	4.117	4.877	8.129	6.667	1.189	31.100
United Kingdom	GBR	2.796	3.875	-1.080	1.666	4.723	5.622	9.571	6.667	1.360	33.900
Average	All	2.917	2.742	0.175	0.531	3.885	4.544	7.435	5.618	1.075	29.003

Source: WEO and EU-SILC database

Listing 2 Countries and variables used in the estimation of baseline results. Year of income inequality measures: 2009.

Country	Code	$\triangle$GDP (%)	Forecast $\triangle$GDP (%)	Forecast Error (%)	$\triangle$*Fiscal* Cons. (%)	Quartile ratio	Quintile ratio	Decile ratio	Percentile *95/5*	Palma ratio	Gini
Year		*2010-11*	*2010-11*	*2010-11*	*2010-11*	*2009*	*2009*	*2009*	*2009*	*2009*	*2009*
Austria	AUT	4.653	3.059	1.594	-1.133	3.225	3.688	5.462	4.500	0.887	25.700
Belgium	BEL	4.133	2.505	1.628	1.362	3.410	3.922	6.029	4.500	0.909	26.400
Bulgaria	BGR	2.241	2.204	0.037	0.173	4.937	5.941	9.654	7.000	1.307	33.400
Cyprus	CYP	1.757	1.216	0.541	-1.732	3.812	4.364	6.541	5.250	1.095	29.500
Czech Republic	CZE	4.333	4.348	-0.015	0.245	3.029	3.456	5.286	4.500	0.888	25.100
Denmark	DNK	2.473	2.776	-0.303	-1.532	3.725	4.635	14.571	4.250	0.891	26.900
Finland	FIN	6.283	3.478	2.805	-0.970	3.258	3.698	5.425	4.500	0.908	25.900
France	FRA	3.787	3.302	0.485	0.403	3.798	4.404	7.000	4.750	1.130	29.900
Germany	DEU	7.387	2.979	4.409	-2.644	3.826	4.500	7.091	6.333	1.059	29.100
Greece	GRC	-11.697	-3.029	-8.668	5.296	4.765	5.771	10.583	9.500	1.283	33.100
Hungary	HUN	2.642	3.030	-0.389	0.708	3.075	3.515	5.098	4.500	0.850	24.700
Iceland	ISL	-1.529	-0.811	-0.718	2.171	3.637	4.226	6.842	4.500	1.135	29.600
Ireland	IRL	1.083	0.361	0.722	3.166	3.737	4.261	6.361	4.500	1.041	28.800
Italy	ITA	2.181	2.011	0.169	0.546	4.408	5.187	8.926	6.667	1.176	31.500
Malta	MLT	5.111	1.938	3.173	-0.544	3.537	3.989	5.684	5.000	0.952	27.400
Netherlands	NLD	2.487	2.667	-0.180	-0.018	3.424	3.989	6.514	4.750	0.970	27.200
Norway	NOR	1.674	2.914	-1.240	0.047	3.061	3.505	5.514	4.250	0.819	24.100
Poland	POL	8.571	6.074	2.497	0.111	4.241	4.938	8.000	6.667	1.187	31.400
Portugal	PRT	0.662	0.948	-0.286	1.298	5.041	6.000	10.370	7.667	1.458	35.400
Romania	ROM	0.984	5.915	-4.931	2.522	5.494	6.754	12.190	10.500	1.399	34.900
Slovak Republic	SVK	7.540	8.785	-1.245	1.094	3.114	3.561	5.622	4.500	0.846	24.800
Slovenia	SVN	1.976	3.189	-1.213	1.659	2.861	3.245	4.707	4.250	0.757	22.700
Spain	ESP	-0.151	0.488	-0.640	1.195	5.157	6.426	15.667	10.500	1.230	33.000
Sweden	SWE	9.682	3.761	5.921	-0.061	3.198	3.667	5.941	4.250	0.831	24.800
Switzerland	CHE	4.796	3.317	1.479	-1.196	4.072	4.756	7.656	6.333	1.145	30.700
United Kingdom	GBR	2.796	3.875	-1.080	1.666	4.438	5.221	8.759	7.000	1.245	32.400
Average	All	2.917	2.742	0.175	0.531	3.856	4.523	7.749	5.804	1.053	28.784

Source: WEO and EU-SILC database