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Banking Shocks and Top Income Shares

Salvatore Morelli

For additional information please contact:

Name: Salvatore Morelli
Affiliation: University of Oxford

Email Address: salvatore.morelli@economics.ox.ac.uk

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Preliminary draft, comments are welcome. Please do not circulate

Salvatore Morelli *

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Abstract

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Introduction

The 2007-2008 financial collapse and its subsequent economic recession brought the distributional impact of macroeconomic shocks back on the research agenda.

This paper attempts to investigate the impact of systemic banking shocks on within-country income distribution since the beginning of the twentieth century and for 27 countries accounting for more than a third of world GDP. In order to do so, we will turn to the investigation of top income shares data, the only available source of information to analyse inequality over a long time span as well as across a number of countries.

However, disentangling the overall distributional consequence of macroeconomic shocks is a challenging and complex task. On one hand banking crises are not isolated macroeconomic events, as they are commonly clustered with other macro shocks. On the other hand, banking crises are often followed by policy interventions which have potential distributional implication as well. Moreover, to complicate the empirical specification of the model even further, a growing body of research is pointing to the role of inequality as a main contributor to financial instability, casting doubts about the exogeneity of the regressors.

In this paper we will attempt to address the most pressing concerns expressed above. Firstly, the use of a set of different covariates, including indexes for a wide

*Department of Economics - University of Oxford and Institute for New Economic Thinking at the Oxford Martin School (INET@Oxford), UK. contact: salvatore.morelli@economics.ox.ac.uk. The work have had the financial support of the INET grant(IN01100021).

range of macroeconomic shocks, will help to disentangle the direct impact of specific banking crisis episodes, net of other relevant macroeconomic episodes. Secondly, with the use of data based on gross income definition we can exclude any direct impact of fiscal policy on our measure of inequality (top income shares). Thirdly, the use of a short time horizon (4 years), we argue, should be sufficient not to worry much about the potential role of new institutional and regulatory framework likely stemming from the crisis. Finally, we test the robustness of our results to the assumption that both systemic banking crises and economic shocks have exclusively lagged effects on the growth of the top shares. This will address the concern of potential endogeneity of crisis indicators to changes in 'inequality'.

Overall, our study builds on existing literature about the distributional implication of crises, including studies by Roine, Vlachos and Waldenstrom (2009), Morelli (2011) and Bordo and Meissner (2011), from now on referred to as RVW, MO, and BM. Specifically, our approach expands the methodology adopted in MO to a panel of countries and builds on previous empirical contributions by RVW and BM. Our work will study the richest fractiles more closely (especially top001) and our specifications make use of the growth rates of the top shares rather than their first-difference. We further depart from RVW and BM's methodological assumptions in different ways. Firstly, we construct a more homogeneous dataset of banking crises across different sources discarding non-systemic episodes. Secondly, we adopt a novel methodology consistent with an 'agnostic' view of the ending date of a banking crisis. Thirdly, we acknowledge the fact that macroeconomic shocks are not isolated events but occur in cluster. This leads us to include other type of shocks as well within our empirical specification, hoping to obtain more accurate estimates of the 'residual' impact of a banking shock. Fourthly, we exploit year-to-year variations and do not average out the data. Similarly, we work with the original series of the WTID and do not interpolate top income shares. Lastly, we estimate our empirical specifications based on the standard homogenous panel models as well as on models based on the recent literature on panel time-series with common-factors (heterogenous panel models which control for more general cross-section dependence). This will test how the results may be driven by the nature of the estimation methodologies. We also provide our results divided by period and country-group sub-samples, marking the importance of a long time *and* cross-country perspective.

In practise, the empirical evidence for this paper is produced by estimating impulse response functions (IRFs) of the rate of growth of top income shares to the systemic banking crises. This methodology is more commonly applied in macroeconomic studies and, to our knowledge, constitutes a novelty within the literature of income distribution. We first generalize this approach to a cross-section of countries and we discuss the estimation of the model based on two main approaches. On one hand we make use of the more standard 'pooled' estimators (i.e. POLS, FGLS). On the other hand we take advantage of the more recent advancements within the heterogenous models and common factors approach to panel estimation (i.e. the family of the Mean Groups estimators). Although still in its infancy and not commonly applied within the empirical literature, these models are particularly suitable for macro-panels with 'long N' and 'long T' structure and strong features of cross-section dependence.

Our results show that systemic banking crises have, on average, no significant additional impact on the dynamic of top shares when using the whole sample of countries and years. Analysing results over time, however, reveals a more complex relationship between inequality and crisis. In particular, our findings show that the pre-1950 crises appear to exert a relatively mild negative impact on the 'inequality' of income (at best, almost a half of what the work by Atkinson and Morelli(2011) considers to be a "salient" change in inequality), whereas the crises occurred within the post-1950 sub-sample do not seem to have any significant effect on the average dynamics of the top shares. However, once we drop from the analysis the observations for the the so called 'developing' and 'southern European' countries (with low coverage of data in the pre-1950 period), recent crises appear, in the short-run and on average, up to three times as disruptive for the richest fractile share compared to the crises occurred in the interwar period. Finally, we also document that the distributional impact of shocks differ across different country groups. Following the classification used in Atkinson, Piketty and Saez's 2011 paper, we broadly found two main macro-groups of countries, according to their different distributional response to banking crises. On the one hand, there are the so called Nordic European, Western English Speaking and Continental European (including Japan) countries, in which the richest fractile share seems to suffer a negative shock following a banking crisis. On the other hand, there are the so called Southern European and the Developing countries which show the opposite response, namely an increase in their top shares. Less clear is the impact of crises on the bottom of the top decile across different country-groups. Indeed, there is more heterogeneity across country groups and its response to shocks is measured with more uncertainty.

The paper is organized in eight sections. The first describes the complexity lying behind the question under investigation whereas the second illustrates the existing literature on the topic. The third and fourth sections analyse in detail the assembled dataset, the methodology and estimation strategies. We further discuss the results and their tentative interpretation in the following two sections. Finally, we conclude and we propose the tables and the charts as well as additional insights about the empirical methodology, in specific appendices.

1 Unravelling the complexity

We are interested in the direct impact of systemic banking crises on within-country income distribution. However, the task is complicated by several factors. On the one hand, banking crises are not isolated events. For instance, they are usually associated with a series of macroeconomic events such as crashes in the stock and real estate markets, economic recessions, together with strong rise in unemployment and bankruptcy rates. These different factors may work in different directions as bankruptcy and falling asset prices may have greater impact on the well-off, but the economic recession may hit those at the bottom hardest. This may also have changed over time as greater stock market participation and widespread home ownership have contributed to spread the gains and losses also to the middle segments of the distribution. Most crucially, macroeconomic crises often occur in cluster and banking crises may be preceded or followed by currency crises, economic slump or debt crisis.

On the other hand, banking crises are often followed by large government and monetary authority interventions, including increases in social welfare spending, nationalization of distressed financial institutions and other bank bailout schemes[1]. Such policy interventions are financed by the fiscal policy which inevitably implies an immediate or future transfer from taxpayers to main beneficiaries of such policies. Policy intervention in the aftermath of a crisis might also tighten the regulation of financial markets, curbing the possibility of future high returns for the financial sector (e.g. credit market regulation, remuneration caps and change in regulation for market concentration).

Disentangling the overall distributional consequence of macroeconomic shocks is, therefore, a challenging and complex task. This is illustrated in the Figure1 for the case of a banking shock.

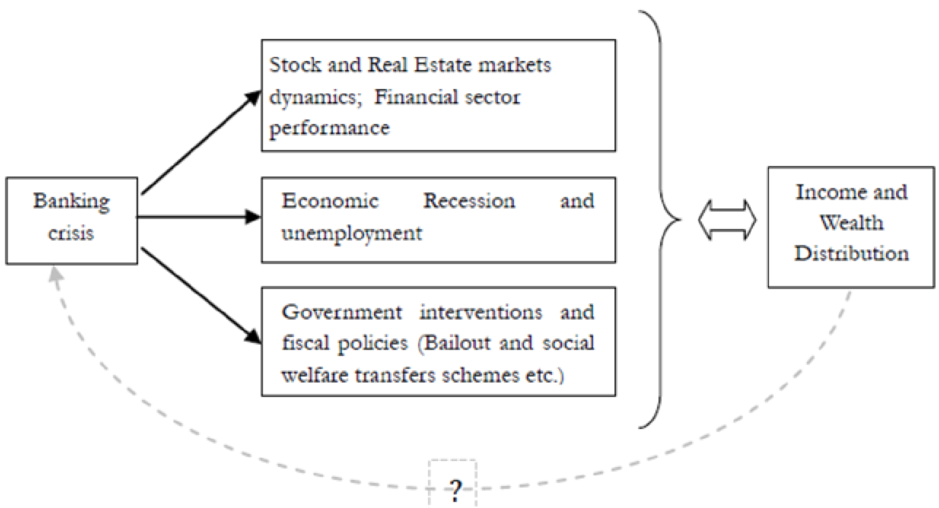
Moreover, to complicate the empirical specification of the model even further, a growing body of research is pointing to the role of inequality as a main contributor to financial instability, casting doubts about the exogeneity of the regressors (for a review and empirical evidence see Atkinson and Morelli 2010, 2011).

In this paper we will attempt to address the most pressing concerns expressed above. Firstly, the use of a set of different covariates, including indexes for a wide range of macroeconomic shocks, will help to disentangle the direct impact of specific crisis episodes. Secondly, with the use of data based on gross income definition we can exclude any direct impact of fiscal policy on our measure of inequality (top income shares). On the contrary, the structural breaks in fiscal policy, such as increase in top marginal tax rates, will certainly have indirect implications on the way households

[1] Rescue packages account on average for 12% of GDP (gross fiscal costs) according to Leaven and Valencia (2008) for a series of 42 systemic banking crises. New estimates for recent crisis started in 2007-2008 suggest that fiscal costs are around three times smaller given the sizeable monetary policy intervention in the market.

report their income. Nonetheless, the literature on behavioral responses to changes in taxation regimes suggests the way to control for this. Thirdly. the endogeneity of crises to the inequality variable will be tested formally and generally our results will be presented also assuming the contemporaneous exogeneity of the growth rate of top share with respect to the occurrence of the crisis. Finally, the use of a short time horizon (4 years), we argue, should be sufficient not to worry much about the potential role of new institutional and regulatory framework likely stemming from the crisis.

Figure 1: Unraveling the complexity



Source: Morelli (2011)

2 Existing Literature

Our study builds on existing literature about the distributional implication of crises. To our knowledge, only three recent works explore, directly or indirectly, the impact of shocks on a measure of inequality directly comparable to ours (top income shares)[2]. The above mentioned studies are respectively Roine, Vlachos and Waldenstrom (2009),

[2]The remainder of the literature generally deals with overall measures of income inequality (i.e. Gini coefficients) and a shorter time horizon. Country-specific studies are also common. Surveying this literature goes beyond the scope of this paper and we refer the interested readers to the recent comprehensive works by Atkinson and Morelli (2010 and 2011), Jenkins, Brandolini, Micklewright and Nolan(forthcoming) and Brugiavini and Weber(forthcoming).

Morelli (2011) and Bordo and Meissner (2011), from now on referred to as RVW, MO, and BM. Whilst MO explores the impact of systemic banking shocks and stock market crashes in the US exclusively, the two other works analyse data for a panel of countries and therefore are more directly comparable to the present work. The main evidence in RVW suggests that banking crises are associated with an average reduction of the top 1 percent, whereas no evidence is found for the so called 'next 9 percent', the poorer groups of households below the 99th percentile up to the 90th. More specifically, RVW's model predicts an average drop of around 0.2 percentage points for every year (out of 5) in which a country is experiencing a banking crisis. On the other hand, no evidence of any sort is found in the case of currency crises. The specification is estimated for the whole set of countries and years and makes use of first-difference variables, including a set of controls (changes in GDP per-capita, trade openness, population, and government expenditure). RVW's work explore 17 countries from the early years of the twentieth century up to 2004 at the latest. Moreover and most importantly, data are averaged over 5 year windows and information gaps on top income shares are occasionally linearly interpolated.

The study by BM uses a very similar empirical specification[3] and explores cross-country data for 16 countries from 1880 to 2000. BM's variable of interest is the absolute cumulated change in the top1 percent over a fixed window of 5-years for the post-WWI period. A different measure of 'inequality' is used for the remaining years: the ratio of unskilled wages to GDP. Unlike RVW, the authors conduct their analysis for three sub-sample of adjacent periods: Pre-WWI, interwar and post-WWII. The presented results suggest that a banking crisis is associated with a reduction in inequality exclusively within the interwar period. The remaining periods see a significant increase in inequality following the banking shock.

The present study expands the methodology adopted in MO to a panel of countries and builds on previous empirical contributions by RVW and BM [4]. However, our work will study the richest fractiles more closely (especially top001) and our specifications make use of the growth rates of the top shares rather than their first-difference. We believe this is important as top income shares are not directly comparable across countries and using their first differences may complicate the interpretation of the results with issues linked to the units of measurement. We also extend the analysis to 27 countries and our distributional data is extended to 2010 in a few cases (i.e. Sweden and the US). We further depart from RVW and BM's methodological assumptions in different ways. Firstly, we construct a more homogeneous dataset of banking crises across different sources discarding the non-systemic episodes. Secondly, we adopt a novel methodol-

[3] Yet, the estimation methodologies are different. While RVW use First-Difference GLS and Dynamic Fixed effects, BM use Pooled OLS. Both studies include period and country fixed effects.

[4] We are particularly grateful to Jesper Roine for sharing their data.

ogy consistent with an 'agnostic' view about the ending date of a banking crisis, a very controversial matter within the literature, as explained further below. Thirdly, we acknowledge the fact that macroeconomic shocks are not isolated events but occur in cluster. This leads us to include other type of shocks as well within our empirical specification, hoping to obtain more accurate estimates of the 'residual' impact of a banking shock. In particular, we include other types of financial crises (currency crises, external debt default, hyperinflation episodes) and economic shocks (real per-capita GDP and consumption crashes)[5]. The latter are particularly important as we would like our measure of banking crisis to absorb the residual dynamic of top share other than what is normally associated to a more common GDP collapse.

Fourthly, we exploit year-to-year variations and do not average out the data. Similarly, we work with the original series of the WTID and do not interpolate the top income shares. We believe this can interfere with our objective, namely analysing the short-term implication of macro-shocks on the top of the income distribution. Lastly, we estimate our empirical specifications based on the standard homogenous panel models as well as on models based on the recent literature on panel time-series with common-factors (heterogenous panel models with control for more general cross-section dependence). We also provide our results divided by period and country-group sub-samples. This will test how the results may be driven by the nature of the sample and the estimation methodologies.

3 Data

The two main database sources needed for this study are those related to the top income shares and macroeconomic shocks. This section reviews the existing information sources on macroeconomic shocks, explaining how these were assembled to create a new comprehensive database. It then describes the World top income database from which we draw information on our measure of within country income inequality, the top income shares. Finally, the study also makes use of other macroeconomic variables, such as measure of *de jure* financial opennes, real per-capita GDP, Stock market capitalization and top marginal tax rates[6] which will be described directly within the text and not in this section.

[5]The study intends to add - in the next version - other type of shocks to the list. Commodity price shocks and fiscal consolidation episodes among others

[6]Stock market capitalization and top marginal tax rates are variables taken from the RVW's database kindly shared by one of the co-authors, Jesper Roine.

3.1 Identification of Macroeconomic Shocks

Drawing from available studies in the literature, we assemble our own database on financial and economic crises. The data includes information about systemic banking shocks, currency crises, external debt defaults and hyperinflation episodes. In addition, the database includes comprehensive information about and real per-capita GDP and consumption collapses, including the duration and the depth of the crises. Including information about other macro shocks and in particular about economic collapses we believe is important to allow the measure of banking crisis to potentially explain any residual dynamic of top shares.

3.1.1 Systemic Banking Crises

"Identifying banking crises is the first step in all research on banking crises" Von Hagen and Ho (2007) recall in their paper, proposing a new empirical method for crisis detection.

For this, we have consulted some of the most authoritative databases of banking crises. These are Bordo et al. (2001), Reinhart-Rogoff (2008, 2009), Reinhart(2010) and Laeven-Valencia (2008, 2010, hereinafter BE, RR and LV. Comparing these sources we have constructed a new list of banking shocks assembling dummy variables taking value of 1 at the beginning year of a crisis and 0 otherwise. Ultimately we identified 88 crises from 1900 to 2009 for a list of 27 countries.

In general the sources do not always speak unequivocally on crisis identification. The heterogeneity reflects both differences in the identification methodology and in subjective judgments. We solved this issue by adopting a form of 'majoritarian' criteria, identical to what detailed in Atkinson and Morelli (2011).

Here, as we mentioned before, we will be concerned uniquely with systemic shocks, disregarding those events that affect isolated banks[7]. For example, among others, the UK banking crisis (1974-1976) is excluded from our database as it was not systemic in nature[8].

Finally, although some scholars have tried to identify the length of the crisis, we take an 'agnostic' stand as we consider this task more controversial than the identification of the starting point. For example Bordo et al. (2001, Appendix) define and calculate the recovery time of a crisis as "the number of years until GDP growth returns to its pre-

[7]RR identifies explicitly systemic and non-systemic shocks while LV lists uniquely systemic crises. Conversely BE adopts, somehow implicitly, a definition of banking crisis which is systemic in nature. Moreover for their post-1970 list of crises they draw directly from the list of systemic banking crises in Caprio and Klingebiel (1996, 1999).

[8]The other two studies investigating the impact of crises on top shares, Roine,Vlachos and Waldenstrom(2009) and Bordo and Meissner(2011), do not discuss explicitly the difference between systemic and non-systemic banking crises.

crisis trend, including the year when it returns to that trend". Similarly, Laeven and Valencia (2010) report the end date for the crisis episodes [9]. Generally speaking, we believe that the above mentioned methodologies are not able to capture with precision when a banking crisis comes to an end. Rather they are more consistent with the identification of the ending date of the recession likely stemming from the financial shock itself.

3.1.2 Economic Crises

Beside systemic banking crises we identify real per-capita GDP and consumption disasters. We essentially extend, back to the year 1900 and for few more countries, the database assembled in Atkinson and Morelli (2011). By doing this, we make use of the very detailed study by Barro and Ursa (2008) which identifies the so called 'disasters' using a threshold of 10 percent cumulative percentage drop[10], from peak to trough, in per-capita real GDP and per-capita real consumption. Using their updated data on the web[11], we have independently implemented the 'Peak to Trough' methodology and obtained a list of GDP and consumption disasters that could be matched with that found in the work of Barro and Ursa in tables C1 and C2 (2008). We confirm most of their listed disasters and add a few others left unnoticed. Finally we extend the list of crises to 2009 and include milder crises episodes for the post-1950 period in order to take into account the role of time trend and agents expectations (practically we include episodes with a cumulative drop of at least 5 percent from peak to trough).

Our dataset on economic crises has very rich information as it identifies the beginning of the crisis but also the precise duration and depth of it. This will turn useful in the empirical estimation.

More information on the identification of the economic crises is found in in the appendix of Atkinson and Morelli (2011).

3.1.3 Other Macroeconomic Shocks

As mentioned within the initial paragraphs, macroeconomic shocks usually occur in clusters. This means that we need to know the distribution of shocks over time and their overlapping features in order to untangle the 'direct impact' of every single of them on income distribution. For this reason we add further information to our crises database. In particular, drawing from the extensive work by BE, RR and LV, we draw

[9] They define the end of a crisis as "the year before two conditions hold: real GDP growth and real credit growth are positive for at least two consecutive years. In case the first two years record growth in real GDP and real credit, the crisis is dated to end the same year it starts."

[10] However, in practice Barro and Ursua often use a threshold of 9.5

[11] $http \ : \ //www.economics.harvard.edu/faculty/barro/files/MacroCrisesSince1870_08_0614.xls$ accessed on September 2011.

information about currency crises, external debt defaults and hyperinflation episodes. Similarly to the case of economic crisis, the dummy variables also indicate the length of the crisis, but no information about depth is recorded. The currency crisis episodes are mainly identified from BE (when BE is not available for recent years LV is used in place) while debt crisis and hyperinflation are taken exclusively from RR.

3.2 Data on top-income shares

Our analysis makes use of the World Top Income Database (WTID), an extensive database[12] of top income shares' annual series based on historical tax statistics covering most of the 20th century for 27 countries[13]. Broadly speaking, this will be will be our information about within-countries income 'inequality'. The present study explores the share of total national income earned by the richest fractile (top001) as representative for the group of the richest within the top 10 percent of the income distribution. Conversely, the share of P90-P95 represents the 'poorer' group within the top decile[14].

The data on top income shares of the WTID, as all economic data, suffers from several limitations[15]. For instance, it is worth mentioning that such data are not particularly appropriate to study the bottom groups of the population. However, tracing the dynamics of a relatively small number of richer households is not uninformative on the general disparity of income distributions (e.g. Gini coefficient) given that they own a considerable share of US total net worth or total income[16].

Generally the series are constructed using tax statistics and they make use of gross type of income (i.e. in the US the gross market income is defined before deductions,

[12]The database, managed by F. Alvaredo, T. Atkinson, T. Piketty and E. Saez, makes use of the findings from the collective research project on the dynamics of income distribution coordinated by A.B. Atkinson and T.E. Piketty (2007 and 2010). On the other hand the database is constantly evolving and new countries and observations are being added.

[13]The number of covered countries will vary according to the specification of the model and will be dependent on data points availability. The countries covered by the WTID, at July 2012, are Argentina, Australia, Canada, China, Denmark, Finland, France, Germany, Iceland, India, Indonesia, Ireland, Italy, Japan, Malaysia, Mauritius, Netherlands, New Zealand, Norway, Portugal, Singapore, South Africa, Spain, Sweden, Switzerland, the UK and the US. We further complement this list with information on Iceland and Malaysia taken from Atkinson and Morelli (2012).

[14]It is not always possible to use these variables as observation availability vary across countries and time. When top001 is not available we revert to top005, top01, top05 and top1 respectively (all of them nest the information about the top001). On the other hand when the share of P90-P95 is not available we will use information about P90-P99 or P95-P99

[15]For a more complete discussion and description of the data we direct the reader to the books edited by Atkinson and Piketty(2007 and 2010) and the work by Atkinson, Piketty and Saez (2011).

[16]For instance, "If we treat the very top group as infinitesimal in numbers, but with a finite share S* of total income, then the Gini coefficient can be approximated by S*+(1-S*)G, where G is the Gini coefficient for the rest of the population" as recalled by A.B. Atkinson (2007, p.19) and proved more formally in Alvaredo (2011).

individual income taxes, payroll taxes and all kind of government transfers.). On one hand, this characteristic is particularly welcome as facilitates the untangling of the impact of fiscal policy on the sources of income. On the other hand, it makes the comparison of levels across countries particularly cumbersome[17]. Indeed, the definition of income has to satisfy the administrative requirements of each specific country. Moreover tax statistics suffer from common problems of tax avoidance and tax evasion as individuals report income so to minimize their tax liabilities (the equivalent of underreporting in the survey-based data).

Ultimately, data on top shares constitutes a unique source of comparable information over time which allows to analyse an extraordinary long time horizon (covering most of twentieth century and the beginning of the twenty-first century). This is a crucial advantage for a study on macroeconomic shocks and especially systemic banking crises which are very rare events in a country's history.

Figures 2-3 depict the top1 and top001 for different sub-groups of countries. The charts show a strong common dynamic of the top shares across different groups. Beside being a renown feature of these data, this suggests a strong feature of cross-section dependence which ought to be taken into account in the empirical estimation.

The grouping of countries follows the work by Atkinson, Piketty and Saez, 2011 (from now on referred to as APS) who summarize their analysis respectively for the Nordic European (Denmark, Finland, Iceland, Norway and Sweden)[18], Southern European (Italy, Portugal and Spain), Developing (Argentina, China, India, Indonesia, Malaysia, Mauritius, Singapore, South Africa and Tanzania)[19], Western English speaking (Australia, Canada, Ireland, New Zealand, United Kingdom and United States), and Continental central European countries (France, Germany, Netherlands and Switzerland) together with Japan. "*The grouping is made not only on cultural or geographical proximity but also on proximity of the historical evolution of top income shares.*" (APS, page 40).

One tends to assume that the groups of individuals/households populating the top10 percent of the income distribution is a relatively homogeneous bunch. In fact, enormous differences in income level characterize the subgroups within the top decile. This is also recalled in APS who posit that *"being in the top 1 percent does not necessarily imply being rich and there are also marked differences within this group. The very rich are different from the rich"*. As an illustration lets take the case of the United States. In 2006, the minimum non-capital gains income in order for a tax unit to be counted

[17] Although the data series are fairly homogeneous across countries and over time, there are also differences in the definition of the unit of analysis (e.g. individuals vs. households). Sometimes the unit of analysis changes over time within a single country. This further complicates the comparability of levels across panel units and over time.

[18] Iceland and Denmark were not yet included in the APS study.

[19] Malaysia, Mauritius, South Africa and Tanzania are newly added countries with respect to APS.

above the P90, P95, P99, and P99.99 percentiles was respectively 111.772, 156.773, 392.922, and 8.568.365 US-2008 dollars[20]. Upper groups do not differ only by the level of income. Its composition varies considerably over time and across income groups as well. In 2007 the incidence of capital income for the bottom group of upper decile was between 5 and 9 percent, depending on whether or not capital income includes realized capital gains. The same figure adds up to 33-42 percent of total income for the richest group. Therefore it does not come as a surprise that the empirical evidence shows that richer fractiles (above P99) and 'poorer' ones within the top decile (P90-P99) seem to form two distinct groups. In the US, their respective shares in total income are negatively and significatively correlated, especially during the period surrounding the financial shocks[21]. By looking at the US data, the top decile share net of the top5 percent (excluding capital gains), grew on average 4 percent during the 5 years after a crisis, while it had a negative average growth of around 1 percent in the years preceding the crisis. Instead, the richest fractile share in total income grew on average around 13 percent preceding banking turmoil. The average dropped to negative 9 percent in the 5 years following the crisis. As shown in the next sections, the present cross-country study will also find similar empirical evidence.

4 Methodology and Estimation Strategy

This paper attempts to evaluate the short-term impact of systemic banking crises on a country's share of total national income detained by the richest segments of the population. The empirical evidence is produced by estimating impulse response functions (IRFs) of the rate of growth of top income shares[22] to the systemic banking crises. This methodology is more commonly applied in macroeconomic studies and, to our knowledge, constitutes a novelty within the literature of income distribution[23]. We first generalize this approach to a cross-section of countries and we discuss the estimation of the model based on two main approaches. On one hand, we make use of the more standard 'pooled' estimators (i.e. POLS, FLS). On the other hand, we take advantage

[20]Moreover, the 2006 ratios between the average incomes of independent fractiles within top decile (P90-P95, P95-P99, P99-P99.5 and P99.99-P100) and the above stated thresholds are respectively 1.17,1.39, 1.21 and 2.55.

[21]In the US the correlation is particularly highly significative for the series including capital gains and it appears robust to the use of different time windows. Moreover, the correlations before crisis appear slightly stronger than the period after the crisis.

[22]We recall the priority is given to the top hundredth percentile (top001). When the latter is not available, for a country or a specific period of time, we revert respectively to the growth rate of the top005, top01, top05 or top1 percent.

[23]The paper by Romer and Romer(1989) constitutes the first example of this methodology. Using a single time-series for the US, they attempted to gauge the implications of exogenous monetary policy shocks on unemployment rate and industrial output.

of the more recent advancements within the heterogenous models and common factors approach to panel estimation (i.e. in the family of the Mean Groups estimators). Applications of this sort are less common in the empirical literature, although being particularly appropriate in the case of macro-panel (long N and long T) with features of non-stationarity and cross-section dependence (see Eberhardt et al. (2011) for a detailed discussion).

More specifically our empirical specifications is a multivariate ARDL model using the growth rate of top shares in order to mitigate the potential sources of non-stationarity and to obtain results free from the influence of the unit of measurement.

$$g_{i,t}^{top} = \alpha_i + \sum_{k=0}^{2} \theta_{i,k} g_{i,t-k}^{top} \ + \sum_{k=0}^{4} \phi_{i,k} D_{i,t-k} + S_{i,t}' \delta_i + X_{i,t}' \rho_i + u_{i,t}. \tag{1}$$

where $g_{i,t}^{top}$ is the growth rate of the top fractional percentile for every country i from year t-1 to year t. $D_{i,t}$ is a categorical variable coded 1 when the systemic banking crisis in country i begins and zero otherwise. $S_{i,t}$ is a vector of other macroeconomic shocks (GDP and consumption collapses, currency crises, external debt defaults and hyperinflation episodes) taking value of one for the whole duration of the crisis and not just at the onset of the shock. $X_{i,t}$ is a vector of regressors including a number of macroeconomic variables, such as real per-capita GDP growth, the growth rate of stock market capitalization, the change in top marginal tax rates and the evolution of a *de jure* measure of capital mobility. At this stage we assume that the list of the variables include all possible regressors in order to exclude, at least within the discussion, any source of the omitted variable bias. The unknown random coefficients are assumed to be of the following structure $\theta_{i,k} = \overline{\theta_k} + \eta_{i,k}^{\theta}$, $\phi_{i,k} = \overline{\phi_k} + \eta_{i,k}^{\phi}$,$\delta_i = \overline{\delta} + \eta_i^{\delta}$, $\rho_i = \overline{\rho} + \eta_i^{\rho}$ with $(\eta_{i,k}^{\theta}, \eta_{i,k}^{\phi}, \eta_i^{\delta}, \eta_i^{\rho}) \sim i.i.d.$
Finally, the structure of the error term $u_{i,t}$ will be discussed more in detail within the estimation subsection and the appendix.

4.1 Derivation of the Impulse Response Function - IRF

This section shows the steps carried out in order to derive the realizations of the IRF for a four years time horizon, reflecting our stated goal of analysing the impact of crises over the short-run. The IRF estimated directly from our empirical specification provides the empirical evidence about the response of the rate of growth of top income shares to the systemic banking crises. However, given our ultimate interest in the impact of the crisis on the level of top shares, we will cumulate the estimated realizations over time.

It is straightforward to show that the first realization of the IRF is the average impact of a perturbation in the dummy variable D (taking value of 1 if shock occurs and zero otherwise) from the estimated parameters of equation (1). The subsequent dynamic multipliers will clearly depend on the feedback effect due to the presence of lagged variables of the top share growth rates. Given that we are dealing with stationary series, every impulse to the dynamic process will automatically decay over time and this approach can be informative about the depth and duration of a change in top shares brought about by banking shocks[24]. We represent below the realizations of the IRF, I_s, for the growth rate of top share evaluated at $s = 0, 1, 2, 3, 4$ years following the banking shock, where $I_s = [g^{top}_{t+s}/D_t = 1 - g^{top}_{t+s-1}/D_t = 0]$.

$$I_0 = \overline{\phi_0} \tag{2}$$

$$I_1 = \overline{\phi_1} + [I_0] * \overline{\theta_1} \tag{3}$$

$$I_2 = \overline{\phi_2} + [I_1] * \overline{\theta_1} + \overline{\theta_2\phi_0} \tag{4}$$

$$I_3 = \overline{\phi_3} + [I_2] * \overline{\theta_1} + \overline{\theta_2}[\overline{\phi_2} + \overline{\theta_2\phi_0}] \tag{5}$$

$$I_4 = \overline{\phi_4} + [I_3] * \overline{\theta_1} + [\overline{\phi_3} + \overline{\theta_2}(\overline{\phi_2} + \overline{\theta_2\phi_0})]\overline{\theta_2} \tag{6}$$

By cumulating the above realizations of the IRF over time we obtain the impulse response function on the level of top shares, $f_i(\psi, t)$, where ψ is the vector of parameters. The estimated version of the IRF $f_i(\widehat{\psi}, t)$, our ultimate interest, represents the residual dynamics of the top income share when a banking shock occurs compared to the no-crisis case. In other words, the model predicts and compare the dynamics of the top income share with and without the banking crisis occurrence and given its past dynamics, time trend and other macroeconomic conditions. For instance, an estimated figure of -0.1 at the third year following the shock (I_3) should not be interpreted as a decreases of top shares by an average of 10%. Rather, the figure of -0.1 means that three years following the beginning of the banking crisis the top income share is still 10% lower than what expected on the basis of its past dynamics and on other macroeconomic condition (excluding the occurrence of the banking crisis). The estimation methodology and the results will be discussed in the sections below.

[24]It is worth noting that the processes underlying the growth rates of top income shares are very volatile and have very low level of persistence. Thus, perturbing such processes will hardly find any significant 'structural break' which goes beyond two years.

4.2 Estimation

Our estimation strategy varies according to the different set of covariates under investigation and to the testable restrictions we are imposing upon the empirical specification with respect to what we believe to be the true data generating process (DGP). In particular, our estimation strategy depends on the assumptions about the nature of the unknown parameters and the unobservable error structure. Our approach begins with the standard panel estimations based on the assumption of homogeneity of the parameters across panel units ($\theta_{i,k} = \overline{\theta_k}$, $\phi_{i,k} = \overline{\phi_k}$, $\delta_i = \overline{\delta}$, $\rho_i = \overline{\rho}$). However this approach can create a list of problems to the estimation, some of which can bias our results. On top of that, the 'pooled' estimators do not control for the correlation between cross-sectional units. This can result in inconsistent estimators, as explored more in detail within the appendix.

In order to mitigate these problems we will also estimate the specifications in equation (1) using the heterogenous panels and the common factors approaches. This methodology assumes away the homogeneity of the unknown parameters and allows to control for country-specific (linear)[25] trends and for a more general structure of cross-section dependence of the error terms. For the sake of this paper we decided to focus respectively on the standard Pooled OLS (POLS), the Feasible GLS (FGLS) and on the Augmented Mean Group(AMG) estimators. These estimators respectively represent the category of 'pooled' and heterogeneous panel models. The appendix explores more into details what lies behind this choice.

The three different estimators described above are also applied sequentially to different sets of covariates. In particular we proceed in four steps for each of the three estimators (POLS, FGLS and AMG).

The first step estimates the main specification excluding all covariates but the lagged observations for the growth rate of the top share and the banking crisis dummy variable. This model can be misspecified, unless every subsequent or contemporaneous relevant macroeconomic events (e.g. other macro-shocks, raise in unemployment, policy interventions and stock market swings) have been directly caused by the banking shock, or they are assumed to be so[26]. Moreover, such an approach is not very informative about the direct and indirect(i.e. caused by other crises) impact of the banking turmoil on the top shares. This will lead us to estimate, in the following steps, the direct impact of banking crises on the top shares uniquely as a residual impact once other macro events have been controlled for.

[25] We believe a linear trend to be sufficient in our case given that the dynamic of top income shares over time can be reasonably approximated by a quadratic trend. Indeed, it is straightforward to show that if y follows an AR(p) model with a quadratic time trend, its first difference will be still linearly dependent on time.

[26] Yet, this is clearly not always the case. For example, the S&L crisis in the US(1988 is our recorded starting year) was preceded and not followed by the 1987 stock market crash.

Indeed, in the second step we control for the list of other macroeconomic shocks, whereas in the third step we also add the change in log of real per-capita GDP and an average (across countries) measure of *de jure* financial openness[27]. The latter should capture some form of common dynamics due to the overall integration of financial markets[28].
Ultimately we add more controls referring to other macroeconomic events such as the change in top marginal tax rates[29] and the the growth rate of stock market capitalization.

We therefore obtain a distribution of 12 different estimates for each single realization of the IRF (four sets of covariates for each of the three empirical estimation methods). This provides enough variation for the estimated realization of the IRF and should also provide confidence about the fact that the results obtained are robust to different features of the empirical specification. The estimates are then averaged out and the IRFs are represented graphically with a two standard deviation confidence band[30]. The IRFs are also charted for different sub-samples of time periods and country groups as shown in the sections below.

4.3 Endogeneity

The consistency of the estimated parameters in the ARDL model rests on the assumption of exogeneity of the crisis dummy variables with respect to the growth rates of top income shares. Up to now, we have systematically assumed away any feedback effect going from inequality to occurrence of crisis. Nevertheless, a growing body of research is now focusing on whether widening income inequality could increase the likelihood of a crisis occurring (both banking and economic crisis). The hypothesis was recently proposed by some prominent scholars such as J.P. Fitoussi, B. Milanovic, R. Rajan and J.E. Stiglitz (see Atkinson and Morelli 2010 and 2011, Lucchino and Morelli (2012) for an extensive review).

If this assumption holds true, we ideally ought to solve the following non-linear structural equation model and possibly work out the reduced form equations.

[27] The measure is very similar to what represented in the renown work by Obstfeld and Taylor(2003)

[28] This was also suggested in APS at page 65

[29] We assume that income reported in top tax bracket depends on the "net-of-tax rate" $1-\tau$. This approach follows latest development in empirical analysis of elasticity of top income to marginal tax rates (Saez , Slemrod and Giertz, 2010).

[30] Conversely, other similar studies in the literature usually report a one-standard deviation confidence band

$$
\begin{cases}
g_{i,t}^{top} = \alpha_i + \sum_{k=0}^{2} \theta_{i,k} g_{i,t-k}^{top} \ + \sum_{k=0}^{4} \phi_{i,k} D_{i,t-k} + S_{i,t}' \delta_i + X_{i,t}' \rho_i + u_{i,t} \\
\\
Pr(D_{i,t} = 1) = F(\sum_{n=0}^{N} \delta_{i,n} g_{i,t-n}^{top} + \mathbf{Z}_{i,t}' \sigma + v_{i,t}) \\
\end{cases}
\tag{7}
$$

A way around the cumbersome task of estimating a system of equation with a panel of countries, is to assume the dynamics of top shares to be exogenous to the banking crisis. This is equivalent of stating that $\phi_{i,0} = 0$ into the first equation of the system. In other words we can assume that systemic banking crises have exclusively lagged effects on the growth of the top shares. Similarly we can assume the first year of an economic crises (i.e. GDP and consumption collapses) to be contemporaneously incorrelated with the growth of top income shares.

Generally, it is worth noting that the available empirical evidence is not unequivocally supportive of the hypothesis that growing inequality could be correlated with higher probability of a crisis[31]. Indeed, Bordo and Meissner (2012) use similar data to ours and cannot reject the hypothesis for the relevant coefficients in the second equation of the system to be equal to zero. Our study also independently replicates this investigation and confirms the finding[32].

Nonetheless all the IRFs above are re-estimated based on the assumptions above, namely that any contemporaneous association between the growth rate of top shares and the occurrence of either a banking or a GDP crisis depend on innovations linked to the rate of growth of the top share. The results are qualitatively and quantitatively similar to what we have so far discussed and they will not be shown in this paper.

5 Results

Table1 shows the average dynamic impact of the systemic banking shock on the level of the share, in total national income, of the richest and the bottom groups within the top decile (typically the share of P99.99-P100 and P90-P95). The estimates are calculated for the whole sample of countries and years and suggest that systemic banking crises have, on average, no significant additional impact on the dynamic of top shares. Despite their poor statistical significance, it is worth noting the main features of the findings for the whole sample. In particular, the two non-overlapping groups seem to be negatively

[31] Such results, however, do not rule out the possibility that higher levels of inequality could be associated to increasing levels of financial instability.

[32] The results are not shown in the paper as they are still very preliminary. The work by Atkinson and Morelli (2010 and 2011) also provides a systematic empirical investigation using a set different measures of economic inequality for a group of 25 countries covering around 100 years.

correlated around crises episodes[33]. Thus, loosely speaking, richest groups appear to "loose" and the less-rich ones to 'gain', in relative term with respect to the whole population. The former finding was already noted in RVW.[34] However, averaging out the results across the whole sample can downplay the role of a panel of data spanning a long time horizon and covering more than a third of the world GDP. Are this finding consistent over time and across countries? The sections below explore the importance of a long term *as well as* a cross-country perspective.

5.1 Results over time

Analysing results over time reveals a more complex relationship between inequality and crisis, as suggested by BM who split the sample into pre-WWI, Post-WWII and interwar periods. In Figure 4 we replicate this approach, showing the results (for the richest shares only) divided by sub-periods samples, namely pre-1950 and post-1950[35].

Figure 4 shows that the pre-1950 crises appear to exert a negative impact on the 'inequality' of income, pushing the richest top shares downward, a fact which is qualitatively comparable to what found in BM's work. In particular, our findings show that at the second year following the crisis, the richest top share is still, on average, around 4% lower than what expected had the crisis never occurred (the result is robust to the exclusion of individual country groups from the sample). This is not a very substantial drop, as it is comparable to an average drop of around 0.08 percentage points in top001, equivalent to one twelfth of its average standard deviation[36]. Alternatively it can be comparable to an average drop of around 0.6 percentage points in the top1 share, equivalent to around one seventh of its average standard deviation[37]. This is considered, at best, almost a half of what the work by Atkinson and Morelli (2011) considers to be a 'salient' change in inequality (around 1 or 1.5 percentage point change

[33]This was anticipated within the data description section with an

[34]However, their findings are statistical significant and refer to the top1 shares exclusively. Besides the differences in the estimation methodologies, we believe that part of the top shares dynamics in our models, is captured by the GDP shocks indicators. In other words, part of the reduction in top shares attributed to the banking shocks in RVW, is in our model associated to economic downturns which usually overlaps with the banking crisis.

[35]Our post-1950 period differ from BM's so called "post-WWII" periods as the latter ends in 2000 whereas our analysis includes the latest financial turmoils (2007-2010). In general, 62 out 88 crises in our sample occur before the 1950, with zero crisis between 1948 and 1977. Only 15 crises are identified between 1900 and 1914 but, due to data limitation, only Japan 1907 is effectively analysed. Therefore our pre-1950 differs from the so called "interwar period" as the latter excludes all the crises occurred during the two World Wars.

[36]For the pre-1950 period only, the mean value of top001 across countries is around 2 and its average standard deviation is approximately 1

[37]For the pre-1950 period only, the mean value of the top1 across years and countries is around 15 and its average standard deviation is 4.2.

in top1 share). Moreover the average drop has a very low persistence as this appears to be fully recovered by the fourth year from the crisis.

Conversely, the crises occurred within the post-1950 subsample do not seem to have any significant effect on the average dynamics of the top shares. However, this result is not robust to the exclusion of 'Developing' and 'Southern European' groups of countries, as shown in Figure 5.

The results are insightful and show that excluding both Developing and Southern European countries (constituting 40% of the countries in our sample) within the time-period analysis, reveals a great deal of information about the average distributional impact of recent crisis on the top shares. Such effect is now qualitatively similar to what found within the pre-1950 sub-sample. Most importantly, its magnitude seems now more than three times as big. More specifically, at the third year following the crisis, the richest top share is found, on average, to be around 15% lower than what expected in the no-crisis scenario. This is now comparable to around 0.1 and 1.2 percentage points change respectively for the top001 and top1 shares[38]. According to the classification in Atkinson and Morelli (2011) this is a "salient" change in inequality. In addition, the change is perceived as more long-lasting as, although recovering, the richest top shares are still around 10% lower than expected at the fourth year from the crisis impulse.

These findings, unlike the ones associated to the pre-1950 sub-period, are at odds with BM's findings about a substantial increase in inequality following the post-1950 crisis[39] It is worth noting that this is occurring despite the use of very similar data, the heterogeneity of these results can be ascribed, we believe, to different empirical methodology as well as data composition. On the one hand, BM's empirical specification, exploring a 5 year cumulated change in top1 share, is evidently less informative about the within-period change in top shares (ultimately our object of interest) and, most importantly, does not control for the within-period time trend. This fact may partly explain their findings about a strong increase in inequality following a banking shock, as all the banking shocks occurring in the so called 'post-1950' are posterior to 1977[40], a time in which top shares are strongly trending upward.

On the other hand, our dataset allows the analysis of banking crisis episodes in the recent years 2007-2010 and extends the coverage to more developing countries especially in the post-1950 period. Generally, observations on top shares are more scarce for the so called 'developing' and 'southern European' groups of countries, especially in the pre-50 period. Such sample composition can potentially drive the difference in findings

[38]The values correspond approximately to 1/5 and 1/2 of their respective average standard deviation in the sub-sample excluding the years prior 1950 and both developing and souther European countries. This is, indeed, an impact between 2.5 and 3.5 times higher than what recorded in the pre-1950 period.

[39]Equivalent to their post-WWII period.

[40]In general, the period within 1947 and 1977 is banking-crisis free for the countries under investigation and according to our database of reference. This applies also to non-systemic banking crises.

between pre and post-1950 sub-periods if the impact of crises is heterogeneous across groups of countries, as will be shown in the next section.

To summarize, the results by different time horizon potentially provides interesting insights and underlines the importance of a long time perspective. In fact, the distributional implication of systemic banking shocks may well differ over time, running somehow contrary to the "this time is NOT different" type of message put forward by the extensive work by C. Reinhart and K.Rogoff. In fact, recent crises appear, in the very short-run and on average, up to approximately three times as disruptive for the richest fractiles share compared to the crises occurred in the interwar period. This appears true also when comparing the estimated changes in top shares to their respective average standard deviation.

5.2 Results across country-groups

In this section, we acknowledge that the distributional impact of shocks may well differ across different institutional and economic features characterizing specific country-groups. Hence, we show the estimated IRFs accordingly.

Following the classification used in APS's paper, Figures 6 and 8 broadly point to two main groups of countries, according to their different distributional response to banking crises. On the one hand, there are the so called Nordic European, Western English Speaking and Continental European (including Japan) countries, in which the richest fractile share seems to suffer a negative shock following a banking crisis. On the other hand, there are the so called Southern European and the Developing countries which show the opposite response, namely an increase in their top shares. This evidence complements the account of the results across time, which are presented respectively with and without the group of countries which appear to be 'outliers'.

Beyond this general description, the features of the response of the richer group's share of total income to shocks appear quite variegated across country-groups.
Figures 10-13, provide a useful mean of comparison in order to assess the relative magnitude of the suggested change in top shares estimated by our models. In particular, the predicted absolute change in top shares can be compared to the standard deviation for the specific country group of reference. In western English speaking countries, for example, our model suggest that the richest top share drops on average by around 6% in the crisis scenario compared to the no crisis case. We can now compare this relative drop to the mean of top001 for English speaking countries in Panel A of Figure 12. This value is then compared to the respective standard deviation in panel B of the same Figure. This suggests that the predicted change by our model is approximately 6% the average standard deviation within the so called 'English' group. This appears quite a modest change. Moreover, the impulse given by banking crisis to top shares in western English speaking countries, has a low persistence, as full recovery occurs

within the fourth year following the shock. As a mere illustration we take the case of the recent US banking crisis when the share of the top hundredth percentile declined by 0.5 percentage points from 2007 to 2010 (a relative change of 14%). If we assume that our model fully captures the change in the top001 following the crisis, then our findings suggest that up to around 30% of such change is associated to the banking crisis episode[41]. Such a change would account for approximately a fifth of one standard in the US distribution of the top001 share. Still, this does not classify to be a salient change. The remaining variation is absorbed by the change in per-capita GDP[42], Stock market capitalization and the common trend across countries. Therefore, even assuming that the documented change in top shares is fully explained by the banking crisis, its magnitude does not appear a substantial one.
The impact of banking crises within the so called continental European group reaches similar magnitude (also relatively to the specific group's standard deviation) to that of the English-speaking countries, although it materializes with slower pace and is measured with less precision.
Particularly outstanding appears the case of the Nordic countries, where the impact of banking crises seems quite substantial on the richest segment of the population, relatively to the rest of the population. The magnitude of the estimated IRF suggests the richest percentile[43] to be around 20% lower than what expected on the basis of the no-crisis scenario within one year from the crisis. The effect continues to be persistent at the forth year following the shock, when the top1 is estimated to be around 60% lower than expected. Although the confidence bands are not narrow, this is equivalent to a reduction of between 1.6 and 4.8 percentage points (this is to be compared to a standard deviation of around 4 and an average value of top1 shares of around 8) with respect to the counterfactual estimated by the empirical model. The change in the richest top shares, within the nordic countries group and over the very short-run, is therefore 'salient'.

Finally, in our sample of developing and southern European countries, the occurrence of a banking crisis seems to justify a substantial marginal increase in the share of the richest groups of the top decile. In particular, in both country-groups, at the second year post-crisis, the share is on average around 20% higher with respect to the no-crisis scenario (corresponding, in the case of top1 share, to roughly half of one standard

[41] In order to show this we note that top001 drops approximately from 3.5 in 2007 to 3.0 in 2010. If we assume that the top share would have continued to grow by .05 points every year, in 2010 it would have been equivalent to approximately 3.7. Our results suggests that our top001 is around 6% lower in the crisis versus no-crisis case. We are therefore comparing the 6% drop to a counterfactual value of $x = (3.7 - 0.7)/0.94 = 3.2$. Then $0.2/0.7 \simeq 0.3$

[42] But no economic shocks such as per-capita GDP or consumption collapse has been recorded in the US for this period.

[43] Indeed, only Finland has information about top001 in the whole group of countries.

deviation or 2.3 percentage points change for developing countries and one standard deviation or 1.6 percentage points in the case of souther countries). These are clearly marked as substantial change in top shares. However, the estimates for the developing countries are more heterogeneous and the estimates are more uncertain, presumably given the number of heterogeneous countries pooled together under the same label.

Figure 7 and 9 show, instead, the impact of crises on the bottom groups within the top decile across different country-groups. Unlike the findings for the richest groups within the top decile, these findings indicates a less clear systematic pattern. Similarly to the case of richest groups, the IRFs to shocks are generally measured with more precision for the case of the continental, southern-European and English-speaking country-groups. In the case of southern European countries the dynamic of the P90-P95'share is closely positively correlated with that of the share of P99.99-P100. This is consistent with a general increase in the top10 percent as a whole. On the contrary, the dynamic of the P90-P95'share is closely negatively correlated with that of the share of P99.99-P100 when observing the continental and English-speaking countries. This is consistent with an overall reduction of dispersion of income *within the top decile* and an indefinite impact on the top10 percent as a whole.

6 Interpretation

In this section we attempt to interpret the findings of our work and contextualize them in a theoretical framework. However, developing a full theoretical model to interpret our results would clearly go beyond the scope of this paper.

Our findings relate to two main features, namely the heterogeneity of impact of banking crises on top shares across time periods and country-groups. In order to understand what may drive these differences it is important to take a step back and analyse the factors influencing the change in top shares. Specifically, we need to carefully consider the potential driving forces of the numerator and the denominator of a top share. For instance, a top share decreases (increases) if the top 'looses more (less)' than the bottom or, putting it differently, if the bottom of the distribution is 'more (less) protected' than the top.

Therefore, the magnitude of such change will depend on the relative exposure of top income sources to the financial cycle and the degree of stability or protection of income sources accruing to the remaining majority of the population.

Broadly speaking, the degree of 'protection' of gross aggregate income is likely influenced by some institutional factors (i.e. labor market institution, layoff policies etc.) and the structure of the economy (i.e. size of the financial sector, nature of automatic stabilizer, diversification of the economy, stock market participation rates etc.). The relative exposure of top income to the financial shock may depend on the composition of income accruing at the top and its relative elasticity to the overall aggregate changes. Both the composition of top incomes and their elasticity to aggregate income have changed over time, and this may lay behind the heterogeneity of our results across different sub-periods.

Ultimately, it is likely to expect the relative exposure of the top and the degree of protection of the bottom of the distribution to be endogenous to each other (As an example, a greater size of the financial sector within the economy influences the exposure of both segments of the distribution. On one hand the rich gets higher share of the profits from the sector and bear the brunt of a financial shock disproportionately. On the other hand, the 'middle class' tend to participate more in the stock market, sharing its gains as well as losses). Before proceeding to the actual interpretation of our findings, the following subsection formalises the discussion above.

6.1 What drives the dynamic of top shares

Morelli (2011), referred to as MO below, explores what stated above more formally and decomposes the dynamic of top shares in two simple ways. Firstly, MO defines the top income share as $s_i = y_i/Y$ for each i top group. Hence it derives the explicit form of the growth rate of top shares as the proportional difference between the growth of income within a specific top income group i and the total income of the remaining households at the bottom of the economy.

$$\frac{ds_i}{s_i} \simeq \frac{dy_i}{y_i} - \frac{dY}{Y} = (1 - s_i)[\frac{dy_i}{y_i} - \frac{dY_{-i}}{Y_{-i}}]. \tag{8}$$

Where the scaling parameter s_i is the share in total income of income group i.

Secondly, MO decomposes the income by different income source components (capital, wage, business etc.). For instance and simplifying, we can decompose the top income into three main sources (Wage and Capital) so that $y_i = W_i + C_i$. By totally differentiating y_i and using simple algebra, we obtain:

$$\frac{dy_i}{y_i} = \frac{dW_i}{W_i}\alpha_i^W + \frac{dC_i}{C_i}\alpha_i^C + . \tag{9}$$

From (9) we can calculate k_i^π (with $\pi = \{W, C\}$), the contribution of each single income source to the growth rate of total income of group i (y_i) such that the sum of all income source contributions is equal to 1 at any time t.

$$\sum \frac{\frac{d\pi_i}{\pi_i}\alpha_i^\pi}{\frac{dy_i}{y_i}} = \sum \kappa_i^\pi = 1. \tag{10}$$

Every k_i^π depends on the growth rate specific to the income source and on the relevance of each specific income source over the total income of group i (α_i^π).

Generally, the information about the relevance of each source of income to the growth of income accruing at the top is not sufficient to fully explain the dynamic of the top share. Indeed, we also need information about the cyclicality of different sources of income at the top. In other words we ought to estimate the elasticity of every source of income to total income. Moreover, we would like ideally to justify the nature of such cyclicality on a theoretical ground.

As an example, MO provides results for the case of the US. For the P99.99-P100 group all income sources were found to be highly cyclical (elasticity higher than 1). Capital income, instead, was found to be the only highly cyclical source of income across all top groups. In addition, capital income was also the most relevant source of income for the richer upper groups ($k_i^C \simeq 60\%$), while wage type of income accounted for most of the income dynamics for the "poorer" groups within the top decile ($k_i^W \simeq 60\%$).These figures are estimated for a 5-year window around crises episodes.

MO also explains the cyclicality of different sources of income at the very top of the income distribution making use of different relevant economic theories.

6.2 Interpreting our results

We now have a framework of reference in order to attempt to explain our results: the different impact of banking crises across time and different country groups.
First of all, why are we observing the impact of crises to differ over time?

Based on our exposition above, and assuming that the sample composition bias has no predominant role, this can have two potential sources of explanation. On one hand, it is likely that the bottom of the distribution was more protected in the post-1950 period. Better job market institutions, welfare policies and better diversification of the economy are indeed in line with the argument (note also that pre-1950 banking crises were more often associated with disruptive collapses in per-capita GDP[44]). On the other hand, some or all of the sources of income may have recently become more cyclical. Similarly, the composition of the income at the top may have tilted, over the years, towards more cyclical sources of income.
We believe that both these explanations have a role to play. For instance, APS discuss, in their extensive survey, how most of the countries in the sample recorded a "*decline in capital incomes and the rise in top earnings*" especially in the post-1950 period. The introduction of bonuses and stock option schemes together with general performance-related pay schemes, makes the latter source of income particularly cyclical[45].

[44]As an example, the recent US banking shock was associated with a rise in unemployment from 5 to 10% and a drop of real per-capita GDP of approximately 3.5%. Conversely, in 1929 crisis, the unemployment rose from from 2 to 25% whereas the GDP per-capita fell by approximately 27% from 1929 to 1932

[45]A more recent study by Parker and Vissing-Jorgenses (2010) posits that top wage income is to be

Using similar arguments, as a second step, we can also attempt to explain why our results seem to diverge or to have different magnitude across country groups. For example, the impact of crises on nordic countries' top shares is qualitatively similar to that experienced by the English speaking ones, although it has bigger magnitude. In light of the above arguments, this is likely to happen if the bottom 99% of the population within the nordic countries is relatively more 'protected' from income fluctuations (income relatively a-cyclical) and if the composition of income accruing to the richest households have particularly cyclical properties. The former is notoriously true within the Scandinavian countries with 'social democratic' welfare state. The latter explanation might also be valid given that the "*major difference between the Nordic countries and the United States is the continuing importance in the former of capital income*" as recalled in APS (2011, pag.55).

Similarly we can argue that the richest groups within the Developing and the Southern European countries are relatively more protected to banking shocks compared to the bottom of the distribution. This would explain why in these countries the poorer individuals appear to bear the brunt of the crises. This can happen for a variety of reasons. First of all the labor market and the industrial corporate sector can be more fragile leading to bigger layoffs and/or wage reduction following the shock. In addition, richest households ought to be more insulated from wage-cuts and unemployment. Secondly, the smaller size of the financial sector and lower level of competition in the economy, relatively to the richest members of the OECD group, makes the income accruing at the top more stable across disequilibriums in the markets. A third purely statistical factor, due to the nature of our data, may also be a driver of the results. In particular, the amount of reported income within the economy can be cyclical to the occurrence of the crisis. Southern European countries as well as countries labeled here as Developing, have notoriously higher incidence of underground economy (part of which by definition escapes the tax records). If we are willing to assume that the propensity to evade increases during crisis periods and that the extent of the *change* in tax evasion is lower for the richest individuals, we can explain at least part of the estimated increase in top shares following the financial shock.

considered one of the main reason for very high levels of income cyclicality at the top of the US income distribution since 1982. The authors argue that the above mentioned cyclicality remains at a similar high level even when excluding those households who have been receiving stock options at least since 1997.

7 Concluding Remarks

This paper attempted to investigate the factual picture of the short-run impact of systemic banking shocks on the top income shares of around 27 countries from 1900 to 2010. Our results describe the residual impact of banking crises once other macroeconomic events and crises are taken into account.

In practise, the empirical evidence for this paper was produced by estimating impulse response functions (IRFs) of the rate of growth of top income shares to the systemic banking crises. This methodology constitutes, to our knowledge, a novelty within the literature of income distribution despite being more commonly applied in macroeconomic studies. After applying this approach to a cross-section of countries we discussed the estimation of the model based on two main approaches. More specifically, we made use of the standard 'pooled' estimation (i.e. POLS, FGLS) and the heterogenous models with common factors approach to panel estimation (i.e. AMG). The latter approach, although still in its infancy and not commonly applied within the empirical literature, is particularly suitable for macro-panels with 'long N' and 'long T' structure and strong features of cross-section dependence.

Using the whole sample of countries and years, our results show that systemic banking crises have, on average, no significant impact on the dynamic of top shares. However, analysing results over time and across countries reveals a more complex relationship between inequality and crisis, demonstrated the importance of such disaggregated analysis. In particular, our findings show that the pre-1950 crises appear to exert a relatively mild negative impact on the 'inequality' of income, whereas the crises that occurred within the post-1950 sub-sample do not seem to have any significant effect unless we exclude the so called Southern European and the Developing countries from the sample. Indeed, once the two latter groups of countries were excluded, even the recent crises appear to 'reduce inequality' on average. In addition, the impact appears to be up to three times as big compared to the crises occurred in the interwar period (the richest top shares within the top decile are found to be around 15% lower than what expected in the no-crisis scenario). In other words, our findings suggest that the share of total income of the richest households is disproportionately and negatively affected by the occurrence of a systemic banking shock in modern democratic societies, with the exceptions of Italy, Spain and Portugal (the three southern European countries included in our sample). Developing countries are also found to be in the group of countries where banking crises seem to have a 'regressive' impact on the income distribution.

In general, the nature and the magnitude of our findings can be explained by commenting on the relative exposure of top income sources to the financial cycle and the degree of stability or protection of income sources accruing to the remaining majority of the population.

Overall, our study builds on other existing works by Roine, Vlachos and Waldenstrom (2009), and Bordo and Meissner (2011). However, despite the use of very similar data, our results are only vaguely consistent with some of their findings. In particular our findings are similar to what found in RVW but only once we eliminate a considerable number of countries from the sample (Developing and Southern European countries). Moreover, the hypothesis that crisis leads to an increase in top shares is not supported for the post-1950 sample as found in BM. As we argued in the course of the paper, these divergences can be due to differences in both empirical methodology, and country and period coverage of the data.

Our work does not provide conclusive evidence about the relationship between macroeconomic shocks and 'inequality', as more efforts are needed to refine the empirical methodology and to obtain more complete data on income distribution. Yet, this work aimed to provide an additional piece of empirical evidence, contributing toward a better understanding of the determinants of income distribution.

Nevertheless, the results we have discussed clearly suggest that systemic banking crises cannot be unequivocally considered as turning-point events for a country's income distribution. Yet this has to be nuanced in view of the specific short time post-crisis window we have examined (4 years). The latter, in particular, does not capture radical changes in the income earning process, such as fiscal policies and financial market regulations, potentially and gradually stemming from systemic financial shocks. Indeed, new waves of policies and political regimes (e.g. the New Deal) are often implemented years from the occurrence of the banking shocks, exerting substantial impact on the distribution of income.

8 References

- Alvaredo, F. (2010). "A Note on the Relationship between Top Income Shares and the Gini Coefficient" Economics Letters (forthcoming).

- Atkinson, A B and Morelli, S, 2010, Inequality and banking crises: A first look, report for the International Labour Organisation.

- Atkinson, A B and Morelli, S, 2011, Economic crises and Inequality, Human Development Research Paper 2011/06. Research Background paper for the Human Development Report 2011, UNDP, UN.

- Atkinson, A B and Morelli, S, 2012, Chartbook of Economic Inequality: 25 countries 1911-2010, discussion paper

- Atkinson, A. B. and T. Piketty (Eds.) (2007). "Top Incomes over the Twentieth Century: A Contrast between European and English-Speaking Countries", (Oxford:Oxford University Press).

- Atkinson, A.B. and T. Piketty (Eds.)(2010). "Top Incomes: A Global Perspective. Volume II", (Oxford: Oxford University Press).

- Atkinson, A.B. , T. Piketty and E. Saez (2011). "Top Incomes in the Long Run of History", Journal of Economic Literature

- Barro, R J and Ursa, J F, 2008, Macroeconomic crises since 1870, Brookings Papers on Economic Activity, 1: 255-350.

  Bordo, M, Eichengreen, B, Klingebiel, D and Martina-Peria, M S, 2001, Is the crisis problem growing more severe?, Economic Policy, 32, Spring 2001: (and web appendix).

- Bordo, M D, and Meissner, CM, (2011), Do financial crises always raise inequality? Some Evidence from History, unpublished manuscript.

- Bordo, M D, and Meissner, CM, (forthcoming), Does Inequality Lead to a Financial Crisis?, Journal of International Money and Finance.

- Brugiavini and Weber eds..(forthcoming), Longer-term consequences on income distribution of the Great Recession. FRDB book.

- Caprio, G and Klingebiel, D, 1996, Bank insolvencies: Cross-country experience, Policy Research Working Paper No 1620, World Bank, Washington, D.C.

- Caprio, G and Klingebiel, D, 1999, Episodes of systemic and borderline financial crises, World Bank.
- Curry, Timothy, and Lynn Shibut (2002), The Cost of the Savings and Loan Crisis: Truth and Consequences, FDIC Banking Review, 13(2), 2635.

  Eberhardt M., Christian Helmers and Hubert Strauss, (forthcoming) , Do spillovers matter when estimating private returns to R&D?, The Review of Economics and Statistics.
- Von Hagen, Jrgen and Tai-kuang Ho (2007), Money Market Pressure and the Determinants of Banking Crises, Journal of Money, Credit, and Banking, 39 (5), pp. 1037-66
- Jenkins,S., A. Brandolini, J. Micklewright and B. Nolan eds.(forthcoming), The Great Recession and the Distribution of Household Income, FRDB book.
- Leaven, L. and F.V. Valencia (2008), Systemic Banking Crises: A New Database, IMF Working Paper No. 08/224.
- Laeven, L. and F. V. Valencia, 2010, " Resolution of Banking Crises: The Good, the Bad, and the Ugly" IMF Working Paper No. 10/146
- Leigh, Andrew (2007). How Closely do Top Income Shares Track Other Measures of Inequality?., Economic Journal, 117: F619F633.
- Lucchino and Morelli (2012), Inequality and Growth, report for the Resolution Foundation, London UK.
- Morelli, S, 2011, Banking crises and stock market crashes in the US: the response of top income shares in historical perspective, draft (September), University of Oxford
- Obstfeld M. and A. M. Taylor(2003), Globalization and Capital Markets, NBER.
- Parker, J. A. amd A. Vissing-Jorgensen. (2009). " Who Bears Aggregate Fluctuations and How?", The American Economic Review vol. 99, no2, pp. 399-405
- Parker, J. A. amd A. Vissing-Jorgensen. (2010)." The Increase in Income Cyclicality of High-Income Households and its Relation to the Rise in Top Income Shares ", Working Paper (September 7th)
- Reinhart, C M, 2010, This time is different chartbook: Country histories on debt, default, and financial crises, NBER Working Paper 15815.

- Reinhart, C M and Rogoff, K S, 2008, Is the 2007 U.S. sub-prime financial crisis so different? An international historical comparison, American Economic Review, vol 98: 334-339.

- Roine, J, Vlachos, J and Waldenstrm, D, 2009, The long-run determinants of inequality: What can we learn from top income data?, Journal of Public Economics, vol 93: 974-988.

- Saez , E., J. Slemrod and S. Giertz, 2010, The Elasticity of Taxable Income with Respect to Marginal Tax Rates: A Critical Review, Journal of Economic Literature.

- Von Hagen, Jrgen and Tai-kuang Ho (2007), Money Market Pressure and the Determinants of Banking Crises, Journal of Money, Credit, and Banking, 39 (5), pp. 1037-66

A Data and Methodology

More on Methodology

A.1 Homogeneous parameters panel - "pooled" estimators

The typical "pooled" estimators used in our analysis include the classic Pooled OLS (POLS) and the Feasible GLS (FGLS) estimators accounting for the autocorrelation structure of the error terms. Following an empirical investigation, these were preferred over the two other common estimators, namely the Fixed Effects (FE) and Random Effects (RE).

Our pooled estimators make use of the general ARDL model discussed in the text (equation (1)). By assumption, these models estimate homogeneous parameters across panel units ($\theta_{i,k} = \overline{\theta_k}$, $\phi_{i,k} = \overline{\phi_k}$,$\delta_i = \overline{\delta}$, $\rho_i = \overline{\rho}$ $\alpha_i = \overline{\alpha}$) and error term $u_{i,t} = \mu_i + \mu_t + \epsilon_{i,t}$, where μ_i represents the time-invariant and country-specific factor, μ_t the so called time effect (common to all panel units) and $\epsilon_{i,t} \sim i.i.d.$

$$g_{i,t}^{top} = \alpha_i + \sum_{k=0}^{2} \overline{\theta_k} g_{i,t-k}^{top} + \sum_{k=0}^{4} \overline{\phi_k} D_{i,t-k} + S'_{i,t}\overline{\delta} + X'_{i,t}\overline{\rho} + \mu_i + \epsilon_{i,t}. \tag{11}$$

For every specification we carried out an Hausmann test for fixed and random effects confirming the non-systematic differences between the estimators and therefore the orthogonality between the individual characteristics and the regressors. This rules out the classic source of bias in a dynamic specification.
Hence, for every RE model we then test the systematic difference across panel units, namely the so called "panel effect". The test for random effects is carried out with a standard Breusch-Pagan Lagrange Multiplier (LM) test with the null hypothesis of zero variance across panel entities, μ_i. The latter is never rejected and this confirms the consistency of the standard pooled least squares estimator (POLS)[46] However, although every model is estimated using residuals robust to the heteroskedasticity (which specific test strongly suggests to be present), using POLS alone cannot control for another classic source of problems for the statistical inference, namely the presence of autocorrelation structure in the error terms (errors are not independently distributed).

For this reason we also estimate the model using FGLS estimator accounting for an AR(1) structure in the residuals. This should result in a more efficient estimation of parameters.

Nevertheless, it is worth noting that the class of homogeneous parameters model can generate a number of problems. On the one hand, the assumption of parameters

[46] We also jointly test the validity of country effects in the POLS regression and we fail to reject the null hypothesis.

homogeneity can be the source of biased estimation as well as the autocorrelation of error terms themselves. On the other hand, other problems may arise from the assumption about the error term composition. In common pooled estimators this is such that to neglect the likely unobserved common factors which can exert different impact across countries and most importantly can drive both the regressors and the residuals. This creates in turn an additional source of bias which can severely distort our estimates of the coefficients.

As a first step we show below that the source of autocorrelation can be endogenously driven by the restriction of parameters homogeneity, when the true DGP is suggesting the opposite. As an example consider the pooled dynamic regression model (equation (11)) when the true DGP is represented by equation (1). For simplicity imagine that we are considering exclusively one lag of the dependent variable and no lags for the rest of the regressors. It is easy to show that the regression residuals will be represented by $v_{i,t} = \eta_i^{\theta} g_{i,t-1}^{top} + \eta_i^{\phi} D_{i,t} + X'_{i,t}\eta_i^{\rho} + \epsilon_{i,t}$ In other words, the assumption of parameters homogeneity implies serially correlated residuals.

Secondly, it is straightforward to show that the homogeneity assumption is also the source of problem for the identification of the slope parameters. Indeed the error term $v_{i,t}$ described above is clearly correlated with the regressors. In fact, one can avoid biased estimates of the mean of the true heterogeneous parameters in case the latter do vary randomly across countries and are orthogonal to the covariates and the error term. However, these conditions are hardly ever satisfied.

Finally, we discuss the problems linked to the exclusion of more flexible and general time common factors from the specification (lack of general control for cross-section dependence)[47]. In particular, this can be another source of bias for the estimated coefficients if the same common factor is driving the residuals and some or all the covariates (an example might be the process of globalization driving both the growth of output, the growth of top income shares and potentially the likelihood of crisis. Another example is provided below.) In a dynamic context like ours this is an inevitable problem, very much similar to the source of bias coming from the time-invariant country-specific effects[48].

A.2 Heterogeneous Parameters Models - Panel Time-Series Models

As discussed above, despite their wide application in the literature, the results obtained with commonly used "pooled" estimators can create a potential list of problems to the estimation, some of which can bias our results. In particular the main sources of potential problems are respectively the assumption of coefficient homogeneity and the lack

[47]Note that the standard time-effects included in the pooled estimations is effectively a specific common factor. However this is assumed to have an homogeneous impact across countries

[48]The latter, however, seems not to be a problematic issue in our specification as recalled above.

of control for sources of cross-section dependence. In order to mitigate these problems we will adopt the novel panel time-series models which combine the heterogenous panels and the common factors approaches. In particular, we estimate our models with the newly developed Augmented Mean Group estimators (AMG- Eberhardt and Teal 2010). The latter has been selected among a list of other estimators belonging to the family of Mean Group Estimators (the motivations are explained below).

On the one hand, the so called 'Mean Group' estimators allow for heterogeneity in the model parameters by averaging out the results obtained from country-specific regressions. The results indicate the average relationship across panel units. On the other hand, *"the common factor approach assumes that the error term, as well as the covariates in the empirical model, contain a finite number of unobserved common processes ('factors'), whose impact may differ across industries or countries. Recent work in this area has emphasised the distinction between 'strong' factors representing global shocks such as the recent global financial crisis, and 'weak' factors such as spillovers between a limited group of industries or countries"* (extract from Eberhardt, Helmers and Strauss, 2011).

This appears rather intuitive as we analyse groups of countries with substantial economic, financial, political, and historical interlinks

As an example, episodes of financial and economic crises, like the ones under investigation, creates spill-overs or contagion effects to "neighbor" countries so that top income shares can be influenced even in countries where there has been no formally detected crisis. Despite a wide literature in financial contagion, our initial empirical specification, for pooled estimators, does not incorporate any notion of contagion or spill-over effect of a crisis from one country to another. An example should help clarifying. If one of the "nordic" country, say Norway, is struck by a crisis it is reasonable to expect that top income shares of some or all of the remaining nordic countries to be contemporaneously affected (with different magnitude). We expect this to hold on the basis of strong commercial, economic and financial ties among the countries. On the other hand, the banking shock that hit Norway in 1987 most probably increased the chance for Finland and Sweden to have a crisis as well (indeed, in 1991 both countries experienced a banking crisis in turn), in a classic regional contagion scenario. The two examples translates into specific features of the empirical specification, namely the presence of cross-section dependence (CSD) and the correlation between the crisis dummy variable and the error term through the unobserved factors. This example applies in the case of other types of macroeconomic shocks as well. For example, during the latest economic slump (in 2008 and 2009), Denmark, Sweden and Finland all experienced a cumulated drop in real per-capita GDP higher than 5%, what we refer to as economic "disaster".

In addition, unobserved heterogeneity can also take the form of global spill-overs or more general common shocks (the evolution over time of remuneration and social norms, political ideology, fiscal confiscation and financial openness) affecting all countries or subgroups of countries in different ways.

In order to illustrate a simplified version of the model, we propose here the example reported in Eberhardt, Helmers and Strauss(2011):

$$y_{i,t} = \beta_i x_{i,t} + u_{i,t}. \tag{12}$$

with a multi-factor error structure and the latent variable f_t driving both the regressor and the residuals,

$$u_{i,t} = \varphi_i f_t + \psi_i + \varepsilon_{i,t} \tag{13}$$

$$x_{i,t} = \varrho_i f_t + \pi_i g_t + \psi_i + \phi_i + e_{i,t} \tag{14}$$

and $\varepsilon_{i,t}, e_{i,t}$ being white noise.

We therefore estimate the original model in eq.(1) using the Pesaran and Smith (1995) Mean Group (MG) estimator, the Pesaran(2006) Common Correlated Effects Mean Group (CCEMG) estimator and the Eberhardt and Teal(2010) Augmented Mean Group (AMG) estimator [49]. The standard (Pesaran-Smith) MG estimator, although it allows for parameters heterogeneity, it does not directly cope with the problem of cross-section dependence[50]. The CCEMG estimator, instead, deals with both above listed problems. The estimation models simply adds cross-section averages of dependent and independent variables to the country-specific regressions. However, for the sake of our study, where a great deal of variables is involved, this approach can be inappropriate. The AMG estimator is a valid alternative to the CCEMG estimator as discussed in Eberhardt (yyyy). The former is implemented in three steps: the first step estimates the 'common dynamic process'; the second augment the country-specific regression with the above-mentioned estimated common factor. The third steps averages out the results across countries.

[49] The Stata implementation of the three estimators is described in Eberhardt(yyyy)

[50] We can exclusively control for a linear time trend in each country specification

B Tables and Charts

Figure 2: The common dynamics of the top001

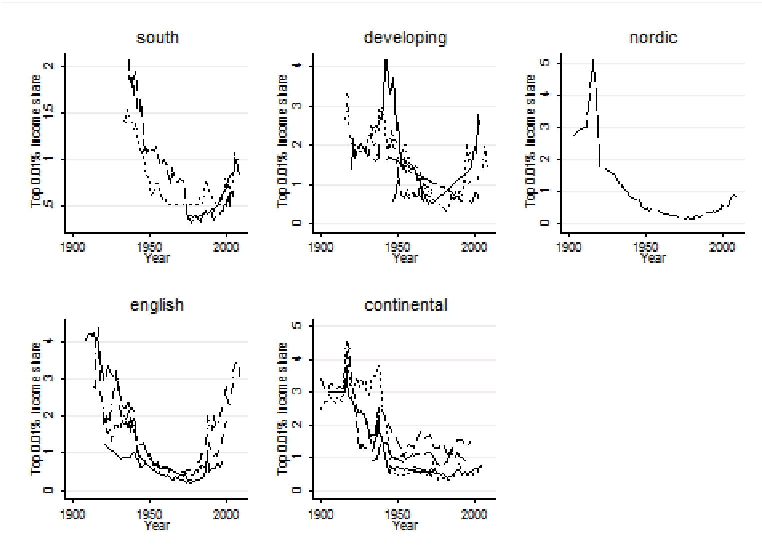


Figure 3: The common dynamics of the top1

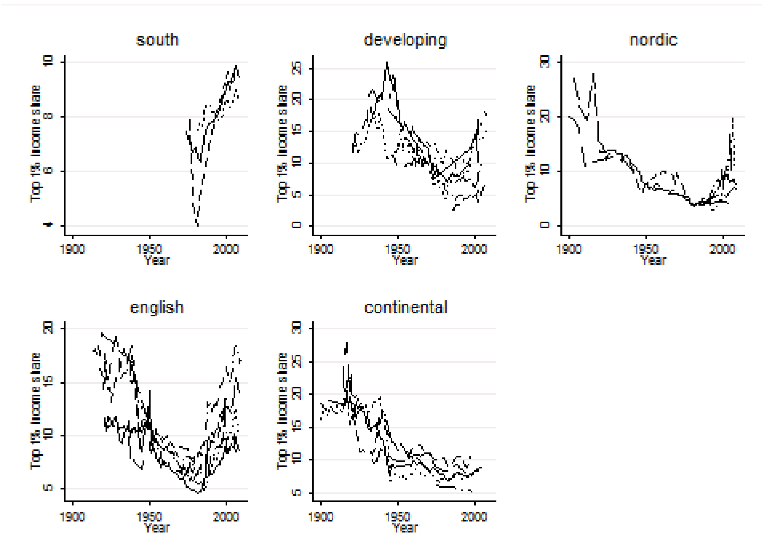
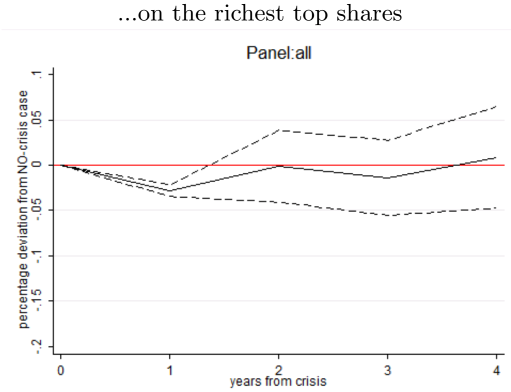


Table 1: Impact of banking shocks

...on the richest top shares



...on the poorer groups within the top decile

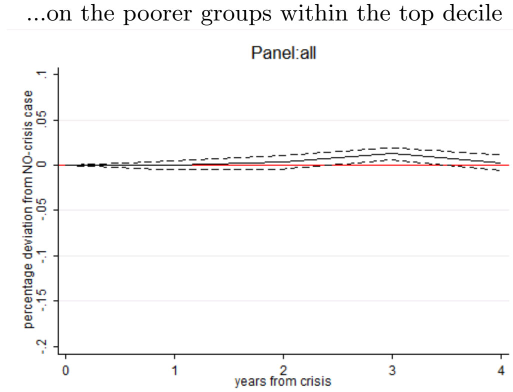


Figure 4: Impact of banking shocks on the richest top shares

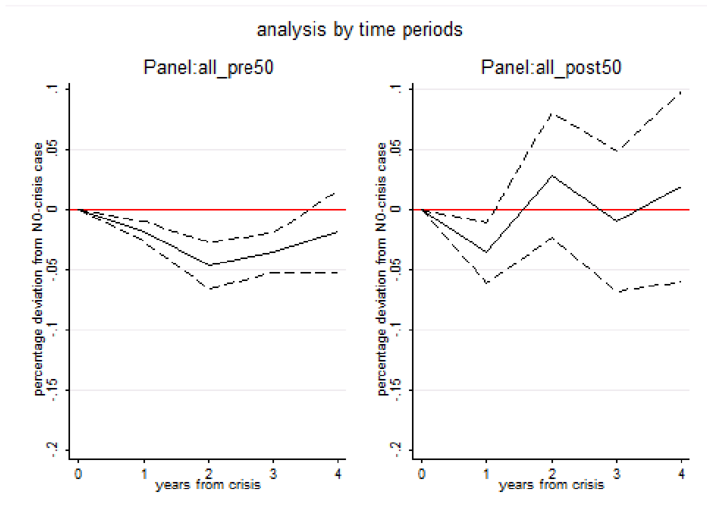
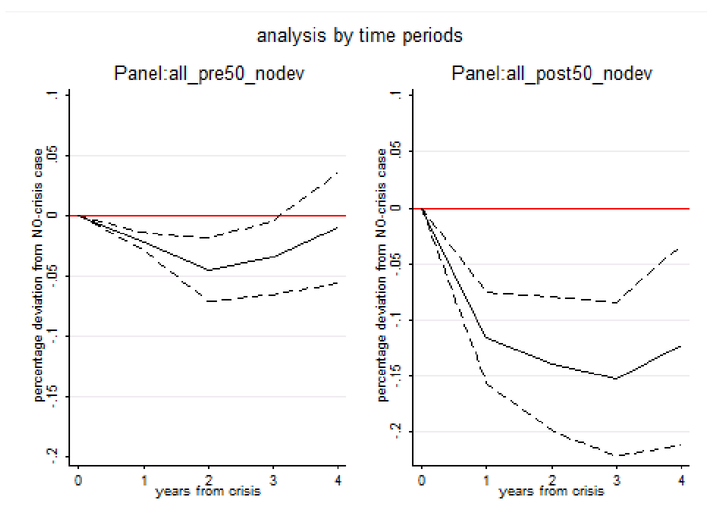
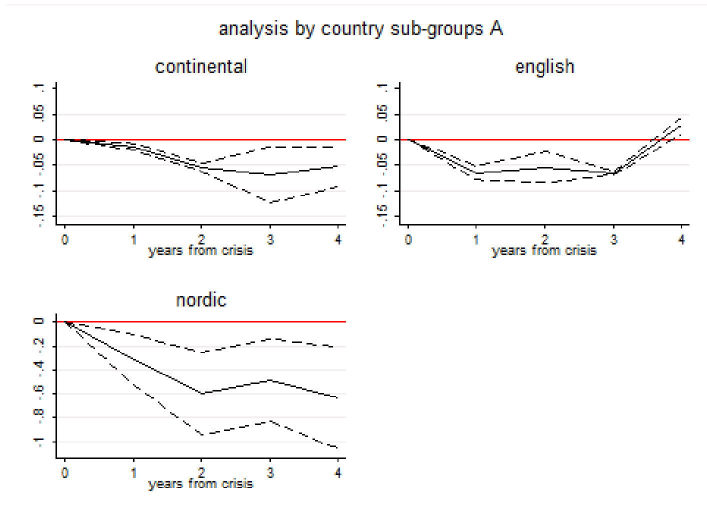


Figure 5: Impact of banking shocks on the richest top shares



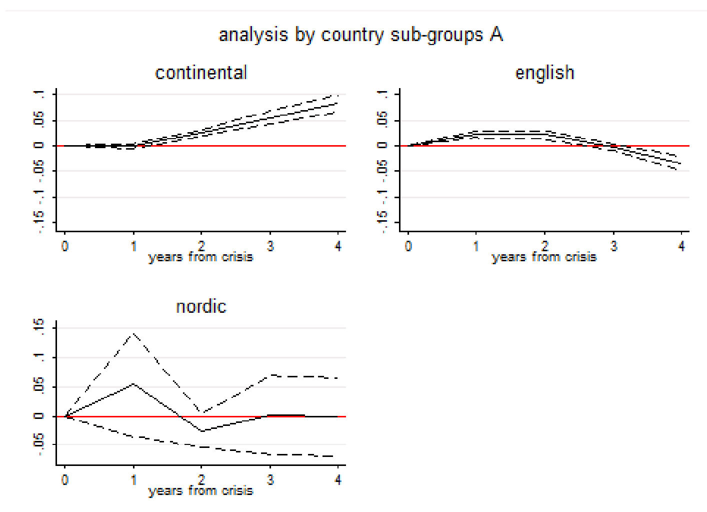
Notes: the IRFs are calculated excluding both Developing and Southern European countries.

Figure 6: Impact of banking shocks on the richest top shares



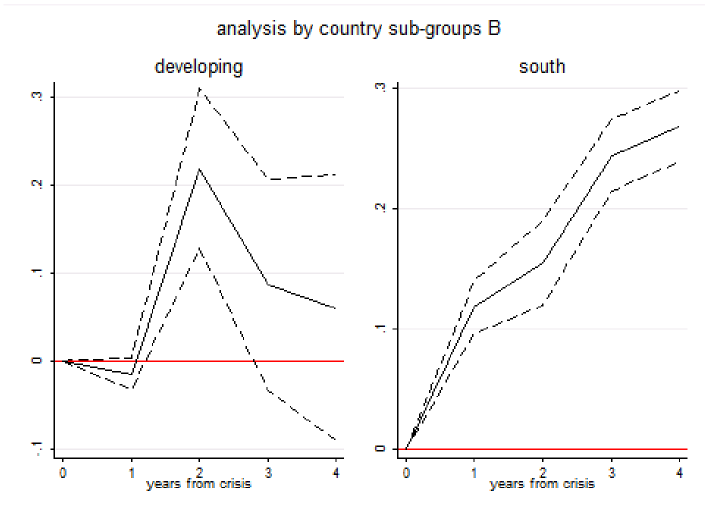
Notes: The Y-axis represents the percentage deviation of top shares from the NO-crisis case

Figure 7: Impact of banking shocks on the poorer groups within the top10 percent



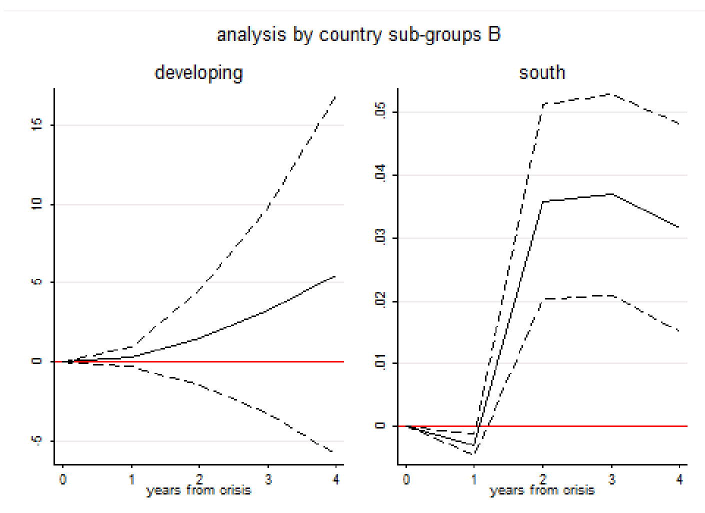
Notes: The Y-axis represents the percentage deviation of top shares from the NO-crisis case

Figure 8: Impact of banking shocks on the richest top shares



Notes: The Y-axis represents the percentage deviation of top shares from the NO-crisis case

Figure 9: Impact of banking shocks on the poorer groups within the top10 percent



Notes: The Y-axis represents the percentage deviation of top shares from the NO-crisis case

Figure 10: Top001 distribution by countries

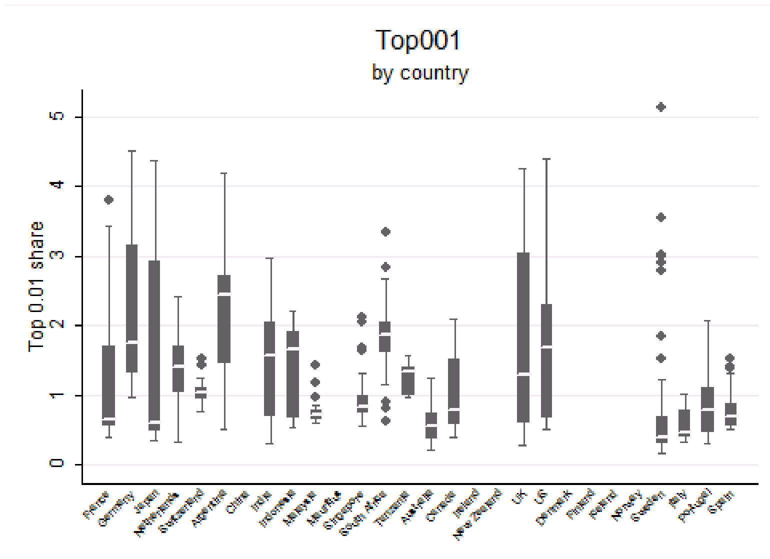


Figure 11: Top1 distribution by countries

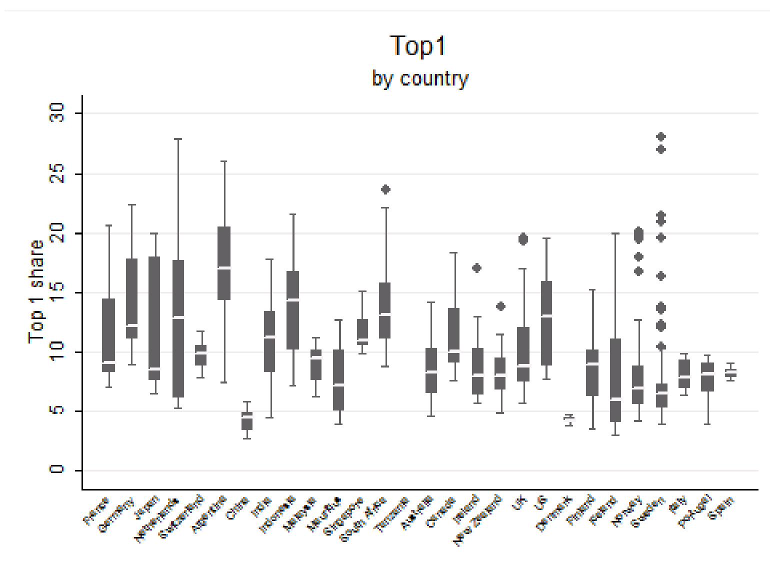


Figure 12: Top001 and st.dev. by country-groups

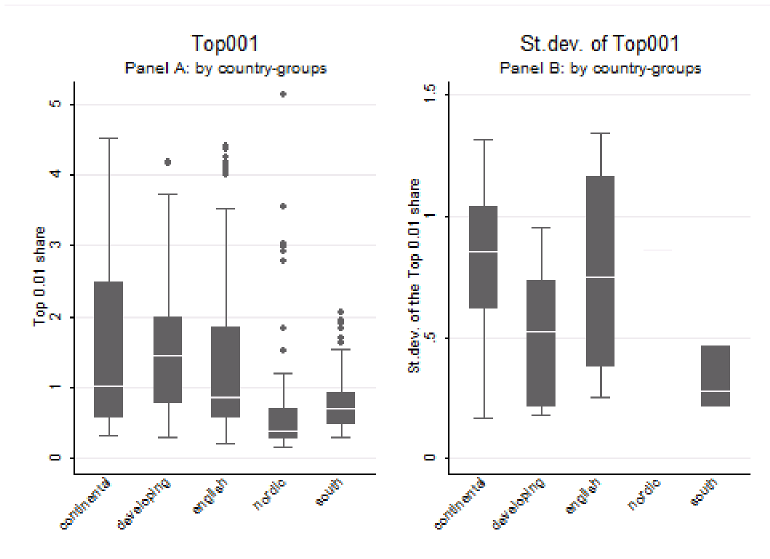


Figure 13: Top1 mean and st.dev. by country-groups