Banking crises and stock market crashes in the US: the response of top shares in historical perspective

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Abstract

This paper examines the response of the national income shares accruing to different groups within the richest decile in the US to the occurrence of major systemic banking crises since the beginning of the twentieth century. The findings suggest that the impact of banking crises on the US top income shares is mostly small in magnitude. Indeed, the estimated total effect of crises is never bigger than one standard deviation of a specific top shares under investigation. Results are robust to a variety of checks and the analysis also highlights interesting heterogeneity across different income groups. Additional results also point out that the short-term impact of crises may be also temporary in nature as top shares recover faster in the aftermath of a shock. These findings lend indirect support to the structuralist hypothesis, namely that only substantial changes in government policies and institutional frameworks can bring about radical changes in income distribution.

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Introduction

The 2007-2008 financial collapse and the subsequent economic recession brought the distributional impact of macroeconomic shocks back on the research agenda. This paper investigates the distributional impact of the three systemic banking shocks detected in the US since the beginning of the twentieth century. In particular and given the very long time horizon under investigation, the paper focuses on the shares in national income accruing to different income groups within the top decile of the distribution. Indeed, the data series on the so called top income shares (taken from the World Top Income Database, WTID) date back to 1913 and provide unique annual observations estimated continuously from the same institutional source. The data also allow, among other things, to decompose income by different sources and to add realised capital gains to total income for the entire period under investigation. These important features would not be replicable for such a long period by any other available data on US income distribution.

The main results suggest that even disruptive systemic banking shocks *per se* do not mark a turning point for top income shares as they exert only a mild impact on the share of total national income accruing to the top of the distribution. This evidence lends some *indirect* support to the conjecture that top income shares are not substantially affected by the market forces stemming from the occurrence of a 'crisis', unless the latter are coupled with substantial changes in regulatory and institutional frameworks as well as taxation and shift in political regimes (see Saez, 2013 and Piketty & Saez, 2012, 2013).[1]

The empirical analysis follows a series of steps. Firstly, I discuss the nature of the data and describe the dynamics of top shares around crises episodes, without any adjustment. Secondly, I investigate whether top shares series deviates from the forecasted pattern as a consequence of the shock. This can be considered as a first step towards comparing actual values with some row measure of counterfactuals. Results are based on two different forecasting techniques. Finally, an Autoregressive Distributed Lags (ADL) model is estimated, where the dynamic series of growth rate of top shares are assumed to be exposed to 'impulses' (banking shocks). This allows to estimate the dynamic impact of banking turmoil on the behaviour of the levels of top shares and recover the *total* effect of crisis on the shares (the so called impulse response function,

[1] The two authors argue that "*Downturns per se do not seem to have long run effects on inequality... The reason why the Great Depression was followed by huge inequality decline is not the depression per se, but rather the large political shocks and policy responses which took place in the 1930s-1940s. The Great Recession is likely to have a large long run impact only if it is followed by significant policy changes.*" Piketty & Saez (2012)

called here IRF). Such an approach is more common in the analysis of macroeconomics perturbations but constitutes one of the first applications of this sort in the study of distributional consequences of macro shocks. Estimates of dynamic multipliers can be accompanied by standard errors which in turn are useful to gauge the statistical significance of the impact of the shocks on *levels* of top shares as well as their *growth* rates. These methodologies draw from both established and recent applications in macroeconomic studies. This work extends their use within the literature of income distribution and constitutes one of the first applications of this sort[2].

Existing literature and contribution of the paper To the best of my knowledge, no study has systematically investigated the pressing question of how gains and losses of different banking crises in US history are borne across different groups of individuals. This paper attempts to fill this gap by investigating the richest fractional percentiles within the top decile (Top 0.01%) and the share of relative poorer households within the richest top decile (ideally the Top 10% excluding the richest 5%).[3] On the contrary, the distributional consequences of general aggregate fluctuations and business cycles have been widely investigated in the US, especially in past decades.[4] As pointed out by Jäntti & Jenkins (2010), this stream of literature has mainly followed two different approaches. On the one hand, the impact of the macro-economy on income distribution has been investigated using parametric distribution functions fitted on the income data (the most notable examples are Metcalf (1969) and Thurow (1970)). On the other hands, income inequality indicators (including quintile group shares) were directly regressed on a set of macroeconomic variables as done by Beach (1976, 1977), Blinder & Esaki (1978), Blank & Blinder (1985), Blank (1989). The latter approach in particular is considered to be plagued by a number of problems if the specification does not address the non-stationarity of the explanatory and dependent variables and no co-integrating relationship is estimated (as recalled by Parker, 2000). Such problems could in theory be addressed by modelling cointegrating relationships using modern dynamic time-series econometrics as done in Neal (2013). Nonetheless, and using Jäntti & Jenkins's words, "*the direct application of the methods of dynamic econometrics to inequality indices or quantile group shares is problematic, as most inequality indices*

[2]Two other papers by the IMF staff were recently made available. The papers use a similar methodology and identify the impact of macroeconomic conditions on measures on income distribution using impulse response functions. Gorodnichenko et al. (2012) explored the distributional implication of monetary policy shocks in the US whereas Ball et al. (2013) analysed the effect of fiscal consolidation on inequality estimating IRFs.

[3]The choice is based on the consideration that banking crises can have heterogeneous impact on top-income groups given their enormous differences in average income and composition.

[4]For studies on the response of inequality indicators to general macro-economic conditions in the UK see Nolan (1986, 1987) and Jäntti & Jenkins (2010).

are bounded and so have a restricted variance". Jäntti & Jenkins, instead, argued "*in favour of fitting a parametric functional form to the income distribution for each year, and then modeling the time series of model parameters in terms of the macroeconomic factors*". It is also worth mentioning that other works have analysed the raw data of income distribution around crises and business cycles episodes using a regression-free approach (Atkinson & Morelli, 2010, 2011, Thompson & Smeeding, 2013 and Piketty & Saez, 2012, 2013) or simply estimated the elasticity of incomes accruing to different income groups to changes in overall personal income (as done in Parker & Vissing-Jorgensen (2009)).

This paper provides a synthesis of all the approaches mentioned above. The investigation begins with a regression-free approach, analysing the temporal association between the shares in total income of different upper income groups within the top decile and the occurrence of a banking crisis. As a second step, I reiterate the concern for non-stationarity of the data highlighted in Parker (2000) and Jäntti & Jenkins (2010) by estimating each model using all variables in growth rates (stationary) in order to back out the predicted impact of crises on the levels of top income shares. This step rules out the concerns for non-stationarity of dependent variables as well as that of regressors. Most importantly, this is achieved by retaining the approach of regressing the inequality indicators directly on macro-variables and by avoiding to model any co-integrating relationship.[5] The approach followed here, as discussed more into details below, also helps to define more clearly the nature of counterfactual in use. Indeed, each model is not conditioned on macroeconomic variables which are thought to be directly influenced by the systemic crisis itself (indicated by a dummy variable).

This paper also adopts the 'preferred' approach by Jäntti & Jenkins (2010) using conditional parametric distribution function. Indeed, US top income shares are estimated based on the assumption that income above a certain threshold follows a Pareto distribution. This allowed me to model the time series of the Pareto coefficient studying its response to the crisis. Finally, in line with what done in Parker & Vissing-Jorgensen (2009), I calculate the elasticity of different income sources to changes in total personal income around crises episodes in order to provide useful information for the interpretation of the results.

[5]The application of time-series econometrics to income inequality indicators and macroeconomic variables requires testing for unit roots and potentially the modelling of the co-integrating relationships. However, this paper shares the view that "*the direct application of the methods of dynamic econometrics to inequality indices or quantile group shares is problematic, as most inequality indices are bounded and so have a restricted variance.*" Jäntti & Jenkins (2010, p. 222) I discuss this issue in more details in the empirical investigation section.

Structure of the Paper The first section describes the problem at hand whereas the second highlights the advantages and the limitations of the data used. A first look at the raw data on top shares around the crisis episodes is given within the third section. The fourth section represents the core of the empirical investigation where two counterfactual analyses are carried out: one based on forecasting techniques and the other based on macro-econometrics and the calculation of Impulse Response Functions (IRFs). In other words, section four investigates the hypothetical scenarios in which no crises materialise and compares them to the actual data estimating the average total impact of a crisis on different top shares. The fifth section confirms the findings by analysing the response of Pareto coefficient to the occurrence of shocks. In the last section, I discuss the robustness of the findings to a variety of different model specifications.

1 Unravelling the Complexity

Identifying the impact of banking crises on top income shares can be quite a challenging task as summarised in Figure 1. Indeed, banking crises are usually associated with a series of other macro-economic events, such as other types of financial and economic crises (i.e. recessions, currency crises, sizeable crashes in stock and real estate markets) as well as government and monetary authority interventions that can largely affect households income and asset holdings.

On one hand, each of three banking crises under analysis in this paper, has been associated to economic downturn and substantial rise in unemployment rate.[6] The National Bureau of Economic Research indicates 1929(III)-1933(I), 1990(III)-1991(I) and 2007(IV)-2009(II) as the beginning and the end years(quarters) of official US recessions. Unemployment also rose dramatically during recessions[7] and this might have strong distributional impact, ceteris paribus depending on the effectiveness of automatic stabilisers[8] such as social security schemes and on the population groups eventually harmed the most by the job-loss.

On the other hand, banking crises are often followed by large government interventions, including increase in specific types of social transfers (i.e. unemployment benefits)[9], nationalization of distressed financial institutions and other bank bailout

[6]However, it is important to notice that according to our data, only the Great Depression was also associated to currency crisis, economic 'disaster' (reduction in per capita GDP and per-capita consumption higher than 10%) and a debt crisis.

[7]Estimates indicate a stunning surge from 2.08 to 25.2% from 1929 to 1932. From 1988 to 1992 unemployment rate went from 5.3 to 7.4, while it almost doubled (from 5 to 10%) from 2007 to 2011.

[8]In a recent paper Dolls et al. (2012) found that 34% of an unemployment shock is absorbed by automatic stabilisers in US.

[9]The National Labor Relations Act (NLRA) in 1935 instituted the minimum wage in the US for

schemes[10]. Such policy interventions are financed by fiscal policy which inevitably implies an immediate or future transfer from taxpayers to main beneficiaries of such policies[11]. However, such fiscal policy may also severely undermine the stability of public finances, depending on the severity of the crisis and this might call for general spending cuts to governmental services and welfare provision and/or for present and future additional fiscal imposition. In particular, for efficiency and equity reasons, taxes can be also levied on groups with higher fiscal capacity[12]. It is also worth noting that 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). Similarly, the Federal Reserve usually intervenes[13] in the aftermath of a banking crises showering the market with liquidity affecting the value of the interest rate as well as the price of assets.[14] Finally, a growing body of research suggested that increasing income dispersion (or high levels of dispersion) could increase the likelihood of a crisis to occur, undermining the exogeneity of crisis indicator and therefore the consistency of the estimation.

the first time and gave the government control over the employer contracts reinforcing substantially the role of labour unions.

[10]Rescue packages account on average for 12% of GDP (gross fiscal costs) according to Laeven & Valencia (2008) for a series of 42 systemic banking crises. New estimates for the recent crisis started in 2007-2008 suggest that fiscal costs are around three times smaller given the sizeable monetary policy intervention in the market. For US the total cost over 2007 and 2009 was around 5% of GDP (Laeven & Valencia, 2010).

[11]For example following the analysis of Curry & Shibut (2000), \$124 out of \$146 billion total estimated costs of the S&L crisis have been borne by the U.S. taxpayers. Only a small share of cost was therefore borne by the thrift industry.

[12]For instance, in 1929 top marginal tax rate on income was reduced to 24% from 25%. It increased back to 25% for two years until 1932 when there has been a substantial increase in marginal rate, reaching 63%. Three years following the S&L shock in 1990, top marginal income tax rate rose from 28 to 31% and then again to 39.6% in 1993. Conversely, no tax rise followed within 5 years from recent financial meltdown. In 2013, instead, the top marginal tax rate increased back to 1993 level (39.6%) for income above 400.000$ and top income tax rates on realized capital gains and dividends increased from 15 to 20%. These changes may well affect the nature of reported income at the top as discussed within the text.

[13]In order to face the economic recession of early 90s the FED reduced the Fed Funds Rate from 8 to 3% from 1990 to 1992. similarly, the FED attempted to reduce the 'cost of money' in the recent crisis by reducing the Fed Funds Rate from 5.25 to approximately 0% from 2006 to 2012.

[14]A notable exception is clearly the 1929 crisis when the FED responded to the crisis with a strongly restrictive policy. *Britain's departure from the gold standard led to widespread fears that US would also leave the gold, and thus to a vast gold outflow. The Federal Reserve responded by raising the discount rate from 1.5 to 3.5 percent in two steps in October 1931. Friedman and Schwartz (1963) consider this restrictive policy highly unusual because the economy was so severely depressed in 1931 and its condition was continuing to deteriorate.*" Romer & Romer (1989, p. 129)

In this paper I propose to address the above mentioned issues as follows:

i) Firstly, the focus is on the *total* short-run effect of a banking crisis rather than on its marginal impact. In other words I do not distinguish between the impact of a banking crisis from that of other contemporaneous shocks or macro-events under the condition that the latter are caused by the crisis itself (e.g. rise in unemployment, economic slump and stock market crash). This is done by performing a so called "ex-post counterfactual analysis", recently postulated in a work by Pesaran & Smith (2012).

ii) Secondly, the use of data based on a gross income definition excludes any direct impact of fiscal policy on the top income shares. Furthermore, consistently with existing literature, I take into account the indirect effects by controlling for changes in marginal tax rates at the top[15])

iii) Thirdly, the use of a short time horizon (5 years), I argue, should be sufficient not to worry much about the potential role of new institutional and regulatory framework likely stemming from the crisis.

iv) Finally, all results are obtained under the assumption that systemic banking crises have exclusively lagged effects on the growth of the top shares. This addresses the concern of potential endogeneity of crisis indicators to changes in 'inequality'.

2 Data

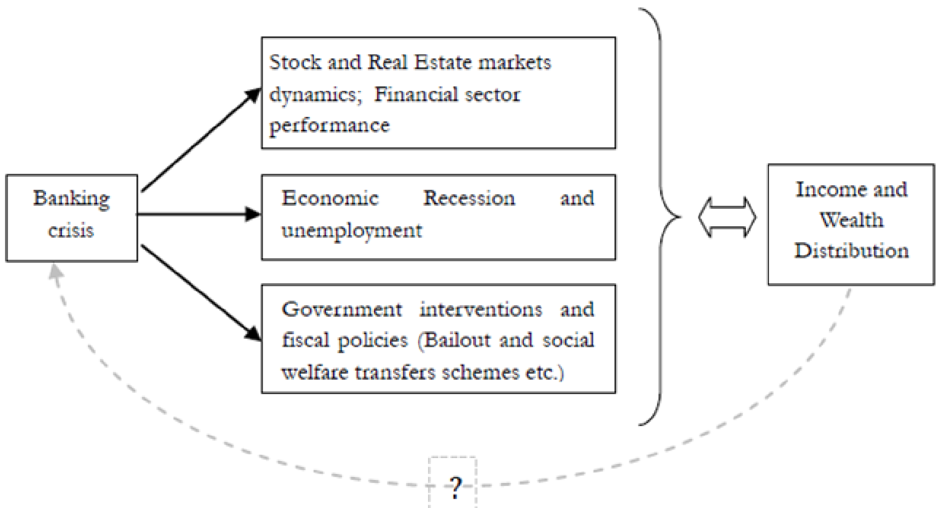
2.1 Data on Systemic Banking Crises

Data on banking crises are taken from three main databases, namely Bordo et al. (2001), Reinhart & Rogoff (2008, 2009), Reinhart (2010) and Laeven & Valencia (2008, 2010)). Here I am concerned uniquely with systemic shocks, disregarding those events that affect isolated banks.[16]

[15] An example of indirect redistribution effect of taxation are the behavioral endogenous responses in income reporting due to changes in tax rates.

[16] For instance, Laeven & Valencia classify an event as a systemic banking crisis (excluding banking system distress events that affected isolated banks), "*when country's corporate and financial sectors experience a large number of defaults and financial institutions and corporations face great difficulties repaying contracts on time. As a result, non-performing loans increase sharply and all or most of the aggregate banking system capital is exhausted and this situation may be accompanied by depressed asset prices (such as equity and real estate prices)*"

Figure 1: Unraveling the Complexity



The crisis databases at hand identify three systemic banking crises in the US since the beginning of twentieth century[17], namely the Great Depression, The Savings & Loans crisis and the recent Great Financial Meltdown. However, despite the focus on systemic shocks, the sources listed above do not always unequivocally identify crisis years given differences in methods and judgements due to their reliance on both qualitative and quantitative measures. The two most recent databases on crises identification agree in detecting the beginning of the latest financial meltdown in 2007. Different appears the case of Savings and Loans crisis, detected in 1984 by both BE and RR while LV consider the crisis as 'systemic' in 1988, considered to be the peak of the crisis. Disagreement is found even for the worst US financial crisis in recorded history. RR points out the beginning of the 'calamity' in 1929 rather than 1930 as reported in Bordo et al.

In this paper, the information in Reinhart & Rogoff is generally preferred to that in Laeven & Valencia as the former tend, on average, to detect the crisis with a year in advance.[18] Nonetheless, in the case of the US S&L crisis I prefer the information by

[17]Other two banking crises occurred in US in 1907 and 1914, however they are both considered non-systemic and therefore dropped from the analysis.

[18]The widely used methodology identifying crises described above mixes quantitative indicators with subjective judgments based on the observation of market events, such as forced bank closures, mergers,

Laeven & Valencia who record the crisis in 1988. Indeed the US S&L crisis (set to begin in 1984 according to Reinhart & Rogoff) had a peculiar feature in its initial outbreak as it mostly involved savings institutions rather than commercial banks before becoming a systemic crisis.

It is also worth noting that, for the sake of the empirical investigation, the crisis variable is a simple dummy variable taking value of 1 at the beginning year of a crisis and 0 otherwise. The simple categorical variable does not allow to explore different intensity and depth of the crises, which can be crucial in an empirical investigation. Similarly, the proposed measure is silent about the duration of the crisis, a widely controversial issue within the literature.[19] Although I do not attempt to say anything about the ending date of a crisis, I adopt here an empirical methodology which is flexible to different durations of a banking crisis.

2.2 Data on the US Top-Income Shares

I draw extensively on the detailed database estimated and assembled by Piketty & Saez (2003) (PS hereinafter[20]). With information gathered from 1913 to 2012, this database is a valuable source to describe the long-run trend of the total *gross* income reported by the top tax units[21] of the US income distribution. Overall, PS present a set of annual series of shares of total income accruing to a number of top fractiles above the 90th percentile. Moreover, as mentioned above PS use a gross definition of income before deductions, individual income taxes and payroll taxes. The income definition excludes

runs on financial institutions and government emerging measures. Generally, such widely used 'event method', it is necessary in order to analyze long-time horizons as quantitative data are not always available in earlier years of the twentieth century. However, conditioning the detection of crises upon the observation of mitigation measures or data on banks balance sheets may lead to detect a crisis with considerable lag (This is also mentioned in Reinhart & Rogoff, 2008 and (Boyd et al., 2009))

[19]Some scholars have tried to identify the length of the crisis but the approaches that have been adopted are, in my opinion, not entirely appropriate for the objective. 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-crisis trend, including the year when it returns to that trend*". Similarly in Laeven & Valencia (2010), the authors reported the end date for the crisis episodes. 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*". Generally speaking, finding the end date of a banking crisis remains a more controversial task than that of finding its starting point . Indeed, although the above mentioned methodologies are suitable to the identification of the ending date of the recession (likely stemming from the financial shock itself) they are not able to capture with precision when a banking crisis comes to an end.

[20]Data updated to 2012 have been downloaded from the World Top Income Database website http://topincomes.g-mond.parisschoolofeconomics.eu/.

[21]A tax unit in the U.S. tax code is either a married couple or a single individuals. Dependents are also included.

all government transfers such as Social Security (retirement and disability benefits) and health benefits (Medicare and Medicaid), compensation schemes for unemployment and all cash and in-kind welfare schemes. For the purpose of this analysis, I make use of data on top fractile income shares in total income both including and excluding capital gains.

These data have obvious limitations widely discussed in a burgeoning related literature (see Atkinson et al., 2011, Saez et al., 2012, Piketty et al., 2011 and Morelli et al.,forthcoming for a thorough discussion on these and other limitations of the data). In particular, an important limitation refers to the fact that tax reported income could very likely differ from real gross income due mainly to tax evasion and avoidance. This makes the households' reported income particularly sensitive to changes in taxation as individuals attempt to minimise their tax liabilities. Moreover, the role of tax avoidance (lawful re-timing of income reporting and income shifting) and behavioral responses to change in taxation can affect the short-term as well as the long-run levels of top shares.

Advantages Nonetheless, the choice to focus the attention on country's richest quantiles shares in US gross income distributions is an informative and a unique exercise for different reasons:

1. Data on top income shares represents a unique opportunity to analyse an extraordinary long time horizon covering most of twentieth century and the beginning of the twenty-first century. No other comprehensive measure of US income distribution would allow studying such a long time horizon continuously over time. The long annual series also allow exploiting the time-series properties of the data better.

2. The financial sector, likely to be harmed during a banking turmoil, is increasingly populated by wealthy and rich individuals. Moreover, the composition of income at the right tail of the distribution is such to make the link with the financial meltdown more plausible.

3. The use of data based on gross income appears of help in order to untangle the direct effect of government intervention through fiscal policies, contemporaneous to the occurrence of a banking crisis.

4. The use of top shares allows including realized capital gains[22] to the total market income accruing to the top US income brackets. Such a source of income has a

[22]It is nonetheless worth noticing that the fractiles are always defined by ranking income excluding capital gains.

sizeable incidence in the total income at the top and it is particularly affected by the occurrence of financial shocks.

5. Data on US top income shares are decomposable by income sources for the entire period under observation which would help to interpret the findings of the work.

In addition, working with subgroups within the top decile may seem just a tiny portion of the overall population. Nonetheless, US is a populous nation with a total 153 million tax units in 2008 (37.7 in 1913) meaning that I am effectively analysing around 15.3 million tax units (3.7 million). Furthermore, enormous differences in income level characterise the subgroups within top decile. In 2006 the minimum non-capital gains income in order for a tax unit to be counted above the P90, P95, P99, P99.5, P99.9 and P99.99 percentiles was respectively 111.772, 156.773, 392.922, 616.387, 1.883.501 and 8.568.365 US-2008 dollars[23]. Finally, such a small population share detains a substantial and economically relevant share of the total national income: in 2012, for the first time in US history, top income decile accounts for more than half of total reported national income.

3 Preliminary investigation

Having described the data I now move to a preliminary empirical investigation of the data without making any adjustment.

3.1 The Levels of Top Shares and Financial Crises

Plotting data on a 5 years window diagram provides an initial evidence of the fact that top shares decrease or slow down their growth following a systemic banking crisis.

Figure 2 shows the behavior of the top hundredth percentile (what it is labeled as Top 0.01%[24]) as well as the top decile share (labeled as Top 10%[25]) in the US income distribution around crises episodes (figures exclude capital gains). More specifically, I set top shares to take value of 100 at the crisis year (period 0). The Top 0.01% share appears to have a cyclical or inverted V-shaped pattern while the top decile seems not to be particularly affected by the occurrence of a systemic banking shock and it generally shows little changes. The cyclical pattern of the share of the richest group

[23] Moreover, the 2006 ratios between the average incomes of independent fractiles within top decile (P90-P95, P95-P99, P99-P99.5,P99.5-P99.9, P99.9-P99.99 and P99.99-P100) and the above stated thresholds are respectively 1.17,1.39, 1.21, 1.61, 1.83 and 2.55.

[24] The top001 share is, in other words, the share in total income of the upper income bracket above the 99.99th percentile (P99.99).

[25] Using the same terminology as before the top decile is the upper income bracket above the 90th percentile (P90)

in the US income distribution has been recently thoroughly documented in Parker & Vissing-Jorgensen (2010). More interesting, however, appears the behavior of the top decile share which can be understood by analysing the behavior of growth rates of the shares around crises. This is done in the next section.

It is worth mentioning, however, that a mere analysis of the temporal association between the shares dynamics and the occurrence of the crises does not take into account the fact that top shares may be influenced by trending patterns and structural changes of any sort[26]. For instance, Figure 2 suggests, at a first glance, that recent banking crises had milder impact on the richest shares in US income distribution compared to the impact of the 1929 Great Depression. However, if one assumes that a positive growth of top shares preceding a crisis is entirely or partially due to a time trend, then the decrease of top shares following the shock may be underestimated during the recent crises episodes. In other words, the pattern around crisis episodes has to be rotated clockwise.

This and other issues concerning the non-stationarity of the series are spelled out more clearly in the following sections.

3.2 The Growth Rates of Top Shares and Financial Crises

Figure 3 summarises the evidence for the Great Crash, Savings & Loans crisis and the recent Financial Meltdown, showing broadly that top shares in total income (including and excluding capital gains) experienced sustained positive median growth rates during the five years preceding a systemic banking crisis[27]. On the contrary, the median growth rates drop to negative values for the three years following the financial shock. However, this is a general description which applies only to richer top income groups. Indeed, the results show that richer fractiles (above P99) and 'poorer' ones within top decile (below P99) seem to form two distinct groups whose shares in total income are

[26]For example I warn the reader that changes in taxation regimes are not taken into account at this stage. A clear illustration is the US Tax Reform Act of 1986 (TRA86) which, among other things, brought the top marginal tax rate on personal income from 50% to 28% in 1988 (the top rate was reduced to 38.5% in 1987). TRA86 also reduced the tax rate on corporate income from 46% to 34%, to a level higher then top tax marginal rate. This might have incentivised income shifting from corporate income to personal income (Slemrod (1996), Slemrod (2000)) and reduced tax evasion at the top. Both could have impacted strongly on the short-term level of top income shares. Indeed the highest fractile share in total US income (top001) grew by 30% from 1986 to 1987 (a year of stock market crash) and by 53% from 1987 to 1988 (when a banking crisis hit). Moreover, a growth rate of 53% is the second highest growth rate recorded from 1913 to 2013. Such behavioral response to TRA86 changes in taxation has also been discussed in Piketty & Saez (2003).

[27]I prefer to summarise the evidence for the three US systemic banking crises with median rather than mean values as the former can smooth out excess variability due to potential outliers in small sample. In any case, mean values have been calculated and they match pretty closely the median ones.

negatively and significatively correlated especially during the period surrounding the financial shocks[28].

For example, the top decile share net of the top5 (called hereinafter Top 10-Top 5%[29]), grew on average 4 percent after a banking crisis (excluding capital gains), 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 (Top 0.01%) grew on average around 13 percent preceding banking turmoil and then it dropped by 9 percent. Such changes[30] around banking crises episodes are all statistically significant mostly at 1 percent significance level, except the case of top decile as a whole (Box A describes the dynamics of the shares around stock market episodes for a comparison).

Given the importance of the discussion above and in order to ease the discussion, the analysis will hereinafter focus exclusively on the Top 10-Top 5% and Top 0.01% fractiles. These two groups, as described above can act, with no loss of generality, as representative groups of respectively the 'poorer' and the 'richer' fractiles within the top decile. To complement the analysis, results are also reported for the top decile as a whole. This will highlight that focusing on different top shares is indeed important and failing to take that into account can lead to misleading conclusions. Next section describes the mechanical dynamics of top income shares, whereas the following two estimates discuss more formally the nature of the counterfactual and used forecasting model and time-series econometric specifications to control for important factors such as time trend and mean reversion.

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[28]The correlation is particularly highly significant 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.

[29]The Top 10-Top 5% share is the share of the upper income group included between the 90th percentile and the 95th percentile, also called P90-P95.

[30]It is also worth noting that I focus the attention on non-overlapping fractional percentiles within the top decile. This avoids artificial positive correlation of growth rates, driven by the direct interdependence of top fractile groups. Indeed, as an example, all tax units within Top 0.01% share are in turn fully contained in Top 0.1% income group. Tax units populating the latter are then contained in Top1 which in turn forms part of Top 10% group.

Box A: Comparison with Stock Market Crashes For a brief comparison one can do a similar analysis in the case of general stock market crashes. I use the dates listed in Mishkin & White (2003) where the two authors, taking 1929 and 1987 as a benchmark, identify stock market crashes when an overall nominal decline of minimum 20% in the stock market index is recorded. The recent 2007 crash also fully qualifies as a market crash according to this criteria.[a].

Having dropped the stock market crashes that coincide with systemic banking shocks (1929,1987 and 2007), I observe that the share in total income (excluding capital gains) of the top hundredth percentile dropped on average by 4 percent during the three years following the crash, after gaining only a maigre 0.5 percent in the preceding years on average.[b]. On the other hand, the dynamics for 'poorer fractiles' within the top decile no longer appears statistically significant and the overall top decile shows a significant average drop of 1 percent following the crash. Hence richer and poorer fractiles within the richest 10 percent group of US households no longer seem negatively correlated around stock market crisis periods. Interestingly and differently from the cases of systemic banking shocks, the richer fractiles don't seem, on average, to earn disproportionate income prior a general stock market crash, while the top decile as a whole looses ground in the three years after the shock.

I argue that the difference observed in the behavior of top shares in the aftermath of the two different financial shocks could be potentially due to the role of unemployment dynamics. Indeed, in the sample used here I do not systematically observe large rises in unemployment and large drops in total reported income following general crashes in stock markets. Conversely this was the case for each of three systemic banking shocks under investigation[c]. However, unemployment cannot explain also the different dynamics prior the occurrence of the two types of shocks. The latter may be due to the role of financial bubbles generating disproportionate gains accruing to the top of the distribution or, more controversially as suggested within recent literature (and explored in detail within Chapter 4, can reflect the role of rising inequality in leading to banking crash.

[a] Crashes identification varies depending on the index used (DowJones, S&P500 or NASDAQ) and depending on the time window used to record a decline in shares price. Using weekly data for Dow Jones only 1929 and 1987 are identified as crashes. Using a three months window crashes are identified in 1907, 1930-1932 and 1987 with DowJones whilst S&P500 identifies also 1929 and NASDAQ 1987 among others. Using a year window and the DowJones one could identify among others,1904,1914, 1915, 1930-33 and 1988. S&P500 identifies 1907, 1917, 1930-33. With the use of NASDAQ one can also add 1984 as a crash year. Even though the analysis of Mishkin and White stops in early 2000, it is easy to check that the 12 months window would certainly list the year 2008 as a "crash" year. DowJones went down more than 20% from the peak of October 2007 to July 2008 and by more than 50% until March 2009.

[b] The difference is significative at 10 percent significance level comparing the three years preceding a crisis, including the crisis year itself, to the three years following a crisis. Differences have been tested statistically also accounting for potential change in variance. In addition, the figures are almost exactly the same for the shares including income from realised capital gains.

[c] I would provide further evidence for such observation in the following sections.

4 Counterfactual Analysis

To what extent can one ascribe the change in top income share to the occurrence of a systemic banking shock? The answer to this question would be straightforward if we knew the inequality pattern in the absence of the crisis, in other words if the counterfactual was known. As also noticed in Jenkins et al. (2013), obtaining a reliable and compelling estimation of this counterfactuals is a very challenging task as we are essentially facing a problem of missing data.[31].

I adopt here two different approaches. First, I exploit historical variation of the series in order to forecast the pattern of the top series from the perspective of each crisis year. This helps to estimate the unforeseeable impact of each of the three crises under investigation on top income shares. Secondly, I estimate an Auto-regressive Distributed Lag (ADL) model which allows me clarify the nature of the counterfactual and to estimate the average impact (and the associated confidence interval) of crises on top shares for every year following the shock.

The main conceptual idea of the empirical specification is similar to that adopted in Romer & Romer (1989)[32] and to the 'ex-post' counterfactual analysis described in Pesaran & Smith (2012).[33]

4.0.1 Counterfactual Analysis Using 'Forecasting'

The objective of this section is to investigate whether the top shares series deviate from their forecast pattern following a banking shock and given their past behavior.[34] This can be considered as a first step towards comparing actual values with some raw measure of counterfactuals.

However, a forecast model performs well if based on stationary series and this imposes a constraint on our model specification.[35] Standard causes of non-stationarity are the presence of a trend (deterministic or stochastic) or any structural break.

[31] Jenkins et al. (2013) recall that ''*...counterfactuals are difficult to estimate with confidence. Hence we are left with the less satisfactory but feasible alternative of measuring changes relative to a baseline distribution for around 2007, while also looking at earlier years to consider outcomes for that year in the context of the previous trends*''

[32] Romer & Romer (1989) have attempted to gauge the implications of exogenous monetary policy shocks on unemployment rate and industrial output. Recent work by Cerra & Saxena (2008) used a similar methodology to explore the role of a set of macro shocks (among others banking crises) on economic performance for a panel of countries.

[33] The two approaches to counterfactual estimation used here are clearly not the only ones possible. This step is nonetheless limited by the nature of the data. Farr & Vella (2008) for instance adopted a different methodology exploiting the micro-data at the individual level for the case of Spain. In particular they used a semi-parametric procedure to link income levels to a combination of individual characteristics and macro-variables. In other words they model the conditional expectation of an individual's income as an unspecified function of two indices. This allows the estimation of counterfactual distributions of incomes conditionally to different macroeconomic conditions.

[34] It would be more precise talking about pseudo-forecast given that I forecast something whose actual value is already known, for comparison needs. Therefore no out of sample forecast is performed.

[35] Stationarity implies that the distribution of the variable is invariant over time. In other words the past observations of the series are informative about its future dynamics. Indeed, in stationary series the future is equal to the past in probabilistic terms.

Data on top-shares in levels (annual data from 1913 to 2012) have a clear non-linear trend, the presence of structural breaks can be detected through standard techniques[36] and one cannot rule out the presence of stochastic trend (unit root)[37]. This leads me to exclude a model specification based on the levels of the shares in favor of one based on their growth rates. As a matter of fact, the growth rate series of top shares do not present any structural break[38] and present a straightforward linear time trend. Once controlling for a linear time trend[39] the series would therefore become trend-stationary[40]. Furthermore, the exercise based on growth rates would carry out straightforward interpretation and can be also useful to estimate the unforeseeable impact of each banking crisis on the levels of top shares, our ultimate interest. Indeed, this can be easily done by cumulating forecast errors estimated on growth rates.[41]

Forecast Model Following the study by Romer & Romer (1989), I adopt a pure time series approach estimating an autoregressive model over the entire period of reference (1913-2012). Estimated parameters are used to calculate forecast value of the rates of growth of top shares ahead in time. The forecast model includes 2 lags[42] and

[36]For example assuming that breakpoint is unknown, the estimation of Quandt's breakpoint statistic helps detecting at least one break for every top share under analysis. For more details and precise estimation of the structural breaks in top income shares series see Roine & Waldenström (2011)

[37]Although there is not much discussion around this issue, some scholars have argued that unit root hypothesis testing on bounded shares present some logical flaws. Indeed, a share (bounded between 0 and 1) cannot have an infinite variance as a 'random walk' would instead formally require. See Jäntti & Jenkins (2010) for further discussion about unit root tests on inequality variables. Even though one is not willing to accept this argument, it remains true that standard unit root testing procedures are not appropriate for bounded series and this issue was largely neglected in the literature. See also the useful discussion in Cavaliere (2005), Granger (2010) and Cavaliere & Xu (2013)

[38]Indeed, the Quandt's score does not detect any structural break

[39]For instance it is straightforward to show that if y follows an AR(p) model with a quadratic trend, its first difference would be still linearly dependent on time.

[40]It should be noted more precisely that the presence of a volatility clustering over time (changing variance over time) provide an additional source of non-stationarity. However this problem can be easily handled using standard Heteroskedasticity consistent definition of Var-Cov matrix in the model estimation.

[41]An alternative approach to the use of growth rate with linear time trend, would consist in using de-trended observations of top shares. For example, the Hodrick-Prescott (HP) filtering technique (Hodrick & Prescott, 1997), like other time series filters, isolates a time-variant trend component $\tau_{i,t}$ and subtracts it from the series $y_{i,t}$ in order to obtain a cyclical component or de-trended high frequency series $d_{i,t}$. De-trending the top shares of income is an interesting exercise but requires an arbitrary choice of parameters and does not carry out straightforward interpretation.

[42]The number of lags has been chosen following the indication of the two standard information criteria. Bayesian Information Criteria and Akaike Information Criteria have been compared over the estimation of autoregressive models from 1 up to 6 lags. Indeed using 2 lags was coincident to a minimum for both BIC and AIC values.

a deterministic trend component T and, as explained above, it is estimated on the growth rates of top shares (not on their levels):

$$g_{i,t} = \alpha_i + \sum_{j=1}^{2} \beta_{i,j} g_{i,t-j} \ + \gamma_i T_{i,t} + \epsilon_{i,t}. \tag{1}$$

The estimations are carried out using Newey-West estimators which allow for heteroschedaticity and autocorrelation of error terms.[43]

I make use of both the so called 's-steps' (or multi-periods) forecast model and the dynamic forecast (or iterated autoregressive) method; the results obtained are very similar.

Every's-steps' ahead forecast requires the estimation of an autoregressive model which includes the lags of forecast variable up to $t - s$, with $s \geq 1$. Conditioning on the information set at time $t - s$, the forecast model (which in my case contains only two lags as above stated) takes the following general form:

$$g_{i,t/I_{t-s}} = \alpha_{i,s} + \sum_{j=0}^{1} \beta_{i,j,s} g_{i,s,t-s-j} + \gamma_i T_{i,t} + \epsilon_{i,s,t}. \tag{2}$$

The parameter estimates vary for different s, which explains the presence of the subscripts in above equation. Note also that with *s=1* (1) and (2) are the same. At any time t then the s-steps ahead forecast takes the following form:

$$\widehat{g}_{t+s/I_t} = \widehat{\alpha}_s + \sum_{j=0}^{1} \widehat{\beta}_{j,s} g_{s,t-j} + \widehat{\gamma}_i T_{i,t+s}. \tag{3}$$

The variables and parameters are now stacked on the number of different income groups i.

The dynamic forecast method instead simply iterates the single-period forecast in (1). For example the 2 steps ahead forecast at time t are obtained by iterating the single-period forecast using the forecast value of g_{t+1} estimated in t.

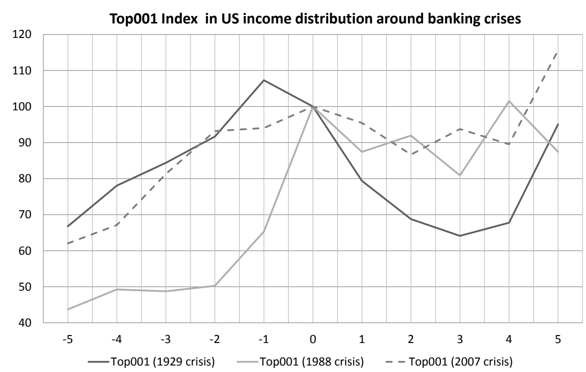
[43] Truncation parameter has been selected using the standard rule $m = 0.75 * T * 1/3$, where T is the number of observations in the specification Andrews (1991). This rule suggests to use 3 lags ($m = 3$) in every estimation. The models appear also correctly specified as the assumption of autocorrelation in the residuals is rejected with very high confidence using conventional portmanteau Q-tests.

Evidence on the Growth Rates Equation (3) has been estimated with both forecasting methods for every fractile for the 1913-2012 period. Then I calculate dynamic forecasts of the growth rates of the top shares. This is done for every top group and for the four years following each of the three systemic banking shocks under investigation. The evidence from the two different forecast methods is almost identical[44], suggesting that the results are not driven by the different methodology adopted.

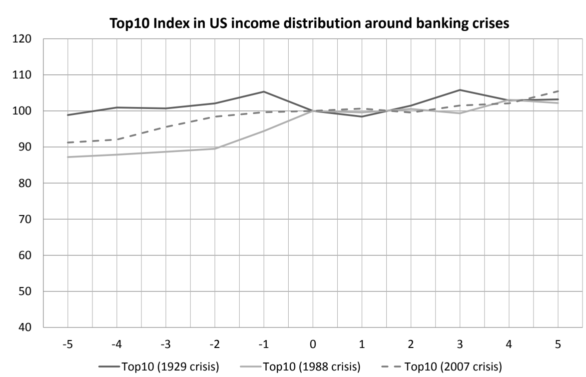
The main findings suggest that the actual post-crisis growth rate for the Top 0.01% tends to be lower than what expected based on the trending features and the mean-reverting property of the series (Figure 4(a)). In particular, the actual values of the top001 growth rate lay systematically below its forecast value. This also happens following the latest 2007 crisis with the exception of the third post-crisis year, when the actual growth rate value is slightly bigger then its forecast value. Note also that a great deal of the drop in growth rate for Top 0.01% which occurred in 1989, was easily foreseeable given the past dynamic of the series (mean-reversion) and, thus, cannot be directly attributed to the crisis. This is a valid example of the reason why I have adopted such methodology. In fact, a drop in the top shares can be simply part of the cyclical behavior of the series and have nothing to do with the financial turmoil. The dynamics of the growth rate of Top 10-Top 5% is instead found to be higher than what forecast (see Figure 5(a)) while the Top 10% growth rate is neither systematically under-forecast nor systematically over-forecast (see Figure 6(a)).

[44]The only exceptions are the 1991 and 1992 forecast of Top 10-Top 5% growth rates, in which case the two different methodologies diverge quite substantially with their estimates.

Figure 2: Top 0.01% and Top 10% Standardised around Crises Episodes: Excluding Capital Gains



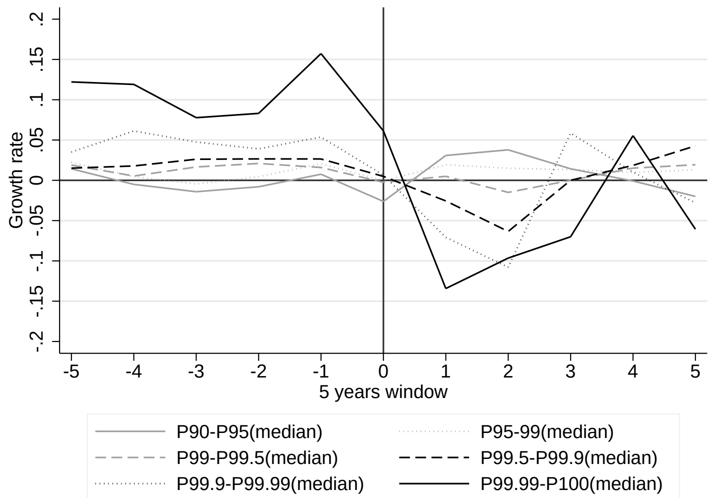
(a) Top001



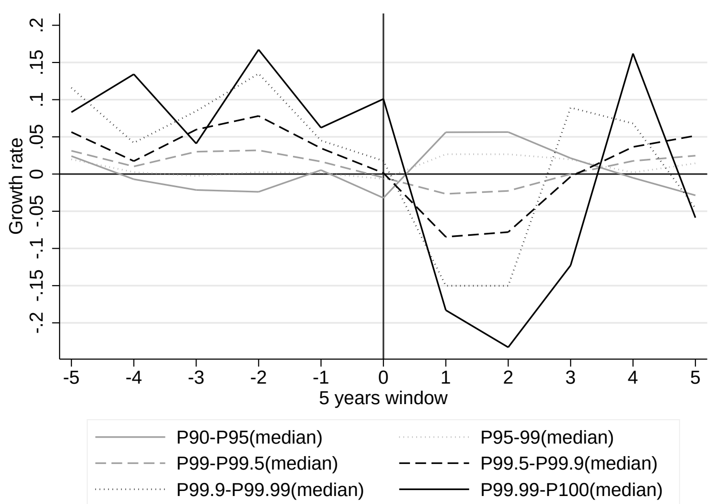
(b) Top 10%

Source: Piketty & Saez (2003) , data updates from Saez (2012) and author's own calculations. Series take value of 100 in period 0, the beginning of a systemic banking crisis.

Figure 3: Median Growth Rates of Different Top Fractiles Share of Aggregate Income around Crises Episodes



(a) Excluding Capital Gains

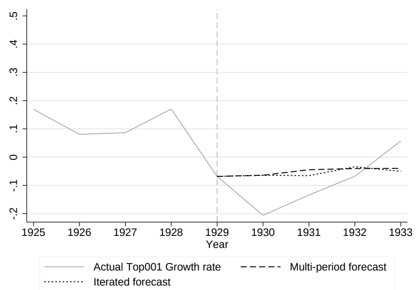


(b) Including Capital Gains

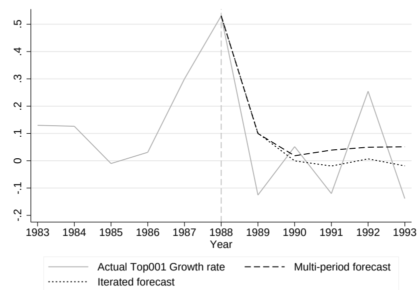
Each data point represents the median value of the growth rate of total income accruing to different non-overlapping upper groups around the three crises episodes under investigation. The period 0 represents the onset of the crisis and I observe the dynamics of the variables in a symmetric 5-years time window.

Source: Piketty & Saez (2003) , data updates from Saez (2012) and author's own calculations

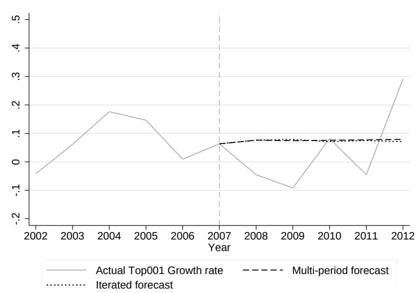
Figure 4: Actual vs. Forecasted Growth Rates of Top 0.01% during systemic banking crises



(a) Great Depression - 1929



(b) S&L crisis - 1988



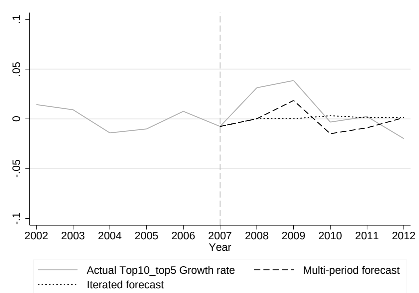
(c) Great Recession - 2007

Notes: The graph shows the dynamics of the growth rate of Top 0.01% share around the three crisis periods under investigation (beginning respectively in 1929, 1988, and 2007) compared to the forecast value estimated at t based on two forecast methodologies, namely the 'dynamic forecast' and the 's-steps forecast'.

Figure 5: Actual vs. Forecasted Growth Rates of Top 10-Top 5% during systemic banking crises

(a) Great Depression - 1929

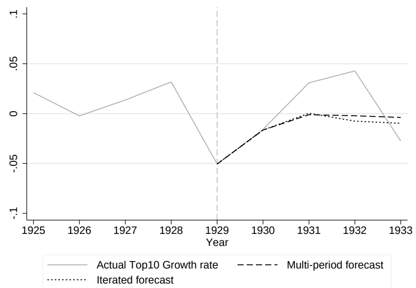
(b) S&L crisis - 1988



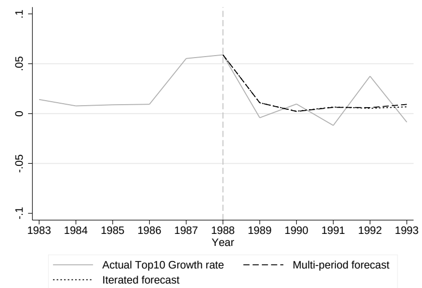
(c) Great Recession - 2007

Notes: The graph shows the dynamics of the growth rate of Top 10-Top 5% share around the three crisis periods under investigation (beginning respectively in 1929, 1988, and 2007) compared to the forecast value estimated at t based on two forecast methodologies, namely the 'dynamic forecast' and the 's-steps forecast'.

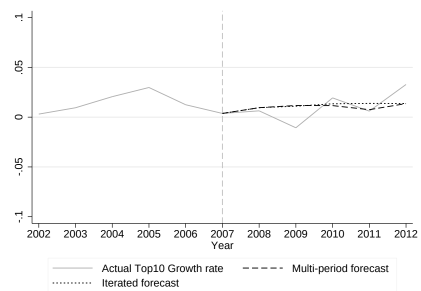
Figure 6: Actual vs. Forecasted Growth Rates of Top 10-Top 5% during systemic banking crises



(a) Great Depression - 1929 - Top 10%



(b) S&L crisis - 1988 - Top 10%



(c) Great Recession - 2007 - Top 10%

Notes: The graph shows the dynamics of the growth rate of Top 10% share around the three crisis periods under investigation (beginning respectively in 1929, 1988, and 2007) compared to the forecast value estimated at t based on two forecast methodologies, namely the 'dynamic forecast' and the 's-steps forecast'.

Evidence on the Levels In order to estimate the unforeseeable impact of each banking crisis on the top shares themselves I cumulate the forecast errors[45] at every year as represented in Figure 7. As shown in the latter figure, every systemic banking shock in US led to a similar drop in Top 0.01% which was not expected on the basis of past dynamic behavior of the series. Three years after the Great Crash in 1929, the Top 0.01% income share was around 30 percent lower than forecast value before beginning a partial recovery. Top shares followed a similar dynamics during the Savings and Loans crisis. However, the drop up to the third year from the shock appeared slightly higher, accounting for around 35 percent deviation from the forecasted pattern. Finally, the richest share is found around 25% below its forecasted value in 2010, three years from the onset of the most recent crisis and, differently from other episodes, the first signs of recovery appeared only 4 years after the shock in 2012[46]. It should also be noted that if I had estimated equations (1) to (3) without using the time trend I would have incorrectly obtained a very high impact for the Great Depression while the drop for recent crises on top shares would be almost halved. The perception that recent crises might have milder impact on top shares could have therefore been driven by the misspecification of the model.[47].

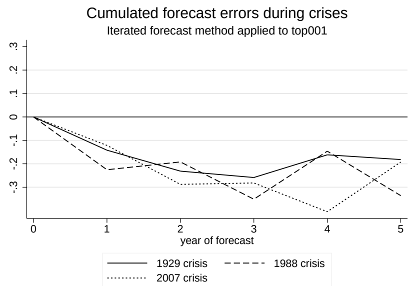
On the other hand, the share in total income for the P90-P95 income group was somehow under-forecasted by the model. This is consistent with the data account within the section of the preliminary results, in which I described the two shares of the bottom and the upper part of the top decile as negatively correlated around the crisis episodes. As a result, not much action is recorded in the Top 10% as a whole. What discussed above underlines again the importance of a disaggregated investigation of the data across different upper income groups.

[45] Note that the use of cumulated errors slightly accentuates the very small differences in forecast estimates obtained with the two different methods. The difference is however negligible and I prefer to make use of iterated method in order to carry on the forecasts exercise with a greater number of observations.

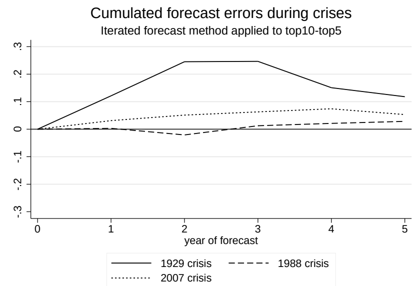
[46] As noted in Saez (2013) this might be partially driven by income retiming to avoid the tax increase in 2013. Indeed "*Top ordinary income marginal tax rates increased from 35 to 39.6% and top income tax rates on realized capital gains and dividends increased from 15 to 20% in 2013. In addition, the Affordable Care Act surtax at marginal rate of 3.8% on top capital incomes and 0.9% on top labor incomes was added in 2013 (the surtax is only 0.9% on labor income due to the pre-existing Medicare tax of 2.9% on labor income). The Pease limitation on itemized deductions also increases marginal tax rates by about 1 percentage point in 2013. These higher marginal tax rates affect approximately the top 1%. Hence, among top earners, retiming income from 2013 to 2012 saves about 6.5 percentage points of marginal tax for labor income and about 10 percentage points for capital income. In words, for top 1% earners, shifting an extra $100 of labor income from 2013 to 2012 saves about $6.5 in taxes and shifting an extra $100 of capital income from 2013 to 2012 saves about $10 in taxes.*" Saez (2013, footnote 1)

[47] Results are not tabulated but available upon request.

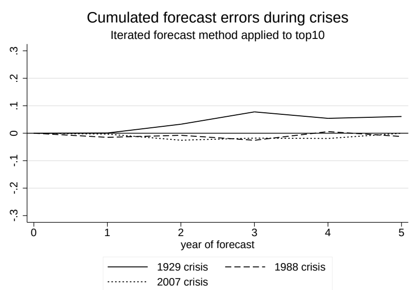
Figure 7: Cumulated Forecast Errors: Top 0.01%, Top 10-Top 5% and Top 10% Income Shares



(a) Top 0.01%



(b) Top 10-Top 5%



(c) Top 10%

Notes: Each single charts represent the cumulative forecast errors in the 5 years following each US banking crisis, The forecast error at any point in time is computed as the difference between forecast value and actual value as represented in Figure ??. The data represents the cumulative forecast error based on the 'iterated' method described in the text.

4.0.2 Counterfactual Analysis Using Macro-Econometrics

In this section I estimate a bivariate autoregressive distributed lags model (see Hendry, 1995) in order to estimate the response of top shares to crises (impulse responses). The ADL model proposed is essentially a general augmented version of the forecast model discussed before[48]:

$$g_{i,t} = \alpha_i + \theta_i g_{i,t-1} \ + \sum_{j=0}^{4} \phi_{i,j} BC_{t-j} + \gamma_i + \rho_i' X_{i,t} + \nu_{i,t}. \tag{4}$$

[48] Note that I now make use of only one lag of the dependent variable. This would ease the derivation of the impulse response functions as shown in the next section. Loosely speaking, this approach allows to associate a confidence band around the cumulated forecast error lines presented in Figure 7.

where $g_{i,t}$ is the growth rate of the top fractional percentile for every income group i from year $t-1$ to year t; $BC_{i,t}$ is a categorical variable coded 1 when the systemic banking crisis in country i begins and zero otherwise; $X_{i,t}$ is a vector of other regressors including the time trend.

Estimation The model (4) was estimated individually for each income group using least squares regressions. The standard errors are computed using the Newey-West formula.

For the estimation I further assume that crisis and top shares growth rates are contemporaneously uncorrelated ($\phi_{i,0} = 0$) so that changes in $g_{i,t}$ at the year of the onset of the crisis would be entirely attributed to innovations to the growth rate process and not to the crisis itself (the assumption turns the crisis variable into a predetermined variable)[49]. The assumption above it is also a simple way to control for potential endogeneity problem, namely that increasing income dispersion could increase the likelihood of a crisis to occur, as recently debated within the literature)[50]. Indeed, the consistency of the estimated parameters in the ADL model (4) rests on the assumption of exogeneity of the crisis dummy variable with respect to the growth rates of top income shares.

As shown in table 1 the coefficients for Top 0.01% of the baseline ADL model are negative for the three years following the crisis and indicate a recovery in the 4th year after the shock occurred. For instance, the growth rate of the Top 0.01% is reduced by around 18 percentage points one year after the onset of the crisis. The opposite happens to the growth rate of the share of P90-95 share. Indeed, the latter growth rate gains around 6 percentage points in the years after the crisis. This is true, though with greater magnitude, even looking a the series including capital gains, represented in the table 1 in the last three columns.

The estimated parameters of the ADL model above can then be used to estimate

[49]The qualitative feature of the results is preserved by assuming that $\phi_{i,0} \neq 0$. Findings are not shown but available upon request

[50]However, the latter problem might not be particularly relevant the available empirical evidence linking the growth rate of income inequality to the occurrence of financial crisis does not yet provide any convincing evidence that such a nexus between the growth of inequality and the occurrence of banking crisis exists. This conclusion was also reached by Atkinson & Morelli (2010, 2011) and Bordo & Meissner (2012). The latter study tested explicitly whether the growth rate of top income shares were increasing the probability of the occurrence of banking crisis. Similarly I tested a probit model linking the growth rates of top shares to the crisis variables and its lags (results are not shown in the chapter but do not suggest any strong relationship between the two variables).

the total effect of crisis on the growth rates as well as the levels of the top shares. This is done by calculating impulse response functions. In other words I treat the growth rate of top income share as a dynamic process subject to impulses (banking crises) and study the response over time. Given the stationary nature of the series (growth rates), every impulse to the dynamic process would automatically decay over time and this approach becomes informative about the depth and duration of a change in top shares brought about by banking shocks. This is further explained below.

Table 1: ADL Model Estimated for BC and Selected Top Shares (Including and Excluding Capital Gains)

	(1)	(2)	(3)	(4)	(5)	(6)
	Excluding capital gains			Including capital gains		
	top10	top001	top10_top5	top10	top001	top10_top5
L.BC	-0.009	-0.189**	0.057*	-0.041***	-0.275***	0.084*
	(0.006)	(0.057)	(0.028)	(0.008)	(0.079)	(0.036)
L2.BC	0.007	-0.064	0.046	-0.013	-0.261***	0.053*
	(0.015)	(0.050)	(0.028)	(0.019)	(0.069)	(0.027)
L3.BC	0.011	-0.056	0.003	0.015	-0.103	0.004
	(0.015)	(0.055)	(0.010)	(0.017)	(0.089)	(0.014)
L4.BC	-0.001	0.063	-0.029	-0.002	0.045	-0.030
	(0.016)	(0.095)	(0.027)	(0.012)	(0.101)	(0.030)
L.Gtop10	0.156			0.044		
	(0.215)			(0.183)		
L.Gtop001		0.194			-0.157	
		(0.134)			(0.145)	
L.Gtop10_top5			0.184			0.163
			(0.177)			(0.165)
Observations	94	96	94	94	96	94

Newey-West Standard errors in parentheses
The table shows the coefficients of the estimation of the ADL model (4) on the growth rate of the top shares. Linear time trend and constant are suppressed from the table
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The *ex-post* counterfactual approach In order to rationalize the derivation of IRFs I describe here the so called *ex-post* counterfactual analysis as discussed in Pesaran & Smith (2012). For every income group 'i' under investigation, I define the information set at time t as $\digamma_T = \{g_t^i, X_t, BC_t\}$ for every $t = (T, T-1, T-2, ...)$. I also define the set of 'crisis off' values as $\mathbf{\Theta}^0_{T+s} = \{BC^0_T = 0, BC^0_{T+1} = 0, ..., BC^0_{T+s} = 0\}$, assuming that the banking crisis lasts for $s+1$ years and begins at year T, where $s = (0, 1, ..., S)$. This leads to define the total impact of crisis on the growth rates of top shares (I^G_{T+h})

as follows:

$$I^G_{T+h} = g^i_{T+h} - E\{g^i_{T+h}/\digamma_T, \mathbf{\Theta}^0_{T+h}\}. \tag{5}$$

Where g^i_{T+h} is the actual growth rate of the top share[51] under analysis and $E\{g^i_{T+h}/\digamma_T, \mathbf{\Theta}^0_{T+h}\}$ represents the objective of the estimation, namely the value of the growth rate of top shares under the condition of no crisis, which depends on the empirical specification.

One can rewrite the model 4 as follows[52]:

$$g^i_{i,t} = \left(1 - \theta_i L\right)^{-1} \left[\sum_{k=0}^{4} \phi_{i,k} BC_{t-k} + \rho'_i X_{i,t} + u_{i,t}\right] \tag{6}$$

and

$$g^i_{i,t} = \sum_{k=0}^{4}\sum_{j=0}^{\infty} \phi_{i,k}\theta^j_{i,1} BC_{t-k-j} + \sum_{j=0}^{\infty} \theta^j_i \rho'_i X_{i,t-j} + \sum_{j=0}^{\infty} \theta^j_i u_{i,t-j} \tag{7}$$

The counterfactual can now be subtracted from $g^i_{i,t}$ in order to obtain the realization of the IRF at the h'th period following the shock.

$$\begin{aligned} I^G_{T+h} = \sum_{k=0}^{4}\sum_{j=k}^{h+k} \phi_{i,k}\theta^{j-k}_{i,1} + \\ & \sum_{j=0}^{h} \theta^j_{i,1}\rho'_i X_{i,T+h-j} - E^0_T\left\{\sum_{j=0}^{h} \theta^j_i \rho'_i X_{i,T+h-j}\right\} + \\ & \sum_{j=0}^{h} \theta^j_i u_{i,T+h-j} - E^0_T\left\{\sum_{j=0}^{h} \theta^j_i u_{i,T+h-j}\right\}. \end{aligned} \tag{8}$$

It is clear from above that one can ignore the last two terms only by assuming that the error term, the convariates and the whole set of parameters do not change with the occurrence of the crisis. Under these strict invariance assumptions one obtains the following formula:

$$I^G_{T+h} = \sum_{k=0}^{4}\sum_{j=k}^{h+k} \phi_{i,k}\theta^{j-k}_{i,1}$$

[51] Note that in the case of an *ex-ante* approach, even the 'crisis on' values of the top shares would be unknown and represented in expectation form. However, this approach can be very useful exclusively in a context of hypothetical macro policy evaluation as discussed in Pesaran & Smith (2012).

[52] This transformation is valid under the assumption of stationarity of g^i

This derivation implies that a simple reduced form model is sufficient in order to assess the *total* effect of a crisis[53] on a specific outcome variable as long as the model is conditioned on variables that, although influencing the outcome variables, are invariant to the occurrence of the crisis itself. This argument has pretty clear implications. On one hand, one should not worry about the estimation of the indirect implications of other macroeconomic shocks or events resulting from the banking shock itself by means of a structural model[54].

On the other hand, the model (4) cannot be conditioned on control variables such as a country's GDP growth, stock market performance, measure of financial development and other macro-shocks. All these variables, although commonly used as control variables given their influence on the growth of top shares, are in fact expected to be influenced by the occurrence of a banking crisis. One can however control for time trend and lagged observations of the outcome variable as the set of crisis-invariant regressors. This would define the counterfactual exclusively on the basis of the trending and the mean reversion properties of the growth rate of top income shares, similarly to Romer & Romer (1989) and to what has been done in the previous section.[55]

Such an approach is certainly less informative about the direct and indirect impact of crises on top shares. However, it is not necessarily misspecified, in the case in which every subsequent relevant macroeconomic event (e.g. raise in unemployment, economic crisis, policy interventions and stock market swings) has been directly caused by the banking shock, or it is assumed to be so.[56]

Estimating Impulse Response Functions. Under the invariance assumptions described above, the derivation of the realizations of the impulse response functions (IRFs) is straightforward. As an illustration, I derive below the first three realizations for the growth rate (this justifies the superscript G) of top shares of specific income group i :

$$I_{i,0}^{G} = \phi_{i,0} \tag{9}$$

[53]Pesaran & Smith (2012) discuss the role of macroeconomic policies instead.

[54]In other words, there is no need of calculating the marginal effect (structural parameters) of each single events using a system of equations relating the entire set of endogenous variables. Most importantly, note that a reduced form model conditioned on crisis-variant regressors is deemed to be misspecified for such a purpose.

[55]As part of the robustness exercise, the empirical model described above is further conditioned on other variables

[56]The beginning of the S&L crisis as I set it in 1988 was preceded by the 1987 stock market crash. However, the origin of the crisis as noted in the literature (see Reinhart & Rogoff, 2009 for instance) traces the origin of the banking turmoil in 1984, well before the stock market crash. In addition the stock market crash is not using annual observation of stock market indexes as recalled in Box A.

$$I_{i,1}^{G} = \phi_{i,0}\theta_i + \phi_{i,1} \tag{10}$$

$$I_{i,2}^{G} = \phi_{i,2} + \theta_i(\phi_{i,0}\theta_i + \phi_{i,1}) \tag{11}$$

By cumulating those responses over time (for every year $j > 0$) one obtains the dynamic cumulated impact on the level of top shares for every income group i, indicated as $I_{i,j}^{L}$.

$$I_{i,0}^{L} = I_{i,0}^{G} \tag{12}$$

$$I_{i,1}^{L} = I_{i,0}^{L} + I_{i,1}^{G} \tag{13}$$

$$I_{i,2}^{L} = I_{i,1}^{L} + I_{i,2}^{G} \tag{14}$$

It is worth noting that every realization of the IRF is a non-linear combination of the parameters of the ADL model 4.

The tabulations of the estimated version of the impulse response functions for both the growth rates and the levels ($I_{i,j}^{G}(\widehat{\psi}, t)$ and $I_{i,j}^{L}(\widehat{\psi}, t)$) for selected income groups are instead reported in Tables 2 and 3.

Table 2: Impulse response function of selected top shares to BC : excluding capital gains

	(1) top10_G	(2) top10_L	(3) top001_G	(4) top001_L	(5) top10_top5_G	(6) top10_top5_L
I_0	0	0	0	0	0	0
I_1	-0.009	-0.009	-0.189**	-0.189**	0.057*	0.057*
	(0.006)	(0.006)	(0.057)	(0.057)	(0.028)	(0.028)
I_2	0.006	-0.003	-0.101*	-0.289***	0.057+	0.114*
	(0.015)	(0.018)	(0.044)	(0.071)	(0.031)	(0.057)
I_3	0.012	0.009	-0.075	-0.364***	0.014+	0.127*
	(0.017)	(0.031)	(0.051)	(0.095)	(0.008)	(0.061)
I_4	0.001	0.009	0.048	-0.316*	-0.026	0.101+
	(0.015)	(0.030)	(0.093)	(0.145)	(0.026)	(0.060)
I_5	0.000	0.010	0.009	-0.307+	-0.005	0.096
	(0.002)	(0.031)	(0.018)	(0.156)	(0.007)	(0.060)
Observations	94	94	96	96	94	94

Table represents the estimated values of the realizations of the IRFs for the level (L) and the growth rates (G). Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results are also shown graphically, in Figures 8 and 9, for all selected top income groups, for both levels and growth rates as well as for both series including and excluding capital gains. The IRFs are represented with a 1 standard-error confidence band.

Table 3: Impulse response function of selected top shares to BC : including capital gains

	(1) top10_G	(2) top10_L	(3) top001_G	(4) top001_L	(5) top10-top5_G	(6) top10-top5_L
I_0	0	0	0	0	0	0
I_1	-0.041***	-0.041***	-0.275***	-0.275***	0.084*	.084*
	(0.008)	(0.008)	(0.079)	(0.079)	(0.036)	(0.036)
I_2	-0.014	-0.056**	-0.218***	-0.493***	0.067*	0.151*
	(0.017)	(0.018)	(0.053)	(0.099)	(0.030)	(0.062)
I_3	0.014	-0.042	-0.069	-0.562***	0.015	0.166*
	(0.016)	(0.025)	(0.089)	(0.103)	(0.012)	(0.067)
I_4	-0.001	-0.043	0.056	-0.506***	-0.028	0.138*
	(0.011)	(0.026)	(0.108)	(0.126)	(0.029)	(0.066)
I_5	-0.000	-0.043	-0.009	-0.515***	-0.005	0.134*
	(0.001)	(0.026)	(0.017)	(0.115)	(0.007)	(0.066)
Observations	94	94	96	96	94	94

Table represents the estimated values of the realizations of the IRFs for the level (L) and the growth rates (G). Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimation of Standard Errors Given the nonlinear combination of estimated parameters, the estimation of SEs are obtained with the δ *method* through asymptotic results [57].

Main Results The empirical evidence using above methodology suggests that the impact of US banking crises so far has been negative at the very top, positive at the bottom of the decile and, as a consequence, 'neutral' for the entire top decile share. Thus, the use of different top income share in the analysis matters as can provide contrasting evidence, marking the importance of the decomposition of income groups at the top. Information on Top 10% solely would lead to conclude that crises have no impact on the 'rich' share of total income. It is also worth noting that the growth rates of the shares of the two independent subgroups under investigation (Top 0.01% and Top 10-Top 5%) are significantly affected in the two years following a banking shock. Negatively in one case (for the Top 0.01%) and positively in the other (for the Top 10-Top 5%). This implies, on one hand, that the level of the richest top share is found to be, on average, lower that what it would have been predicted in the absence of crisis, based on previous dynamics of the series and including trend patterns. On the other hand, the bottom group within the top decile (P90-P95) gained in relative terms in the years following a systemic shock. Moreover, due to the substantial shock to the growth rates, the effect on the levels is not entirely re-absorbed in the medium-run. Indeed,

[57] The asymptotic variance-covariance matrix is effectively estimated through the command 'nlcom' in Stata 12 routine, following the estimation of each model.

the top hundredth percentile share in total non capital gains income is found to be 19 percent lower (with respect to the counterfactual) during the first year following the crisis and it is still 31 percent lower after five years (table 2, column (4)). These figures drop respectively to -28 and -52 percent if I include capital gains in the definition of income (table 3, column (4)). These figures, translated in Top 0.01% units, imply that the share is found, after 5 years from the crisis and on average, to be 0.43 percentage points lower than the counterfactual value in the case of the share excluding capital gains. This is equivalent to almost a third of a standard deviation[58]. If one includes capital gains, the recorded drop in Top 0.01% is equivalent to 1.2 percentage points, accounting for almost one standard deviation[59].

In other words, the estimated effect of crises on the shares is not substantial in magnitude but appears relatively long-lasting. However, it is worth stressing that, although the clear signs of recovery of top shares at the 4th year following the shock are not sufficient to bring the levels of the shares back to the no-crisis 'equilibrium' path, such qualitative feature of the results may not be very robust to changes in the specification, controlling for other variables. This becomes clearer in the robustness section.

The evidence for the Top 10-Top 5% share is almost specular to that of the Top 0.01% but the magnitude of changes are only at a first glance smaller. Indeed, one year after the shock the level of the share in total income of the P90-P95 upper group is on average around 6 percent higher than the no-crisis scenario. The series remains at around 10 percent above the counterfactual even 5 years following the shock, respectively for the series excluding capital gains (figures for the series including capital gains raise to respectively 8 an 13 percent). This is equivalent to say that the share is found to be 0.7 (0.9) percentage points above the counterfactual measure at the 5th year from the crisis if one considers the series excluding (including) capital gains. This is equivalent to approximately 1 standard deviation.[60]

5 Modeling the time series of the Pareto coefficient

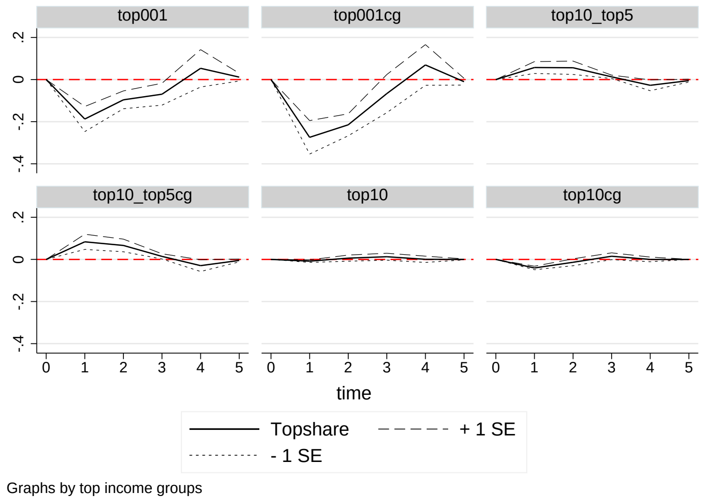
The modeling of the time series of the top shares suggested that the impact of US banking crises has been negative at the very top, positive at the bottom of the decile and, as a consequence neutral for the overall top decile. In other words, concentration

[58]These figures are calculated by noting that the average value of Top 0.01% is 1.4 and its standard deviation is .97 over the entire period.

[59]The average value of Top 0.01% including capital gains is 2.3 and its standard deviation is 1.3 over the entire period.

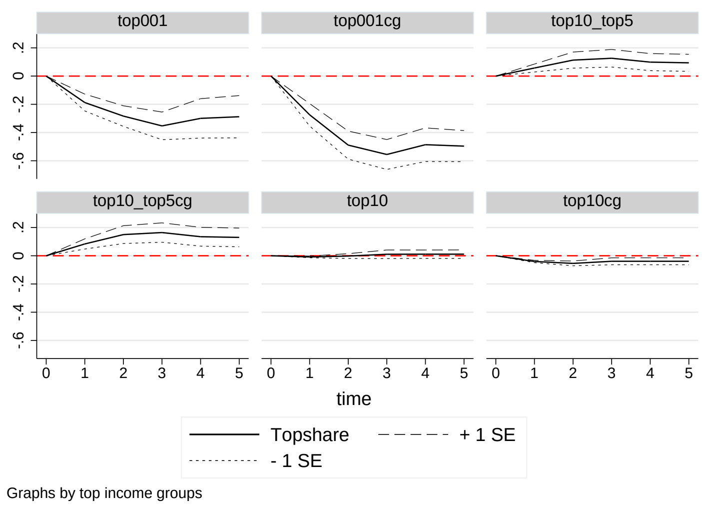
[60]The average values for Top 10-Top 5% shares are 11.45 and 11.24 respectively for the series excluding and including capital gains. The relative standard deviation values are 0.87 and 0.84.

Figure 8: The Impulse Response to US Banking Crises on the Growth Rates of the Shares of Selected Top Groups.



Note: the suffix 'cg' means that the series are computed by including net realized capital gains income (net of capital losses).

Figure 9: The Impulse Response to US Banking Crises on the Levels of the Shares of Selected Top Groups.



Note: the suffix 'cg' means that the series are computed by including net realized capital gains income (net of capital losses).

of income at the top shrank following the onset of a banking crisis. An alternative way to show these findings is to model the time series of the parameters of the distribution that fits the upper income groups well and study their response to the occurrence of the crisis. As discussed within the introduction, this is similar to the approach adopted in Metcalf (1969) and Thurow (1970) and re-proposed by Jäntti & Jenkins (2010).

The focus on the top of the distribution makes this task easy to accomplish as the data on US top shares are estimated with the assumption that income of upper groups is distributed according to a Pareto distribution[61]. Each Pareto distribution is sufficiently described by the Pareto coefficients and thei estimates are readily available from the WTID database for most of the countries and years, including the US.

According to the Pareto distribution, the proportion of tax units with income above y is defined as follows[62]:

$$H(y_i) = k^{\alpha} y_i^{-\alpha} \tag{15}$$

where k is a constant and α is the so called Pareto coefficient, representing the constant reduction rate of the proportion of 'individuals' with income greater than y_i as one increases the income threshold. From the Pareto distribution it also follows that the average income of tax units with income higher than y_i is a constant multiple of the income threshold y_i:

$$\frac{y_i^{avg}}{y_i} = \frac{\alpha}{\alpha - 1} = \beta \tag{16}$$

This constant multiple β is also called the 'inverted' Pareto coefficient and represents the so called 'advantage of the rich". In other words, as β increases (α decreases), the smaller the right-tail density of the income distribution becomes. Thus, as β declines, very high incomes become less probable and income concentration at the top declines.

I therefore, compute here the dynamic response of β coefficient to the occurrence of a crisis. The estimates are plotted in Figure 10(a) in which β coefficient shows a clear sign of reduction in the aftermath of a systemic banking crisis consistently with findings

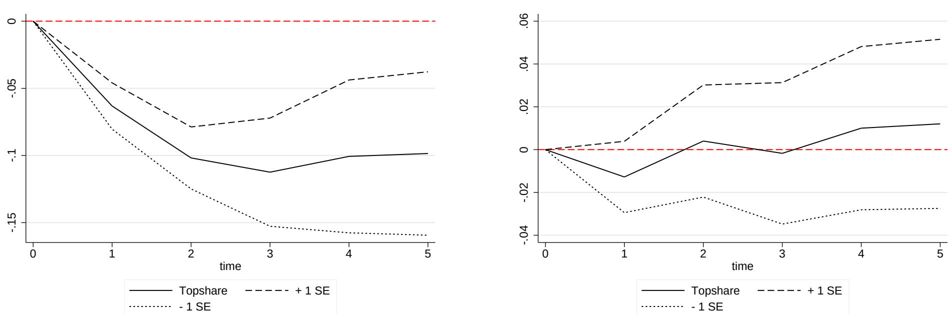
[61] "*Top income shares are mostly calculated from detailed historical tabulated income tax statistics. Alternatively, tax administration micro-data are also increasingly used especially for recent years. Information contained within the tax statistics is then combined with control totals for population and income. Essentially, tax statistics provide the total income and the total number of tax units for given income ranges so that we could compare these values to the totals in the economy. It is important to note that, when using group tabulations data, the precise share of income accruing to a specific percentile within the top decile is obtained through interpolation techniques as the ranges of tax units within tabulations do not necessarily coincide with the percentage of the population for which we would like to assemble our data. Interpolation is commonly applied using distributional assumption about the top tail of income distribution (e.g. Pareto distribution)*" Morelli et al. (ming, p.34)

[62] For each Pareto coefficient $\alpha > 1$ and constant $k > 0$.

obtained so far by combining the evidence from the IRFs computed with different top shares.

Conversely, the response of the income concentration at the top to the onset of general stock market crises are not statistically different from zero (see figure 10(b)).

Figure 10: The response of the 'inverted' Pareto coefficient to systemic banking crises and stock market crashes



(a) Systemic Banking Crises (b) Stock Market Crashes

Notes: The two graphs show the impact of banking crises and general stock market crashes on the inverted-Pareto coefficient($\frac{\alpha}{\alpha-1}$, where α is the Pareto coefficient). The estimates of the dynamic effects are obtained from the estimation of ADL models using the growth rate of the inverted Pareto coefficient and general crisis dummy variables and time trend. The estimated parameters of the model served to calculate the Impulse Response Functions. Data on banking crises are assembled from Bordo et al. (2001), Reinhart & Rogoff (2008, 2009), Reinhart (2010) and Laeven & Valencia (2008, 2010). Data on stock market crashes are obtained from Mishkin & White (2003) who identify crashes when an overall nominal decline of minimum 20% in the stock market index is recorded. Calculations are based on stock market crashes that do not coincide with systemic banking shocks (e.g. 1929,1987 and 2007 crashes are excluded).

6 Robustness

In this section I check that the robustness of the main results using different covariates, different specifications and different set of crises.

6.1 Omitted Variables

As mentioned above, banking crises are usually accompanied by a series of policy interventions, shocks to the economy, the labour market and the financial markets. Thus, augmenting the baseline model (4) with additional variables other than time trend, crisis dummy and top shares lags might play a crucial role in driving the top shares.

In particular, I control below for two additional variables: the percentage change of the marginal net-of-tax rates and the change in the average real GDP per-capita for all countries for which we have data, to proxy the global economic activity.

As discussed earlier, the IRFs remain identified under the assumption (exclusion restriction) that the short-run changes in such additional variables are not directly ascribed to the banking crisis[63].

Change in tax rates As mentioned in the introduction, the use of taxation-based data makes the households' reported income particularly sensitive to changes in taxation as individuals attempt to minimise their tax liabilities. The role of tax avoidance (lawful re-timing of income reporting and income shifting) and behavioral responses to change in taxation can affect the short-term as well as the long-run levels of top shares[64]. For instance, in 1929 top marginal tax rate on income was reduced to 24% from 25%. It increased back to 25% for two years until 1932 when there has been a substantial increase in marginal rate, reaching 63%. Three years following the S&L shock in 1990, top marginal income tax rate rose from 28 to 31% and then again to 39.6% in 1993. From 2001 to 2004 a series of fiscal reforms brought the top marginal tax rate down to 35% a threshold preserved until 2013 when the rates increased back to 1993 levels (39.6%).[65] Hence, one can control for such taxation regime shifts in order to compute estimates of the (average) elasticity of reported income to changes in tax rates. This allows to attribute part of the drop in the top shares following banking shocks to a behavioral response in reporting income for tax purposes. Moreover, one can obtain unbiased estimates of the total effect of crisis on top shares under the relatively mild assumption that no change would have occurred to top marginal tax rates in the absence of the banking crisis.

In practice, I followed Saez et al., 2012 and estimated the augmented ADL model by including the change in log of the group-specific net-of-tax rate[66].

[63]Indeed, as discussed within the text, the estimated counterfactual (the estimated value of top share in the absence of a crisis) is not valid if one conditions the model on variables which are directly affected by the crisis itself. In the latter case a correct derivation of the IRF would also require the estimation of the dynamic of the additional covariates in the absence of a crisis.

[64]This is extensively discussed in Atkinson et al. (2011), Saez et al. (2012), Piketty et al. (2011) and Morelli et al.(forthcoming).

[65]Also top income tax rates on realized capital gains and dividends increased from 15 to 20% in 2013.

[66]Data on top marginal tax rates are taken from Sialm (2009) and all the observations are updated to 2012. For income group at the bottom of the top decile (Top 10- Top 5%) I make use of the marginal tax rate for income ranging from 100k to 250k (2008 US dollars). The marginal tax rate for income higher than 250k is associated to the top decile as a whole (which contains also richer households). Top marginal tax rate is associated to the richer fractile (Top 0.01%). In order to be more precise, one could associate different marginal tax rates to different tax units using micro data and the TAXSIM

Change in average real world per-capita GDP I also expanded the baseline model (4) by including the change in the average real GDP per-capita for all countries for which we have data[67], allowing to control for general economic activity in countries other than the US. This prevents to capture the changes in top shares that are linked to a general depression effect, involving other countries and affecting the US above and beyond the total effect of the US banking crisis.

As recalled above, this becomes problematic to the extent that one believes that the average world per-capita GDP is affected by the occurrence of a systemic banking crisis in the US.[68] In the latter case a correct derivation[69] of the IRF would also require the estimation of the dynamic of the average world GDP per-capita in the absence of a crisis. This is a very difficult task and I do not attempt to solve this issue within the paper. However and in order to downplay the latter concern, it is worth noting that the inclusion of the additional covariate in the model specification captures the general and average interrelation between world per-capita GDP growth and the US top income shares growth over the entire time period under analysis. Not just across crisis or recession periods.

Findings Tables 6.1 and 5 show how the use of additional covariates affect the estimation of the relevant parameters under investigation. The interaction of these parameters for the estimation of the IRS is then shown graphically in 11 where it is clear how the inclusion of additional covariates changed the qualitative feature of the results. More specifically, the dynamic impact of banking shocks on the top shares appears now less persistent[70]. At the fifth year from crisis, indeed, the impact of the crisis on non-capital gains richest share seems to be almost entirely re-absorbed. This suggests that most of the negative impact on top shares originally found from the 4th year, may be partially due to income reporting behavioural changes and/or to general crisis spill-over effects as top shares in one country may be substantially affected by top shares dynamic in

simulator elaborated by the National Bureau of Economic Research. This however could be done only from 1960 on and using micro data (see Saez, 2004).

[67]Data are taken from Barro & Ursúa, 2009

[68]Especially during the post-Second World War period, the United States it has been the leading economic power of the world economy and it is possible that a US crisis has a direct impact on other countries' national income.

[69]The world average growth in per-capita GDP might in turn be affected by the US top income share. In other words the additional covariate might be endogenous so that the estimated parameter becomes biased. However, this is probably too strong a concern as it seems implausible that what happens to the rich tail of the US income distribution have a strong impact on the world average per-capita GDP growth rate.

[70]A more persistent impact of banking shocks is preserved only for the share in total income of the richest group, once capital gains are included.

other countries (not necessarily depending on the geographic proximity).

It is also worth noting that most of the 'dampening effect' on the IRF is due to the inclusion of cross-country average growth of per-capita GDP to signify that spill-over effects from and to other countries can be strong in magnitude. The latter information is clear by looking at Figure 12[71].

Table 4: Augmented ADL Model Estimated for BC and Selected Top Shares : including changes in marginal tax rates

	(1)	(2)	(3)	(4)	(5)	(6)
	top10	top001	top10_top5	top10 CG	top001 CG	top10_top5 CG
L.BC	-0.012	-0.182***	0.057*	-0.045***	-0.268**	0.083*
	(0.009)	(0.053)	(0.028)	(0.006)	(0.084)	(0.036)
L2.BC	0.010	-0.065	0.049+	-0.009	-0.260***	0.057*
	(0.013)	(0.049)	(0.029)	(0.017)	(0.067)	(0.027)
L3.BC	0.014	-0.028	0.010	0.018	-0.053	0.010
	(0.019)	(0.064)	(0.008)	(0.020)	(0.094)	(0.013)
L4.BC	-0.001	0.064	-0.028	-0.002	0.049	-0.030
	(0.016)	(0.094)	(0.027)	(0.012)	(0.097)	(0.030)
Changes in marginal	0.196**	0.114+	0.378*	0.197*	0.192**	0.335+
tax rates	(0.066)	(0.058)	(0.183)	(0.077)	(0.066)	(0.200)
L.Gtop10	0.136			0.047		
	(0.180)			(0.160)		
L.Gtop001		0.168			-0.170	
		(0.13)			(0.141)	
L.Gtop10_top5			0.119			0.108
			(0.130)			(0.125)
Constant	-0.240	-2.446**	0.155	-0.268	-2.760+	0.185
	(0.154)	(0.921)	(0.262)	(0.217)	(1.601)	(0.287)
Observations	94	96	94	94	96	94

Standard errors in parentheses
The table shows the coefficients of the estimation of the augmented ADL model including the log change of the inverse of marginal tax rates: Dlog(1-t).
We assumed contemporaneous incorrelation between crisis and top shares
Linear time trend and constant are suppressed from the table
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2 Different Specifications

The robustness of the results are checked now by changing the baseline empirical specification in model (4).

In particular, I first consider different lag structure of the banking crisis dummy variables up to 8 lags. Indeed, autoregressive distributed lag models may be sensitive to such change in specification.

Secondly and most importantly, I consider a situation in which the banking crisis lasts for 5 years and not only one year as assumed in the baseline estimation of the impulse response functions. In other words this can be taken into account by simply assuming that the crisis dummy variable takes value equal to 1 for the 5 years following

[71]The issue of spill-overs can be analysed more properly by studying the impact of systemic banking shocks on top shares across different country groups.

Table 5: Augmented ADL Model Estimated for BC and Selected Top Shares : including changes in marginal tax rates and world per-capita GDP

	(1)	(2)	(3)	(4)	(5)	(6)
	Excluding capital gains			Including capital gains		
	top10	top001	top10_top5	top10	top001	top10_top5
L.BC	-0.019*	-0.162*	0.043+	-0.050***	-0.242**	0.070*
	(0.009)	(0.067)	(0.022)	(0.010)	(0.081)	(0.030)
L2.BC	-0.003	-0.016	0.017	-0.017	-0.200**	0.024
	(0.014)	(0.043)	(0.022)	(0.017)	(0.070)	(0.021)
L3.BC	0.004	-0.036	-0.008	0.007	-0.100	0.000
	(0.024)	(0.087)	(0.017)	(0.026)	(0.093)	(0.017)
L4.BC	0.001	0.164**	-0.046	0.003	0.156***	-0.051+
	(0.023)	(0.062)	(0.028)	(0.016)	(0.037)	(0.029)
Changes in marginal	0.207**	0.074	0.396*	0.207**	0.142*	0.354+
tax rates	(0.064)	(0.059)	(0.172)	(0.077)	(0.070)	(0.189)
average 'world' growth	-0.277*	0.824	-0.568+	-0.210	1.051	-0.555+
in GDP per-capita	(0.121)	(0.528)	(0.287)	(0.188)	(1.038)	(0.306)
L.Gtop10	0.198			0.095		
	(0.194)			(0.188)		
L.Gtop001		0.199			-0.155	
		(0.121)			(0.153)	
L.Gtop10_top5			0.181+			0.161
			(0.102)			(0.099)
Observations	91	93	91	91	93	91

Standard errors in parentheses
The table shows the coefficients of the estimation of the augmented ADL model including average growth of World real GDP per-capita and the log change of the inverse of marginal tax rates: Dlog(1-t). We assumed contemporaneous incorrelation between crisis and top shares
Linear time trend and constant are suppressed from the table
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 11: Controlling for Tax Rates and 'World' Average per-Capita GDP: the Impulse Response to US Banking Crises on the Levels of the Shares of Selected Top Groups.

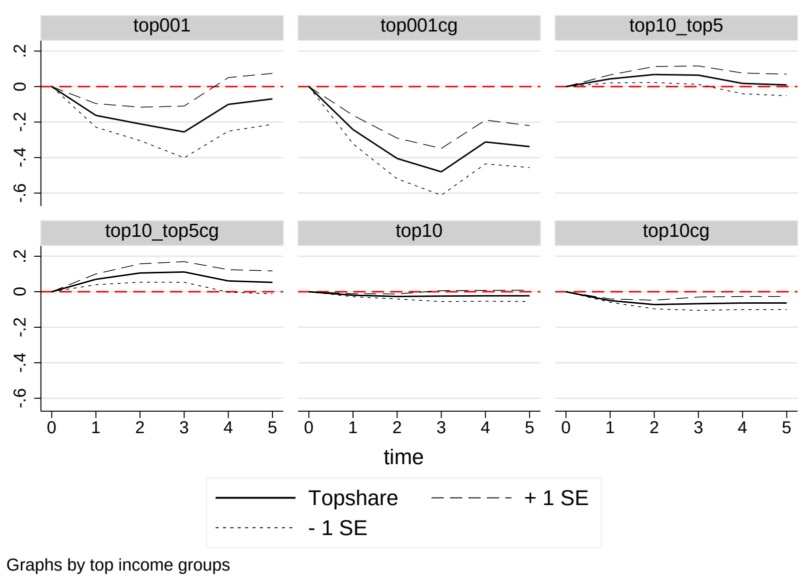
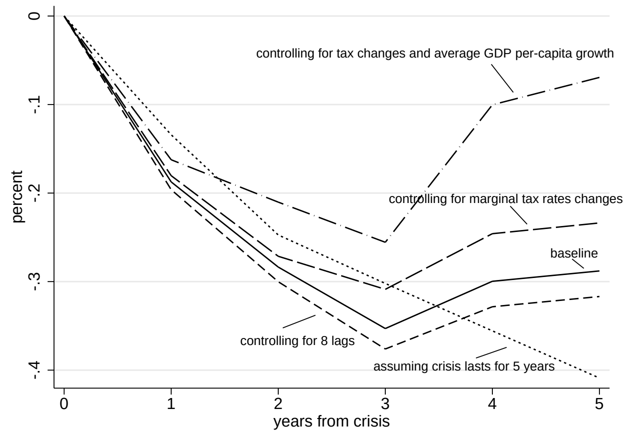


Figure 12: Comparing the Impact of Banking Crisis on Top 0.01% across Different Model Specifications



The baseline model represents the original ADL model in which one assumes contemporaneous uncorrelation between crisis and the growth rates of top shares. The IRFs are computed using income shares without capital gains.

the beginning of the crisis. As discussed in the section of the derivation of the IRF, this would give an 'upper-bound' measure of the size of the impact on top income shares.

Results suggest that extending the specification to 8 lags barely affects the estimation of the total impact of the crisis on all upper income groups. However, this is not the case if one extends, by assumption, the duration of each crisis to 5 years. Indeed the size of the impact of systemic banking shocks on richest top shares during the first three years following the crisis is slightly reduced. On the contrary, from the fourth year the richest top shares continue to loose ground with respect to the estimated counterfactual, showing no signs of recovery. diverging from the rest of the results presented above. The results discussed in this section compared to the others discussed before can be observed in a single chart in Figure 12. The latter shows, for the Top 0.01% only (excluding capital gains)[72], how the impact of banking crises changes across different specifications discussed so far. Note also that the model controlling for a 5-years long banking crisis can only be meaningfully compared to the baseline case in which the crisis is assumed to last for 1 year.

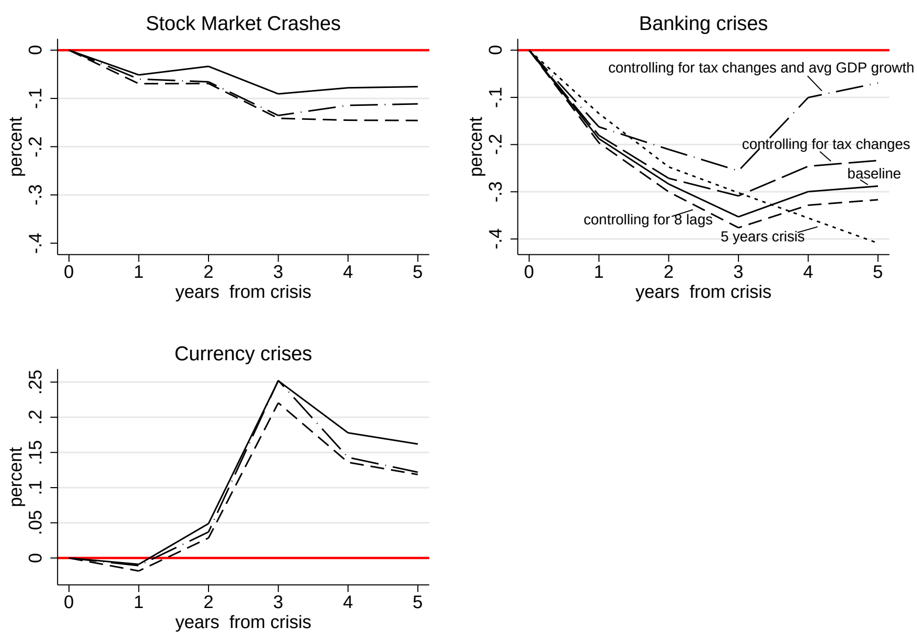
[72]Results are also available for the other income groups and including capital gains but are not shown in the text.

6.3 Different Financial Crises

The last step in the empirical investigation explores whether the impact of systemic banking shock on top shares is actually different from other types of crisis. This would help discerning whether what I captured in the outcome of the investigation is a generic crisis effect which would have occurred in any other type of crisis. To investigate this issue I collect data on US stock market crashes since the beginning of the century (as described before in Box A) as well as information on currency crises[73]. Results are shown for the case of Top 0.01% in figure 13. The latter provides comparable information for the three different financial shocks and the empirical specifications I have described above. The impulse response functions are calculated only for those episodes which are not coincident to a systemic banking crisis (i.e. 2007 stock market crash is not part of the estimation). Results show that the US stock market crashes had, on average, a milder impact on the richest top shares compared to banking crisis (the impact is more than halved). Instead, the currency crises seem to have the opposite effect on inequality at the top, namely are associated with a mild permanent (over the short run) increase in the richest top share. The Figure also reports the IRFs controlling for a different specification of the ADL model including 8 lags and for the tax rate changes as well as the average 'world' GDP growth (as done for the case of banking crises discussed before). In particular, it is worth noting that the latter control did not affect the results substantially as done in the case of banking crises.

[73]Data on currency crises are taken from and Bordo et al. (2001) until 1970 and from Laeven & Valencia (2010) after 1970.

Figure 13: Comparing the Impact of Banking, Stock Market and Currency Crises on Top 0.01% across Different Model Specifications



The baseline model represents the original ADL model in which one assumes contemporaneous uncorrelation between crisis and the growth rates of top shares. The IRFs are computed using income shares without capital gains. The estimated model specifications are the same for every crisis analysed with the exception of the specification controlling for 5 years length crisis which is specific to the analysis on banking crisis.

7 Interpreting the Findings: Conceptual Framework

The existing literature does not provide a comprehensive theoretical model to interpret the results including different income sources and developing such a model here goes beyond the scope of this paper.

Nonetheless, it is worth noting that recent literature (Philippon & Reshef, 2007, Atkinson et al., 2011, Roine et al., 2009, Neal, 2013) has discussed some of the structural factors potentially driving the top income shares. Among these factors is worth mentioning the role of global economic integration (global trade and international financial integration), taxation policy for different types of income and wealth (e.g. change in top marginal tax rate and corporate taxes), social norms and practices in remuneration, financial development and sectoral changes within the economy (e.g. rise in the share in total value added of the financial sector), changes in political regimes (e.g. war effort, transition to democracy from dictatorship or *vice versa*, changes in political partisanship, end of colonial rule etc.) and shifts in regulatory frameworks (e.g. substantial changes in the regulation of banks and financial markets).

One can assume that the above mentioned vector of structural factors I (I call it here 'institutions' to indicate the set of formal and informal rules constraining human economic behaviour as in Douglas C. North's tradition[74]) affect the equilibrium level of the share (S^*) as well as the speed of disequilibrium adjustment ($\lambda(I)$). Hence the actual top share (S) can be defined as composed of an equilibrium component and a temporary deviation from it (depending on both deterministic and stochastic factors):

$$S_{i,t+1} = S_{i,t} + \lambda(I_i)[S^*_{i,t}(I_i) - S_{i,t}] + \varepsilon_{i,t+1}$$

It becomes therefore crucial to understand to what extent a systemic banking crisis hinges structurally on the income earning processes of top groups or, alternatively, affects temporarily the sources of income. In particular, one can plausibly argue that structural factors are only rarely substantially affected by banking crises, especially within the course of the 5-years horizon under investigation within this paper. One should therefore describe the possible theories which better explain the short-term deviations from a share equilibrium value as a consequence of the crisis.

In order to develop a qualitative conceptual framework and identify the relevant economic theories for the interpretation of the quantitative results obtained so far, it is crucial to understand how the composition of income varies across top groups and over time as well as to estimate the contribution of each single source of income to the the dynamics of a specific top share[75]. This investigation is conducted below.

[74]See for instance North (2005)

[75]This issue clearly overlaps with the important identification issue of the segments of the income

7.1 Income Decomposition

Measuring what top incomes are composed of is key to understand the dynamics of such shares over time as well as around banking crises episodes. Piketty & Saez (2003, 2006) extensively discussed about the sharp change in composition of income sources at the top of the US income distribution over the twentieth century. According to their estimates, capital income (excluding capital gains[76]) and especially dividend income gradually left place to an increasing share of wage, business income and realised capital gains[77]. Figure 14 shows how the incidence of wage income within the Top 0.01% group went from 7% of total income in 1929 to 31% in 2007 (the incidence of capital income on total income, including capital gains, decreased from 77 to 47% over the same time period). As for the the Top 10-Top 5% income group, the incidence of wage income over the total went from 48% in 1929 to 85% in 2007, and that of capital income (including capital gains) went from 22% to 9% respectively.

This phenomenon is mainly interpreted by Piketty and Saez as a gradual replacement of 'rentier' class by the so called 'working rich', especially in latest decades[78]. Yet, such a drastic composition change at the top of the income distribution, whether it really occurred or not[79], might have not reduced the correlation of top income shares

distribution driving the dynamics of top shares. As discussed before, in order to understand the mechanics of the dynamics of a share one should naturally look at the driving forces of the numerator and the denominator at the same time. Putting it simply, in a context of aggregate income shock to the economy, the share decreases (increases) if the top group 'looses more (less)' than the bottom or, putting it differently, if the bottom of the distribution is 'more (less) protected' than the top.

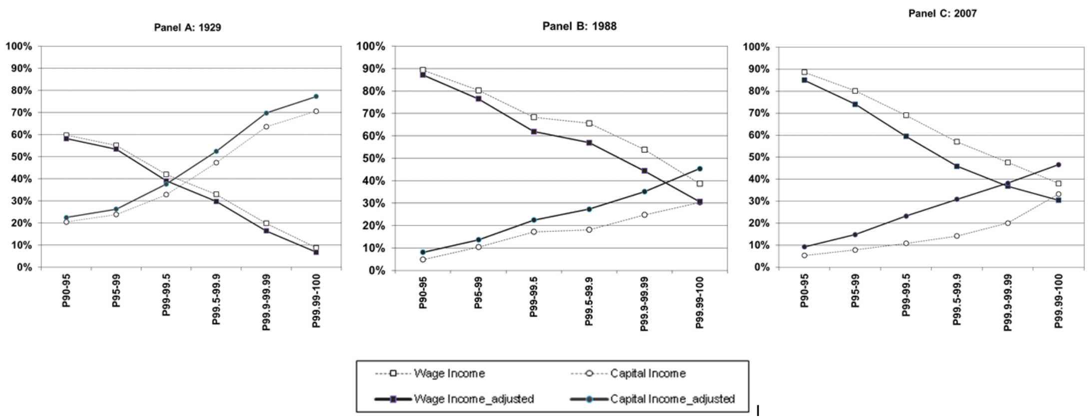
[76]In their 2003 paper Piketty and Saez maintain that *"Realized capital gains are not an annual flow of income (in general, capital gains are realized by individuals in a lumpy way) and form a very volatile component of income with large aggregate variations from year to year de pending on stock price variations"*. For this reason they exclude capital gains and include only dividends, rents, interest rates and royalties within their main representation of capital income. Although I acknowledge their argument as reasonable, I have also conduct the analyses by including capital gains in the definition of capital income given their importance for richest upper income brackets.

[77]However, as the two authors show in their work, dividends incidence on the corporate income sector was remarkably stable over time and it has been slightly rising since early 80s. Conversely capital income share in the personal income sector had been almost always increasing since the end of WWII, and this is consistent with a considerable redistribution of wealth within US population over time.

[78]The first estimation published by PS were updated to the year 1998, when top capital income share was at its historical minimum. Subsequent years witnessed a revival of capital income as Atkinson et al. (2011) clarify. I have also shown in early paragraph that the role of capital income in top income brackets is considerably higher once capital gains are taken into account.

[79]Other scholars did not find convincing evidence about the 'rentier class' being overtaken by a rich 'working class'. The main reason being that the measure for capital income used in Piketty and Saez might have underestimated the true incidence of 'unearned' income over total income. For example Wolff & Zacharias (2009), after adjusting the wealth income in order to better "*reflect the advantage*

Figure 14: Role of Capital Gains across Income Groups and over Time: Recalculating Capital and Wage Income Share



The adjusted series are calculated by including capital gains income in the definition of capital income. However, capital gains were not considered for the definition and calculation of the fractiles. Share of business income is not represented in the graph. Source: Piketty & Saez (2003) and Saez (2012) data updates and author's own calculations.

with stock market and financial sector performance. This also happened as other sources of income became very sensitive to macroeconomic performance, such as top remunerations, bonuses and stock options. This may suggest that financial shocks hit shareholders harder in the early twentieth Century, mainly through a change in dividend income and change in realised capital gains and losses[80]. In contrast, more recent crises episodes also require the investigation of more classic job market channels.

Furthermore, one could also calculate the incidence of each single source of income to the growth of total income. As an illustrative example I decompose the top income into three main sources (Wage, Capital[81] and Business income[82]) so that $y_i = W_i + C_i + B_i$. By totally differentiating y_i and using simple algebra, one obtains:

from asset ownership or the disadvantage from liabilities", conclude that 'working rich' and 'rentier' classes appears to co-habitate the top end of US economic ladder in recent decades. See also the discussion about the role of capital gains within capital income.

[80] There was also less interventionism in the market and troubled banks, firms etc. were usually not bailed out.

[81] I can in turn decompose capital income into realised capital gains, dividend and other forms of income (rental and interest income). Therefore I am focusing here on income including capital gains only.

[82] Business income represents profits from S-Corporations (entities whose profits are taxed only at the individual level) plus profits from Partnerships and sole proprietorship businesses (Schedule C income).

$$\frac{dy_i}{y_i} = \frac{dW_i}{W_i}\alpha_i^W + \frac{dC_i}{C_i}\alpha_i^C + \frac{dB_i}{B_i}\alpha_i^B. \tag{17}$$

From (17) one can calculate b_i^π, the contribution[83] of each single income source to the growth rate of total income of group i (y_i), where $\pi = \{W, C, B\}$. Every b_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. Moreover, the sum of all income source contributions is equal to 1 at any time t.

$$\sum \frac{\frac{d\pi_i}{\pi_i}\alpha_i^\pi}{\frac{dy_i}{y_i}} = \sum b_i^\pi = 1. \tag{18}$$

The average value of income sources contribution to the top income growth can be computed by estimating the following equations individually:

$$\begin{cases} \frac{\triangle W_{i,t}}{y_{i,t-1}} = \frac{\triangle W_{i,t}}{W_{i,t-1}}\alpha_{i,t-1}^W = a_{i,t}^W + b_{i,t}^W \frac{\triangle y_{i,t}}{y_{i,t-1}} + \varepsilon_{i,t}^W \\ \\ \frac{\triangle C_{i,t}}{y_{i,t-1}} = \frac{\triangle C_{i,t}}{C_{i,t-1}}\alpha_{i,t-1}^C = a_{i,t}^C + b_{i,t}^C \frac{\triangle y_{i,t}}{y_{i,t-1}} + \varepsilon_{i,t}^C \\ \\ \frac{\triangle B_{i,t}}{y_{i,t-1}} = \frac{\triangle B_{i,t}}{B_{i,t-1}}\alpha_{i,t-1}^B = a_{i,t}^B + b_{i,t}^B \frac{\triangle y_{i,t}}{y_{i,t-1}} + \varepsilon_{i,t}^B \end{cases} \tag{19}$$

Least squares estimates [84] of b_i^π are obtained through regressing one by one the equations in the system[85] (19). Findings using the observations around crises only (5 years window) are shown in Table 7.2. It indicates that the role of capital sources of income is the predominant driver of the income growth in richer fractiles within the top decile, whilst the growth of the total income of poorer quantiles depends to a greater extent on wage type of income.[86]

[83] Ideally one would like to understand the role of marginal distributions of each source of income as well as their joint distribution for the dynamic of the right tail of income distribution. This is discussed in Atkinson et al. (2011) and Alvaredo et al. (2013) for two sources of income, namely wage and capital.

[84] Standard errors are robust to heteroskedasticity. Newey-West standard errors are even smaller and are not tabulated.

[85] System estimation such as Seemingly Unrelated Regression can only be carried out on all equations but one as, by construction, the variance covariance matrix of estimated coefficients would be singular.

[86] The role of wage types of income at the bottom of the top decile is reduced if one considers only the observations around stock market crashes episodes (3 years window), whereas it remains substantially unvaried for the richest tax unit. This is another piece of evidence supporting the fact that bottom groups within top decile are particularly sensitive to the aggregate economic conditions. For example the group could be relatively more shielded against higher unemployment rates. This issue is further discussed below.

The above results can be now complemented with the information about the cyclicality of different sources of income at the top. To present this, I regress the growth rate of each single income source accruing to a specific upper income group against the growth rate of total income in the economy (including capital gains). The slope coefficients are represented graphically across income groups in Figure 15 after further decomposing capital income into capital gains, dividends and other types of income[87]. Findings indicate that the elasticity to total income of every source of income is higher than 1 only for richer groups. Capital type of income is instead the only source of income to be highly cyclical across all groups. As I have seen before, capital income is also the most relevant source of income growth for the richer upper groups, while wage type of income is a-cyclical and accounts for most of the income dynamics for 'poorer' groups within the top decile.

Summary and Further Discussions Results from the investigation of different sources of income at the top of US income distribution reveals that capital and wage income are nowadays the most important sources of income for the richest group (see Figure 14). Moreover, even if both sources of income are highly cyclical, (meaning that their growth rates elasticity to that of total income in the economy is higher than 1), capital income (including capital gains) appears to drive most of the growth of total income for the richest fractile around crises episodes. Conversely, wage income appears to be the most important source of income, as well as the main driver of total income growth, for the P90-P95 group. However, wage income is not very cyclical for this income group meaning that its growth rate elasticity to that of total income in the economy is lower than 1.

Such quantitative findings require nonetheless a qualitative justification and some tentative explanations which constitute the objective of the following subsections. In particular I focus the attention on the two most important sources of income, wages and capital and explore how different factors such as unemployment, top remunerations, the role of financial sector as well as that of stock holdings can help justify the main features of the findings of the empirical investigation described above.

It is also important to underline that the documented changes in income are not necessarily exogenous, as they could reflect optimal endogenous response of agents. On one hand, individuals might lose their job, suffer a wage or dividends distribution cuts as the results of decisions by the corporate management. On the other hand, individuals could independently decide not to to realise their capital gains (conditionally

[87]Interest income plus rental income plus royalties

Table 6: The Contribution of Different Sources to the Top Income Growth During Banking Crises Episodes

	(1) P90-95	(2) P99.99-100	(3) P90-95(B)	(4) P99.99-100(B)
Wage	0.564***	0.210***	0.479***	0.209***
	(0.095)	(0.059)	(0.077)	(0.047)
Business	0.158*	0.146***	0.270***	0.154***
	(0.079)	(0.042)	(0.047)	(0.034)
Capital	0.276***	0.641***	0.2485***	0.627***
	(0.0346)	(0.079)	(0.041)	(0.063)
N	29	29	62	64

Least square regression with robust standard errors. Capital income includes realised net capital gains. Columns (1) and (2) use sample restricted to the 5-years period around the three crises episodes. Columns (3) and (4), instead, provide estimates restricted to the three years around stock market crashes episodes.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

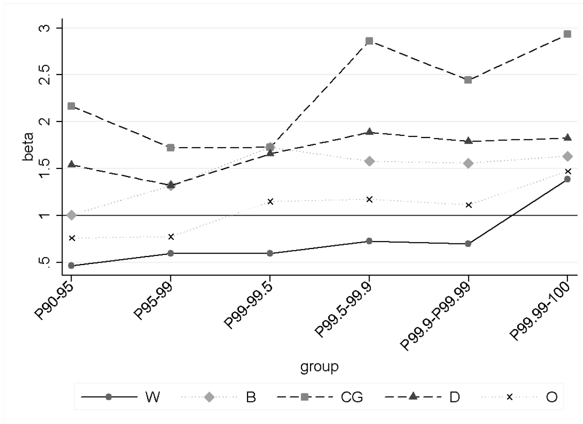
on holding the stocks) or to liquidate their risky financial positions during financial turmoils so that the resulting reduction in dividend income can be the result of optimal restructuring of their financial portfolio. Similarly they can choose not to exercise their stock options or to reduce their hours of work[88]. These considerations would not modify the qualitative feature of the empirical findings. Nevertheless, it would considerably change the underlying economic models one could use to interpret those results.

7.2 Explaining the Relative Gain in Top 10-Top 5% Share

As discussed within the data description section, tax units belonging to the P90-P95th income bracket have a total market income between 110.000 and 160.000 US 2007 dollars. Assuming that a tax unit is composed of two individuals, this is suggesting that total individual annual income belonging to this income bracket is between 55.000 and 80.000 US 2007 dollars, consistent with upper middle class workers income. As explained above the Top 10-Top 5% share was found on average to be above its predicted path in the absence of the crisis. Indeed, data confirm that the decrease of Top 10-Top 5% income was much smaller than the reduction in total income during crisis years. This evidence is consistent with two main explanations.

[88]In practice the reduction of the hours worked conditioned on keeping the job accounts only for a small share of total variation in hours during business cycles due to the indivisibility of job. For instance, in US the variation in total hours worked is mostly (3/4) explained by variation in employment (Furman & Stiglitz, 1998).

Figure 15: Elasticity of different sources of income to total income across top groups



Beta represents the elasticity of sources of income to total income Estimation sample refers exclusively to years around crises (5 years window) W:Wage B:Business CG:Capital Gains D: Dividends O:Other

First of all, this may be the result of a purely mechanical effect due to the structure of the data. Indeed, movements in Top 10-Top 5% share can be driven by composition change of the fractiles during crises as data on top income shares do not track the same individuals over time. This was recalled in Parker & Vissing-Jorgensen (2009) who refer to the fact that growth rates of top income in Piketty and Saez's database are likely to be a downward biased representation of the effective growth rates of the total income of a given group of upper tax units. This happens as they do not track the same households over time. Hence, to say it with their words, "*If high-income households are more exposed to aggregate fluctuations, some of them will fall into lower percentile groups when aggregates fall and will rise up the distribution when aggregates rise. This composition could actually bias down the relative exposure of high-income groups.*"[89]

Secondly, I contend that the evidence may be the results of a relative higher protection against unemployment and wage cuts of the Top 10-Top 5% group compared to the bottom of the distribution. Although it is not possible to untangle the relative validity of the two competing explanations, the hypothesis is somewhat consistent with both theoretical and empirical considerations. On the theoretical side, economic theories based on non-competitive markets suggest that labour mobility is higher for less

[89]Note that in the case of richest percentile (Top 0.01%), a likely bias is constrained, as by construction new tax units can 'enter' the fractile only from the bottom and no tax unit could 'leave' the top group because of higher income level.

skilled workers[90]. Under the assumption that low skilled individuals also have lower remunerations on average, this suggests that the rise in layoffs and unemployment rates during economic downturn disproportionately affect the bottom of the income distribution (say the bottom 90%). On the empirical side, there are four main findings that are consistent with the statement above:

First, as shown in the forecast section, Top 10-Top 5% share increased much more in 1929 and 2007 crises when the change in unemployment was particularly pronounced.[91] Second, as explained above, the great majority of this income of Top 10-Top 5% group takes the form of wage income (around 85%) but this source appears not very cyclical, perhaps suggesting that the loss of income for the bottom of the distribution (presumably with lower skills) is much higher than the loss of wage income within this top group (presumably with higher skills). Third, I have shown within the text that Top 10-Top 5% share does not tend to rise following standard stock market crashes which are not associated to systemic banking crises. Fourth, wage income accounts for approximately 60% of total income growth for Top 10-Top 5% share during banking crises and this figure drops by 10 percentage points during general stock market crashes as shown in Table . This suggests that poor cyclicality has a stronger role during banking crises. The latter two points are indeed relevant as substantial surge in unemployment rate was only found following US systemic banking crises and not following general stock market crashes.

7.3 Explaining the Relative Loss in Top 0.01% Share

As discussed within the data description section, the 15.000 tax units belonging to the P99.99-P100th income bracket (what I called Top 0.01%) have a minimum total market income of 8.5 million US dollars. Differently from the P90-P95 case, we are dealing here with the richest individuals within the US. Indeed, CEOs and top executives in non financial and financial industries represent a sizeable portion of upper income groups (up to 13% of top tax AGI brackets or higher according to estimates in Kaplan & Rauh, 2010).

It is also important to recall that capital income and not just wage income plays a

[90]Efficiency wage theories and search theories provide a clear support for these conjectures as argued in Furman & Stiglitz (1998). The two authors, for instance, show in a simplified model of efficiency wages with two agents (low productivity and high productivity) that as the demand for labour falls during a recession, the agents on the low-productivity efficiency wage curve are '*rationed out of the market*'.

[91]Each of three banking crisis cases under analysis in this paper, has been associated to economic downturn and substantial rise in unemployment rate. Unemployment rose dramatically during recessions. Estimates indicate a stunning surge from 2.08 to 25.2% from 1929 to 1932. From 1988 to 1992 unemployment rate went from 5.3 to 7.4, while it almost doubled (from 5 to 10%) from 2007 to 2011.

crucial role for the dynamic of the income of this group. In what follows I provide a tentative explanation about how capital income and wage income can negatively affect the Top 0.01% share around crisis episodes.

7.3.1 The Role of Capital Income

I have shown before that capital income appears to be the main driver of income growth at the very top of the US income distribution, especially during banking crises. In this section I discuss the theoretical explanations underlying the changes, around crisis episodes, in the two of the main sources of capital income, dividends and capital gains. The latter sources of income are both clearly linked to stock holdings and portfolio choices which are the focus of the discussion below.

In particular I contend that most of the observed variation in capital income is due to endogenous responses of investors to swings in the market as opposed to 'exogenous' shocks[92] Although I cannot prove the validity of this argument against the data at hand, I support its empirical and theoretical relevance with the help of the existing literature, respectively on stock holding behaviour and on dividends income distribution. In particular I point out that it is more likely for rich investors (compared to their poorer counterparts) to actively trade stocks during market swings, secondly I discuss how dividends income is usually smoothly distributed across disequilibrium. Therefore, the observation of highly cyclical capital gains income appear more consistent with changes in stockholding rather than endogenous changes of the timing of realization of capital gains. Similarly, the high cyclicality of dividends income would be mainly due to changes in stock holding status rather than to adjustments of dividends distribution policies over the crisis. This is also consistent with the theoretical prediction about the relative inertia in dividend distribution policy.

[92] As discussed before, changes in dividend income may be the result of exogenous or endogenous response to the banking shock. Given the holding of share, on one hand, a company may decide not to distribute dividends or to reduce their payment ratio during downturn (exogenous change). On the other hand, shareholders may independently decide to liquidate the share during a market downswing, receiving as a consequence, zero future income from dividends of the specific share (endogenous change). Both decisions to sell or not to sell stocks can also influence the stream of income from capital gains. Firstly, in case the shareholders are liquidating their risky positions, it is possible to obtain positive or negative realised net capital gain depending on the values of the liquidated shares versus the original purchase price. Secondly, the stream of income coming from the realised net capital gains can be also influenced by the decision of not selling stocks during downswings (i.e. postponing the realisation of the capital gains to better times).

The Role of Stock Holding Simple theory can be of guidance in order to explain why changes in stock holdings are linked to the swings in share values, and ultimately to financial shocks. In order to do so, one should ideally model the way portfolio decisions vary around upswings and downswings in the market conditionally on the choice to participate on the stock market. Indeed, a financial shock may lead some investors out of the stock market and some others to simply liquidate their riskier positions conditioned on their participation.

For instance, a conventional simple dynamic model of portfolio choice, with constant relative risk aversion utility function and participation costs, predicts that a shock in wealth would optimally drive out some investors from the stock market. The remaining invest a constant share α in risky assets[93]

Other theoretical models of household portfolio choice with background income risk (see, e.g., Haliassos & Bertaut, 1995, Heaton & Lucas, 2000, Viceira, 2001, Haliassos & Michaelides, 2003, Gomes & Michaelides, 2005) imply that households should adjust their stockholding participation[94] status or portfolio shares of risky assets in response to household-specific changes (e.g., in wealth, income or age) or to changes in the market environment (e.g., expected returns or volatility)[95]

It is worth mentioning that, despite the clear theoretical predictions of different models, stock holding (conditional and unconditional on participating in the stock market) together with stock trading behavior, are topics which are not well understood and studied in the empirical literature. For example, two studies by Brunnermeier & Nagel (2008) and by Bilias et al. (2010) find that "*a vast majority of households do not*

[93]This type of model usually solves the following problem: $maxE_t \sum_{\tau=0}^{\infty} \delta^{\tau} \frac{(C_{t+\tau})^{1-\gamma}}{1-\gamma}$ subject to $W_{t+1} = (1 + R_{p,t+1})(W_t - C_t)$ where $R_{p,t+1} \equiv \alpha_t(R_i - R_f) + R_f$.

[94]Brunnermeier & Nagel (2008) find little evidence of participation fluctuating together with wealth. Similarly Bilias et al. (2010) show that there is tendency of the vast majority of households to exhibit the same participation status over time (using the same PSID data). Results suggest that stock market downturns mainly discourage nonparticipants from entering rather than encouraging a mass exodus from the stock market. Households with lower resources, however, are found to have higher probability of exit during downswings. Nevertheless, it should be mentioned that one cannot be sure that the same results would apply to extreme events such as systemic banking shocks and more evidence is needed.

[95]In alternative, if one is willing to assume that ups and downs in the market are linked to swings in investors' risk aversion, then a simple Arrow two-assets model of portfolio choice justifies the increase in the optimal share of risky assets during boom times. A further example is represented by a model of portfolio with consumption habit which effectively allows the RRA to change with wealth fluctuations (mostly used in asset pricing and macroeconomics). In other words the proportion of wealth invested in risky asset could vary with wealth: $maxE_t \sum_{\tau=0}^{\infty} \delta^{\tau} \frac{(C_{t+\tau}-X)^{1-\gamma}}{1-\gamma}$. Within such a model, the agents should make sure to have enough financial resources to ensure that future consumption is above the habit level. The consumption path with $C \leq X$ with nonzero probability are assigned infinitely negative utility.

trade".

However, examples of 'flight to security' or 'flight to quality' (selling risky stocks in order to buy safer bonds securities) are commonly found within the accounts of financial downswings. Indeed, evidence in the latter study by Bilias et al. (2010) suggests that more education, higher income or higher net financial wealth encourages trading especially following the downswing. Similarly, using the FED Survey of Consumer Finances (SCF) data, the same study finds that households with brokerage accounts (especially those who are very wealthy) trade frequently, both during upswings and downswings. This observation is consistent with Fisher's claim that during every market downswings ('Bear Market') there could be rallies (lasting from several days to months and sometimes years) which can produce "*gains for investors or traders who make careful and educated choices, while constantly monitoring their positions*" (1930).

The Role of Distributed Dividends It is generally recognised that shareholders may dislike changes in dividends policy for different reasons. First dividends payment is a secure income source for shareholders compared to volatile gain in the value of the share due to investments financed by profit plough-back (i.e. market may somehow undervalue investments). Secondly, dividends provide important signals to the market which in turn influence shareholder's expectation on future firms' profits (i.e. a firm that can sustain dividend through tough times is considered to be a solid one). Third, sudden changes in dividends policies might cause costs to shareholders 'clientele' which no longer recognises the firm's dividend policy as its preferred (see Wood, 1975).

One may therefore argue that because dividends policy is usually smooth across small short-term disequilibria, most of the observed change in dividends income at the top of the distribution must come from the 'flight to quality' or the 'flight to safety' operations described above (i.e. assets liquidation).

However, it is worth noting that although one could define a banking crisis as a short term disequilibrium, there might be good reasons why a smooth dividends policy is not to be considered optimal throughout a systemic banking crises. Dividends, especially in a credit crisis, might be seen as a crucial form of available capital for underpriced companies that face strong liquidity crisis (not necessarily insolvent). It can be easily theorised that in such cases shareholders might be better off with a zero dividend or a dividends cut that might save their companies from bankruptcy. Evidence from the Great Depression period is provided in Baker (1939), who has analyzed how companies listed in the New York Exchange distributed their earnings respectively to executives and to shareholders (dividends) over the period 1928-1936[96]. In his analysis,

[96]It is worth noting that executives compensations share in total earnings in largest companies was

total dividends for biggest corporations raised initially from 1928 to 1930 by 38% and subsequently plummeted cumulatively by 87% up to 1933, when dividends started raising again (distributed dividends were up by 25% from 1928 to 1929 in smaller companies and down to zero in 1932 and 1933).

Summary The discussion above might suggests that most of the observed cyclicality of capital income around crisis episodes might be driven by endogenous behavioural response of investors to market conditions. Indeed, it appears more likely for rich investors, compared to their poorer counterparts, to actively trade stocks during market swings. Moreover, investors might liquidate their risky assets during downswings and re-purchase assets once the market prospects are improving. This would justify part of the cyclical movements of the shares. However, very little is known in practice about these mechanisms and their effective validity. Shedding more light on these important issues seem however an important avenue for future research.

7.3.2 The Role of Top Wage incomes

Remuneration at the top also matter for the dynamics of the top shares. Indeed, as mentioned above, CEOs and top executives in non financial and financial industries represent up to 13% of top tax AGI brackets or higher according to estimates in Kaplan & Rauh, 2010).

The high ciclycality of top wage income is not surprising given that the remuneration structure at the top end of the income distribution increasingly comprehends incentive schemes, including stock options as well as short-term and long term bonuses linked to corporate shares performance[97]. However, as argued before, CEOs can also choose not to exercise their stock options or to influence the timing of the collection of the bonuses and this might affect the nature of the cyclicality we are observing in the data. The endogenous nature of cyclicality does not exclusively drive the cyclicality of wage incomes. Indeed Parker & Vissing-Jorgensen, 2010 found that wage income at the top remains substantially cyclical even when stock options and bonuses are excluded. Consistently, Frydman & Saks (2010), analysing a representative sample of the largest

on average 5% for 1928-1936 period. Conversely dividends accounted for 71% of total earnings. These figures become respectively 25% and 62% for smaller corporations. The authors select 51 out of 84 largest industrial corporations (with asset worth more than 100 millions 1929$) and 53 out of more than 200 smaller corporations (assets worth less than 10 millions 1936$) listed in New York Exchange.

[97]This does not seem surprising as managers' remuneration schemes have been increasingly designed to be 'aligned' with the shareholders' interest in order to cope with classical agency problem (at least in theory). Note also that under efficient incentive contract design, the remuneration can be optimally set to be relative to general stock market or sector performance rather than corporate performance alone.

200-300 public-traded US firms, documented that an increasing share of executive compensation is linked to market or firm performance through stock option schemes[98] and other forms of incentive pays since the 1950s[99]. In particular, the correlation between the stock market index and the pay of publicly-traded firms executives has been strong only starting from 1980. In addition, the fraction of executives receiving an option has increased over time reaching 82 percent by the 1990s (it was only 16 percent throughout the 1950s). Moreover, the median value of options award has steadily increased over time passing from around 15 percent of total compensation in the mid-1950s to around 37 percent in the late 1990s (it was around 15-30 percent in mid '80s)[100].

Summary The discussion above suggests that the structure of the remuneration at the top of US income distribution over the past decades creates cyclical fluctuations (down in bad times and up in good times) in 'wage' type of income for the top income brackets pushing the top income shares to be pro-cyclical[101]. Moreover, the role of the top remunerations, bonuses and stock options can also contribute to explain why the richest share in total US income may recover fast after the recent post-1980 banking shocks.

[98] They don't include gains from exercised options but the value of stock option grants only. This would set the compensation value independent from firms shares' swings in valuation and from executives' endogenous choices about when to exercise the options.

[99] It should be noted that restricted stock option were introduced in 1950. These types of options were subject to a special fiscal regime which allowed them to be taxed as capital gains and not as labour income. Hence, the marginal tax rate on restricted options was only 25 percent rather than a considerably higher tax rate for high income earners (the maximum tax rate on labour income was 91 percent from 1954 to 1963). This reasonably constituted an enormous fiscal advantage which incentivised the new executive pay schemes.

[100] Similar results were already found in Hall & Liebman (1998), using data from large U.S. corporations from 1980 to 1994. The authors found that CEO pay has become much more sensitive to corporate performance than it once was. And they credit stock options for this change. ("*The responsiveness of CEO compensation to firm value more than tripled from 1980 to 1994, rising from 1.2 to 3.9*",but(...) "*the elasticity of salary-plus-bonus (with stock and options excluded) to firm value was much lower, although it had increased from 0.13 in the early 1980s to 0.24 in the late 1980s and early 1990s*"). However, they also point out that remunerations are more sensitive to sector or market performance rather that corporate performance.

[101] A recent study for the US, by Parker & Vissing-Jorgensen (2010), found that top wage income is indeed to be considered one of the main reason for very high levels of income cyclicality at the top of the US income distribution since 1982. They also 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.

Conclusion

In this chapter I have shown that the level of the richest top share is found to be, on average, lower than what it would have been predicted in the absence of crisis, based on previous dynamics of the series, including trend patterns. On the contrary, the bottom group within the top decile (P90-P95) gained in relative terms in the years following a systemic shock. 'Inequality' at the top of the US distribution, thus, tends to shrink following a systemic banking crisis. This also implies that the overall effect on the entire top decile share is mostly insignificant. Thus, the use of different top income shares in the analysis matters as it can provide contrasting evidence, marking the importance of the decomposition of income groups at the top. Top income groups are heterogeneous in nature and their relative response to systemic banking shocks appears to be different. Information on Top 10% solely would lead to conclude that crises have no impact on the 'rich' share of total income.

However, despite the interesting heterogeneity of results across income groups, the magnitude of the estimated changes in top shares is always lower than 1 standard deviation so that it appears that banking crises are followed by relatively mild changes in top shares.

More specifically, using the baseline empirical specification, the investigation founds that the top hundredth percentile share in total non capital gains income is 31 percent lower than the counterfactual level even after five years from the onset of the banking crisis. This is equivalent to almost a third of the Top 0.01% standard deviation or to approximately a 0.4 percentage point drop. The effect is tripled using the share including capital gains which is found to be be approximately 50% lower than the counterfactual after 5 years from the shock, equivalent to more than a 1 percentage point change in the share (almost one standard deviation).

The evidence for the Top 10-Top 5% share is specular to that of the Top 0.01%. Indeed, the share of the P90-P95th percentile is found to be 0.7 (0.9) percentage points above the counterfactual measure at the fifth year from the crisis if one considers the series excluding (including) capital gains. Both figures account for approximately 1 standard deviation of the respective shares.

The results that income concentration at the top shrinks in the aftermath of a systemic banking crisis was also confirmed by the direct modelling of the time-series of inverted-Pareto coefficient. The latter is a direct measure of the 'fatness' of the right-tail of the income distribution (under the assumption of Pareto distribution) and it is observed to decline significantly following the onset of systemic banking crises and not following general stock market crashes.

The results described above controlled for the reverse direction of causality, namely the case where the probability of crisis may be affected by growing share of income accruing to the top of the distribution, as recently debated within the literature. Moreover, findings are generally robust to different specifications. In particular the analysis is robust to the inclusion of additional lags of the crisis dummy variable in the baseline specification, to controls for longer duration of the banking crises and to controls for changes in taxation (controlling for changes in reported income at the top) and world level GDP growth (controlling that the effect of the crisis is net of the 'contagion' effect from other countries). It is however worth mentioning that in the latter case I found that the initial shock is almost entirely reabsorbed by the 5th year from the crisis if I restrict the analysis to the series which exclude the capital gains.

Therefore, there also appears to be some, although non conclusive, evidence that the total effect of crises on US top income shares are not just small in magnitude but also temporary in nature as richest top shares tend to recover fast following the initial hit with respect to the .

Finally, the investigation also controlled that other types of financial crises like stock market crashes and currency crises do not have a similar effect on the top shares. This provides some evidence on the fact that the effect I captured for the banking crises is not a generic crisis effect which would have occurred in any other type of crisis.

These findings, taken together and irrespectively of the findings about the duration of the crisis effect, lend some indirect support to the conjecture recently advanced in Saez (2013) and Piketty & Saez (2013), suggesting that only radical changes to the institutional framework and to the income earning process (i.e. changes in labor market institutions, social norms concerning inequality, radical fiscal policies and financial regulations) may substantially affect the share of total income accruing to the top of the distribution. New waves of policies are often gradually implemented in the aftermath of major macroeconomic shock like a systemic banking crisis and these can have more substantial impact on top shares. Indeed, "*The non-market mechanisms that shaped the postwar Golden Age had roots in the Great Depression and the New Deal.*" as recalled in Levy & Temin (2007, p. 15).

One may also be tempted to extrapolate these results further and argue that systemic banking crises are not turning-points for the US income distribution as a whole. Indeed, the literature has provided some justification about the fact that tracing the dynamics of top income shares may be informative on the general disparity of income distributions (e.g. Gini coefficient)[102]. Although it might be reasonable to assume that it is unlikely to have substantial distributional implications without a considerable change in the top decile of the income distribution, one should be cautious about drawing a direct link between top shares and the overall income distribution, especially in the short-run. The factors affecting the bottom of the distribution during a systemic banking shock may be substantially different from those documented and discussed here for the top of the distribution and this work remain silent about this crucial difference. To what extent crises are likely to exert permanent impact on the distribution of income as a whole is an interesting question which remains open for future investigation.

To conclude, the work is also silent about many dimensions of individuals well-being, like wealth, consumption and human capital accumulation. Similarly, the analysis does not analyse important 'horizontal' dimensions of economic inequality issue. Irrespectively of the well-being indicator under investigation, different person may be concerned about the distribution of gains and losses across generations, gender and social classes. This paper does not touch upon these very important issues.

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[102]Indeed, as recalled by Atkinson & Piketty (2007, pg. 19), and proved more formally in Alvaredo (2011),"*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*". Empirical evidence on the link between top shares and overall measures of income distribution is provided, among others, in Burkhauser et al. (2009) and Leigh (2007). For fresh evidence of the empirical association between top shares and Gini coefficients see the recent work by Morelli et al. (ming)

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