Does more finance mean more inequality in times of crisis?

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Abstract

Whole arrays of recent empirical studies show that both banking crises and the increase in the size of the financial sector play a central and important role in the evolution of income inequalities over the last decades. To our knowledge, no study has so far sought to link these three elements with the aim to investigate the role of the size of the banking sector in the amplification of income inequalities after the outbreak of banking crises. This paper seeks to address this issue based on a sample of 69 banking crises in 54 countries over the 1977-2013 period. Our analysis reveals that the size of the banking sector significantly increases income inequalities after banking crises. This result is robust to a broad range of alternative specifications and is unaffected by various potential sources of endogeneity. Finally, we bring the empirical evidence that the effect of the size of the banking sector on the redistributive effect of banking crises appears to be linear and to be stronger for developing countries.

Keywords: size of the banking sector; banking crises; income inequalities

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I. Introduction

In its 2013 report, "*Crisis squeezes income and puts pressure on inequality and poverty*", OECD brings the evidence that, between 2007 and 2010, the subprime mortgage crisis has caused a sharp increase in income inequalities (hereafter IncI) in most developed and developing countries. This increase is even above the one observed over the last three decades. The triggering of the subprime crisis occurred in a framework of an important increase in the size of the banking sector (hereafter SBS) over the long run, especially in developed countries. This was due to the rise of financial innovation and the implementation of policies of financial liberalization which began in the 1980's. This has led to a sharp increase in loans and financial assets held by banks as well as surge in the debt level. Far from supporting the stability and the resilience of financial systems, the growth of SBS has been responsible for a large bubble in the real estate market, whose bursting generated very large losses for banks and triggered an unprecedented banking crisis.

The question then arises of the role played by SBS in the increase of IncI observed after the outbreak of the subprime mortgage crisis. On a broader level, the question is to know if SBS amplifies the effects of banking crises on IncI. Regarding this subject, although the empirical literature underlines the central role played by both SBS and banking crises to explain the dynamics of IncI, to our knowledge no paper has linked these three elements. The amplification of IncI by the SBS after the outbreak of crises is not addressed by the literature. That is why this is the point of our research question. The interest and the newness of our work is to provide a new empirical approach to analyze the consequences of banking crises by focusing on the effects of SBS on the dynamics of IncI subsequent to banking crises.

In order to answer this research question we use a dataset covering 69 banking crises which occurred in 54 countries over the 1977-2013 period. Since the effect of banking crises on IncI could operate rapidly, we have defined an indicator allowing us to assess the dynamics of IncI during the three years following the outbreak of a crisis. The multidimensional nature of SBS is measured through a composite indicator based on a Principal Component Analysis relying on a set of six variables. In view of the limited size of our sample, the selection of a restricted set of control variables to be put in the econometric model is based on a Bayesian Model Averaging. Finally, the estimate of the effects of SBS on the dynamics of IncI is based on Ordinary Least Squares.

Our results are as follows. First, we show that following the outbreak of banking crises a larger size of the banking sector lead to a significant increase in IncI. Second, this result remains unchanged when taking into account potential sources of endogeneity, as well as a large set of robustness checks including the use of alternative metrics for both SBS and redistributive effect of banking crises, the use of alternative estimation methods, a change in the structure of the database, and finally the introduction of proxies for the degree of development of stock markets and the degree of liberalization of financial systems. Third, further estimates suggest that the relationship between SBS and the redistributive effect of banking crises seems to be linear and strongest in developing countries.

In an international framework characterized since the subprime crisis by an increase in financial instability and sluggish growth, this article contributes to the intense public debate on the role played by the financial systems in the amplification of IncI. Our results suggest that SBS is not a countercyclical component since it tends to reinforce the concentration of wealth as a result of the outbreak of banking crises.

The remainder of the paper is organized as follows. Section II presents the literature related to the effects of banking crises on IncI, to then show how SBS could represent a key factor of amplification of increased IncI following banking crises. Sections III and IV respectively present our data and econometric methodology. Section V presents the first econometric results and that taking into account different potential sources of endogeneity. Section VI focuses on robustness checks. Section VII extends our analysis by considering the possible existence of nonlinear effect of SBS on the redistributive effect of banking crises, and the heterogeneity related to the level of economic development. Section VIII concludes.

II. How can the size of the banking sector influence the effect of banking crises on income inequalities?

2.1 From banking crises to income inequalities

Five main channels of transmission have been highlighted in the literature seeking to depict how banking crises, and more generally financial crises, may cause a change in the distribution of income (Bazillier & Héricourt 2017). Three of these channels are caused by a contraction of the economic activity in the financial sector: an asset prices decline, a worsening access to the credit market and a weakening of the exchange rate. The two other channels are associated with a downturn in the real economy, namely: an increase in the unemployment rate and the implementation of policies of strict fiscal austerity.[1]

We first consider the effects of banking crises on IncI transiting through the dynamics of the financial sector.

First, following the outbreak of a banking crisis, asset prices (both financial asset and real estate) tends to sharply drop due to the reversal of expectations and heavy selling of assets made by strongly indebted economic agents in order to satisfy their need for liquidity (Minsky, 1992; Kindleberger, 2000). Since securities and real estate are mainly held by wealthy households (Piketty & Saez, 2013; Piketty, 2014), banking crises can therefore lead to a reduction of IncI (Baldacci *et al.*, 2002; Meyer & Sullivan, 2013; Morelli, 2014).

Second, solvency problems and liquidity shocks banks undergo may lead them to significantly reduce credit supply (Laeven, 2011; Claessens & Kose, 2013). This worsening access to the credit market may particularly penalize the poorest households. They indeed lack sufficient resources to meet the requirements of banks to access credit (Demirguc-Kunt & Levine, 2009; Beck, 2011). The income of the poorest household is more vulnerable to an economic downturn. As a consequence a significant reduction in credit supply is therefore more likely to affect them and thus lead to an increase in IncI (Bazillier & Héricourt, 2017).

Third, the more important the subsequent difficulties faced by the financial sector, the more voluntary will be the expansionary monetary policies implemented by central banks. The

[1] Some of the studies quoted here relate to the effects of currency crises on IncI. The mechanisms they highlight can also account for the effects of banking crises on income distribution.

aim here is to provide financial institutions with liquidity (Laeven & Valencia, 2010). This policy exerts downward pressure on the exchange rate and thus raises the cost for imports. When it has an impact on the price of essential goods, like food, it leads to significant income losses for the poorest households and may lead to an increase of IncI (Baldacci *et al.*, 2002).

We now consider the effects of banking crises on IncI transiting through the dynamics of the real sector.

First, the sharp reduction in credit supply, accompanied by a severe decline in asset prices and a contraction of private spending –for the economic agents to put their debt on a downward track–, causes a decline in aggregate demand. This leads to a sharp slowdown in production and therefore to an increase in the rate of unemployment (Reinhart & Rogoff, 2009). The poorest households facing a higher risk to lose their job due to lower skills will experience a decrease in their market income. The upward trend in unemployment, caused by a banking crisis, may thus lead to an increase in IncI (Elsby *et al.*, 2010; Hoynes *et al.*, 2012; Morelli, 2014).

Secondly, due to its recessive impact on the real economy, banking crises lead to an increase in public spending, via the use of countercyclical policies designed to boost aggregate demand and increase social transfers (especially for the benefits of the unemployed). They also lower tax revenues. This causes deterioration in public deficit and an increase in public debt (Reinhart & Rogoff, 2011). Governments facing such a situation are willing to continue to raise funds on the financial markets and may also implement policies of strict fiscal austerity (Reinhart, 2012). Lewis & Verhoeven (2010) show that in order to rebalance their budget, governments mainly target spending cuts in the social protection system. These cuts in social transfers mainly impact the poorest households which are the main beneficiaries of social insurance mechanisms and thus lead to a decrease in their disposable income (Ball, 2013; Woo *et al.*, 2013). This channel is another source of growing IncI after the outbreak of banking crises (Jenkins *et al*, 2013; Morelli, 2014).

These mechanisms suggest that banking crises lead on average to an increase in IncI. Only the channel of asset prices goes in the opposite direction, namely reducing IncI. While on the other hand, the channels associated with credit market conditions, exchange rate, unemployment rate and policies of budgetary austerity go in the sense of an increase in IncI.

However, the empirical literature fails to achieve a consensus on the effects of banking crises on the IncI. For example, based on a panel of 62 both developed and developing countries observed over the 1980-2006 period, Agnello & Sousa (2011) show that banking crises lead to a significant decrease in IncI. Conversely, based on a dataset of 25 banking crises between 1911 and 2010, Atkinson & Morelli (2010) point out that IncI tends to increase as a result of banking crises. However, this result is invalidated by Denk & Cournede (2015). Based on a sample covering 33 countries over the 1970-2011 period, they bring the empirical evidence that banking crises are not a source of significant increase in IncI.

Given the lack of consistency concerning the effect of banking crises on IncI and the role played by the dynamics of the financial sector –especially that played by the banking sector– in the strengthening of the recessive consequences of banking crisis (Kindleberger, 2000; Reinhart

& Rogoff, 2009; Claessens & Kose, 2013), we now move to a section investigating how an increase in SBS may amplify the effects of banking crises on IncI.

2.2 From the size of the banking sector to the redistributive effect of banking crises

The influence the SBS could have on the redistributive effect of banking crises is twofold. We *a priori* can distinguish between *stabilizing* and *amplifying effect*.

Regarding the *stabilizing effect*, the previous studies about the macroeconomic consequences of financial development report that a rise in SBS lead to an increase in the offer of loanable funds, but also lead to a better risk management and a better risk diversification for the banking industry (Levine, 2005; Beck, 2013; Panizza, 2014). In this regard, a vast literature underlines that a higher level of SBS leads to a more equitable income distribution. It can be a direct effect due to increased opportunities for the poorest households to accumulate human capital (Aghion & Bolton, 1992; Galor & Zeira, 1993; Galor & Moav, 2004), to entrepreneurship (Banerjee & Newman, 1993; Mookherjee & Ray, 2003; Jeong & Townsend, 2007, 2008), and to the smoothing of shocks impacting their income (Jacoby & Skoufias, 1997; Baland & Robinson, 1998). It can also be an indirect effect due to the fostering of economic growth (Greenwood & Jovanovic, 1990) and the boosting of demand for low-skilled workers (Gine & Townsend, 2004).[2] As a result we can conclude that SBS play a countercyclical role since the poorest households have the opportunity to stabilize their income by mitigating the rise of IncI.

For this SBS stabilizing effect to efficiently operate, the banking industry must be able to ensure a stable allocation of credits among the different categories of economic agents. Self-evidently this is not the case after the outbreak of a banking crisis (Mishkin, 1996). On the credit market, the sharp increase in informational asymmetries is a consequence of a rising uncertainty within the financial system and also a consequence of the loss of wealth incurred by some economic agents. This leads banks to reduce risk exposure and credit supply, thus reinforcing the recessive impact of banking crises (Laeven, 2011). This situation particularly hinders the poorest households, whose incomes are more sensitive to economic turnarounds (Demirguc-Kunt & Levine, 2009; Bazillier & Héricourt, 2017). Hence one should note that this is essential to address the mechanisms by which SBS could modify the impact of banking crises on IncI.

This brings us to the *amplifying effect* of SBS on the redistributive effect of banking crises. The history of financial crises teaches us that the way the banking sector operates is central in both origins and consequences of banking crises. The accumulation process of risk relates to a self-sustaining process linking credit supply and asset prices (Kindleberger, 2000). This contributes to the recessive impact of banking crises. The more the banks contribute to the emergence of an upward financial trend, the more they strengthen the endogenous dynamics of the cycle. Consequently when asset prices collapse, it amplifies both losses incurred by banks, credit contraction and cause a significant contraction in private demand. These banking crises are then characterized by a greater duration and a greater cost, due to the severe difficulties banks have to maintain funding for economy (Claessens & Kose, 2013).

[2] However, concerning econometric analysis, there is no clear consensus about the relationship between SBS and IncI. A first set of studies shows that SBS significantly reduces IncI (e.g. Li *et al.,* 1998; Clarke *et al.*, 2006; Beck *et al.*, 2007; Mookerjee & Kalipioni, 2010; Hamori & Hashiguchi, 2012; Naceur & Zhang, 2016). A second set of studies bring the evidence that SBS does not have a significant effect on IncI (Law & Tan, 2009; Bahmani-Oskooee & Zhang, 2015), or a significant upward effect (Rodriguez-Pose & Tselios, 2009; Gimet & Lagoarde-Segot, 2011; Jauch & Watzka, 2012; Jaumotte *et al.*, 2013; Li & Yu, 2014; Denk & Cournède, 2015; De Haan & Sturm, 2016).

The pro-cyclicity of the banking activity is a key issue to understand the recessive effect of crises. The more SBS increases during the upward phase of the cycle, the higher the debt level. This phenomenon is also accompanied by asset bubbles which foster the endogenous increase in the financial fragility of the whole system, particularly in case of economic turnaround and market downturn (Allen *et al.*, 2009). This in turn amplifies the recessive dynamics of both financial accelerator and debt deflation.

When lenders suffer from an information asymmetry, the theory of the financial accelerator shows that the financial situation of economic agents creates a pro-cyclical dynamics in the access to financing and allows accounting for the magnitude and the persistence of a shock adversely affecting their wealth (Bernanke & Gertler, 1989, 1995; Bernanke *et al.*, 1999). The theory of debt deflation points out that a higher level of debt means more constraints to access credit and thus causes a significant drop in asset prices when the banking industry is in crisis. In order to pay back their debt, the economic agents then massively sell both their financial and real estate assets. It leads to a sharp contraction in private spending which strengthens the recessionary impact of the initial shock (Fisher, 1933; Minsky, 1992).

Therefore, after the bursting of a speculative bubble, a banking crisis is triggered if it the balance sheets of banks previously engaged in speculative activities is impacted. The sharp decline in asset prices, as well as the significant increase in defaulting loans significantly affects banks' balance sheets. Due to the financial accelerator, their wealth is negatively impacted and banks experience more difficulties to finance themselves, whether in the form of deposits or interbank market. Shareholders equities and liabilities are in turn impacted, leading thus to an increase in financial fragility (Gertler & Kiyotaki, 2010). Furthermore, in order to meet their liquidity requirements and to deleverage, banks sell significant amounts of assets. The mechanism of debt deflation reinforces the decline in asset prices and thus weakens financial intermediaries. Financial accelerator and debt deflation are self-reinforcing mechanisms, leading to a significant contraction in the credit supply, which can even cause if the worst comes to the worst a *credit crunch*.[3]

Due to reduction in credit supply and decline in asset prices, firms encounter difficulties to obtain financing. Reasons for this include their activity slowdown and a loss in value of fixed assets (Bernanke & Gertler, 1989; Kiyotaki & Moore, 1997). Households also experience difficulties in accessing credit due to a drop in the real estate prices, which is the main collateral they use to obtain loans (Aoki *et al.*, 2004; Iacoviello, 2005). In consequence, a significant contraction in aggregate demand arises. It is even greater if the agents are highly indebted, since they will have to proceed to a sharp debt deflation in order to repay their loans (Minsky, 1992). The result is a stringent contraction in the amount of credit to the economy, due on the one hand to a reduction in the credit supply, induced by the financial accelerator mechanism, and on the other hand to a reduction in the credit demand following the decrease in private expenditure triggered by debt deflation. This will in turn cause a decline in production, a rise in the unemployment rate and a further decline in asset prices. A feedback dynamic that affects the health of the financial sector then begins: the growing number of defaulting borrowers and the fall in asset prices negatively impact bank's balance sheet assets and as a consequence the credit

[3] After the outbreak of a banking crisis, the credit contraction may be more important when the banking industry faces macro prudential regulation and pro-cyclic accounting standards (Allen & Carletti, 2008; Laeven, 2011).

supply declines. In turn it amplifies the recessionary spiral in which the real economy is stuck (Kindleberger, 2000). At this stage of the crisis, the implementation by public authorities of expansionary economic policies is therefore necessary to limit the recessionary impact of banking crises (Claessens & Kose, 2013). This is likely to result in an increase in the public debt and a fall in the exchange rate.

Theories of the financial accelerator and debt deflation thus highlight the central role played by the banking industry in amplifying the consequences of crises. It is due to the strengthening of pro-cyclical variations affecting the credit supply. These are caused by both financial cycle downturn and the transmission to the whole economic system of the initial fall in asset prices. An upsurge in SBS during the upward phase of the financial cycle, by exposing more banks to significant shocks due to sharp asset prices declines, may therefore play a key role in fostering the recessionary effect of banking crises. This is confirmed by a whole array of recent empirical studies examining the determinants of the real cost of banking crises. They show that SBS, generally measured as the ratio of banks credits to the private sector to GDP, is one of the most insightful determinants to understand the magnitude of the severe decrease in both GDP and GDP growth rate after the outbreak of banking crises (e.g. Boyd *et al.*, 2005 ; Angkinand & Willett, 2008 ; Abiad *et al.*, 2009 ; Cecchetti *et al.*, 2009 ; Pesic, 2012 ; Wilms *et al.*, 2014).[4]

Within this framework, an increase in SBS may lead to an amplification of the five transmission channels documented in section 2.1, which explain the effect of banking crises on IncI. However, since only one among them lead to a reduction in IncI (the asset prices channel), it derives from our previous discussion the following testable hypothesis: the higher the SBS prior to a banking crisis, the higher the ensuing increase in IncI. The remainder of the paper aims to answer this research question.

III. Data

In order to estimate the effect of SBS on the redistributive impact of banking crises we use a dataset of 69 banking crises that occurred in 54 countries during the period between 1977 and 2013.[5]

Since the upsurge of banking crises in recent decades affects both developed countries (DVs) and developing countries (DCs), we have decided to include the widest number of countries in our analysis. Although the structure of financial systems varies significantly depending on the level of economic development, this approach is suitable since as mentioned previously the pro-cyclical dynamics of SBS is a key mechanism explaining the origin and the consequences of banking crises in both DVs and DCs.

The period covered by our study –the last three decades– allows us to account for the trend growth in IncI and financial instability in both DVs and DCs. This is also a period during which financial systems have changed at a global scale and SBS has increased.

[4] This SBS amplifying effect is also confirmed from a microeconomic standpoint by Kroszner *et al.* (2007). By extending the analyzes of Dell'Ariccia *et al.* (2008), these authors show that the negative impact of banking crises on the growth rate of business value added is significantly higher in countries with a higher SBS, measured as the ratio of a bank credit to the private sector to GDP.

[5] Table A in Appendix 1 lists the countries and banking crises in our sample.

Finally we have chosen a cross section analysis instead of a panel. Since only 13 countries have experienced more than one banking crisis over the 1977-2013 period, our unit of observation is at the crisis level (not the country level). We indeed lack repeated crises observations in the time dimension to consider a panel analysis.

Following the usual method used in empirical researches seeking to assess the real cost of banking crises (Wilms *et al.*, 2014), we consider each banking crisis as our basic unit and we assess the redistributive effect for each one. The relevance of our cross-sectional analysis is also justified by the very nature of data about income distribution which varies slowly over time but varies significantly across countries. Hence the relative inertia of IncI must be taken into account in order to rigorously capture the effects of banking crisis on income distribution. The coverage of this inter-country heterogeneity is addressed through our cross-sectional analysis.

3.1 Measuring the redistributive effect of banking crises

In order to assess the redistributive effect of banking crises, we first document the year the crisis erupts. This dating relies on the database provided by Laeven & Valencia (2012) which is considered as the most relevant in the academic literature.

To take into account the counter-cyclical effect of redistributive government policies on IncI dynamics ensuing banking crises (OECD, 2013), IncI are measured in terms of disposable income. Based on the recommendations provided by the *Canberra Group* (2011) we assess disposable income at the household level correcting for size. This method allows us to make significant comparison. As mentioned earlier in section II, banking crises impact the distribution of income, this means that both high and the low incomes can be hit. To capture the variations of the mean income inequalities we have chosen the Gini coefficient to measure IncI.[6] The latter is interesting since it is available for a broad spectrum of countries and it is the proxy mainly used in the empirical studies linking IncI, SBS and banking crises. It contributes to the external validity of our estimates.[7]

Based on Gini coefficients, several international database measures IncI correcting for the size of households. The following ones are considered as the most reliable: *Luxembourg Income Study*, OECD, *Eurostat*, *Chartbook of Economic Inequality* (Atkinson & Morelli, 2014). They indeed guarantee a standardized and homogenous metrics. The *Luxembourg Income Study* covers 49 countries on the period between 1967 and 2014. The mean number of observations per country equals 5.5. The data points are mainly available for developed countries since the beginning of the 1990s.[8] The *Income Distribution Database* is provided by the OECD. It comprises 37 countries on the 1974-2014 period. The mean number of observations per country equals 13.3.[9] The *Eurostat* database covers the 27 countries of the European Union plus the UK and Turkey over the 1995-2016 period (with an annual frequency). But once again the availability is quite poor with a mean number of observations per country equal to 14.5. The *Chartbook of Economic Inequality* covers 25 countries (mainly OECD ones) in annual frequency over the 1900-2013

[6] This is not the case if we consider the share of top incomes in total income (for instance the top 10%, 5%, 1% incomes) as considered by Atkinson & Morelli (2010), Bordo & Meissner (2012), Kumhof *et al.* (2012), Perugini *et al.* (2015), Morelli (2014).
[7] See for instance the works of Clarke *et al.* (2006), Beck *et al.* (2007), Law & Tan (2009), Ang (2010), Kappel (2010), Mookerjee & Kalipioni (2010), Jauch & Watzka (2012), Kim & Lin (2011), Ball *et al.* (2013), Belletini & Delbono (2013), Woo *et al.* (2013).
[8] Another concern with the *Luxembourg Income Study* database is the frequency. Observations are only made every 3 or 5 years.
[9] The OCDE dataset is available in yearly, quarterly and monthly frequency. Our calculations are based on annual data.

period, with an average number of observations per country equal to 23.6. However, most of the data are available only recently, mainly since the 1980s. Although the databases provided by *Luxembourg Income Study*, OECD, *Eurostat* and *Chartbook of Economic Inequality* rigorously measure IncI (which ensures high comparability of IncI), their coverage in terms in both countries and time dimensions is not sufficient to conduct an international study of IncI resulting from banking crises. The *World Income Inequality Database* (WIID) provided by the World Bank represents a suitable alternative since it includes Gini coefficients for 161 countries. They are observed annually between 1867 and 2013.[10] Based on the selection criteria proposed by Jenkins (2014), if we only use countries and periods where the Gini coefficient is calculated on the basis of household disposable income correcting for size (and also based on surveys that cover all age groups and the whole territory) the number of available observations sharply drops to 78 countries.[11] If among these countries only those with at least five observations are kept (which is a very non-restrictive criterion), their number drops to 60. Finally, if we match these remaining countries with the data about banking crises provided by Laeven & Valencia (2012), the number drastically drops to 32 (mainly for developed countries since the 1990s). Using the WIID would once again lead to the loss of too many banking crises. Such a dataset would be insufficient to conduct a relevant empirical analysis of our research question in an international setting.

For the purpose of our research, Solt's *Standardized World Income Inequality Database* (SWIID) (2014) seems to be a particularly relevant database because it includes Gini coefficients based on household disposable income correcting for size for 174 countries. They are observed in annual frequency between 1960 and 2013. The average number of observations per country is 36.8. The majority of data are available since the 1980s and the number of developing countries is particularly important. If, as for WIID, countries that do not have at least five observations are suppressed, we still have 161 available countries. Similarly, if we compare these 161 countries with the crises documented by Laeven & Valencia (2012), we get IncI data for 76 episodes. To obtain such a high coverage, it is essential to bear in mind that SWIID data are not observed data, but estimated data resulting from an imputation process based on econometric modeling. The aim of Solt (2014) is also to impute the *Luxembourg Income Study* dataset based on other sources available in the WIID. The expected benefit is to provide researchers with high quality IncI data offering an important level of comparability and proposing a significant coverage in an international setting over a long period of time. Consequently, we have decided to base our study on the Gini coefficients provided by the SWIID of Solt (2014).

Now that we have defined the source of the data for banking crises and IncI, we present the calculation of our indicator for the redistributive effect of banking crises. It is based on a five steps calculation. First, we determine a time window to measure the IncI dynamics associated with each banking crisis. We have underlined above in Section II that the channels modifying income concentration after a crisis tend to operate over a short to medium time horizon. In order to isolate the direct consequences of banking crises on income distribution income, we therefore have chosen to consider a four-year interval from the year of occurrence of each banking crisis (t) to the third year following its release ($t + 3$). To take into account the dynamics of IncI before

[10] To obtain such a high coverage, the WIID centralizes data from many sources, such as: *Luxembourg Income Study*, *OECD*, *Eurostat*, *Socio-Economic Database for Latin America and the Caribbean*, *Transmonee*, but also inequality dataset taken from national statistical institutes and academic works.
[11] In order not to reduce too much the number of observations available, we kept the data for which an adjustment procedure for household size is taken into account and that regardless of its type.

the outbreak of each banking crisis, we have defined a pre-crisis time interval which – for the sake of symmetry – covers the three years preceding the occurrence of each crisis.

Second, we have converted the 100 estimated series of Gini coefficients on SWIID into a single series. For this, we have calculated for each country and each year the average value of these 100 series.

Third, based on this new set of Gini coefficients, we have dropped the banking crises lacking IncI data on the ($t-3$, $t+3$) time span. In this configuration, 21 banking crises, out of the 76 mentioned above, were removed from our sample.

Fourth, since the SWIID data are estimated, and based on Solt's (2014) recommendation, we removed the remaining banking crises with a high degree of uncertainty in the imputation process. For each country and for each year, we have calculated the average standard deviation for the 100 series of interpolated Gini coefficients. Based on this proxy for coefficient uncertainty, we have calculated the mean standard deviation for each period surrounding a crisis, namely the time span ranging from $t-3$ to $t+3$. To comply with a sufficient number of reliable observations, the banking crises with a standard deviation above 3 were dropped.[12] This calculation step results in eliminating 6 more crises. It finally leads us to a sample including 69 banking crises observed in 54 countries between 1977 and 2013.

Fifth, the measure of the effect of banking crises on IncI has to be defined. As mentioned above, the redistributive effect tends to occur immediately in the years following the outbreak. However, given the strong inertia of IncI, it is important to compare two years sufficiently distant and that for the channels of transmission to operate. For each banking crisis, the measure of the redistributive effect equals the difference between the Gini coefficients observed in $t+3$ and t (hereafter *Diff.Gini*). Table A in Appendix 1 details the *Diff.Gini* values for each of the 69 banking crises episodes in our sample and Table B4 in Appendix 2 presents the descriptive statistics.[13]

3.2 Measuring the size of the banking sector

As outlined earlier, SBS seems to be a key factor driving the redistributive effect of banking crises. Moreover, SBS is a multidimensional concept associated with the size of both assets and liabilities of banking sector's balance-sheet. The usual variable Credit/GDP cannot solely account in a relevant way for SBS. Therefore, using a composite index seems to be particularly relevant to summarize the general level of SBS relating to several variables.

This is the reason why – following e.g. Ang & McKibbin (2007), Campos & Kinoshita (2010), Samargandi *et al.* (2015) – we measure SBS through a composite index corresponding to the first factor derived from a Principal Component Analysis (PCA) applied to a set of six variables taken from the World Bank's *Global Financial Development Database* (GFDD, 2016). Each of these variables is measured the year preceding the banking crisis. First, the *Liquid liabilities*

[12] The choice of this value is particularly appropriate since, after postulating different threshold values (2.5, 3, 3.5, 4 and 4.5), our results clearly bring the evidence that the majority of bank crises with a high level of IncI uncertainty are above an average standard deviation of 3.
[13] We did not use the average annual growth rate of the Gini coefficient between t and $t+3$. The strong short-term inertia in the income distribution could indeed lead to underestimate the redistributive impact of banking crises. Similarly, we did not use the cumulative annual growth rate of the Gini coefficient between t and $t+3$, since we want to measure income distribution after being affected through the different transmission channel. Considering in this case the short-term values of the Gini coefficient (in $t+1$ and $t+2$) would once again underestimate the effect of banking crises on IncI.

variable (ratio of M3-to-GDP) captures the size of financial intermediaries' liabilities, and proxies the liquidity in the economy. Second, the *Bank assets* variable (ratio of deposit bank assets-to-GDP) measures the size of financial intermediaries' assets, and assesses the place of commercial banks in savings allocation process and risk-taking before banking crises. Third, the *Bank deposits* variable (ratio of bank deposits-to-GDP) captures banking sector's capacity to mobilize available savings. Fourth, the *Assets ratio* variable (ratio of commercial bank assets to the sum of commercial bank assets and central bank's assets) measures the relative size of commercial banks compared with central banks.[14] Fifth, the *Credits* variable (ratio of credits to the private sector by banks-to-GDP) captures the activity of financial intermediaries in their crucial task of channeling savings towards investment; this way, we also proxy the effect of credit-risk, and as such capture the pro-cyclical dynamic of credit supply during the upward phase of the financial cycle. Sixth, the *Credits/Deposits* variable (ratio of credits to the private sector by banks-to-deposits) measures the intermediation capacity of the banking sector, and also the risk-taking behavior of financial intermediaries that may lead to an increase in liquidity risk in case of a bank panic.[15]

Using a PCA to calculate a synthetic index of SBS is highly relevant since as shown in Table B1 (Appendix 2), except for *Credits/Deposits*, the variables used to proxy SBS are strongly correlated. Thus, a PCA allows us not only to extract a large proportion of the variability shared by these variables but also to avoid multicollinearity issues in our econometric analysis (Voghouei *et al.*, 2011; Samargandi *et al.*, 2015). Table 1 gives the results of the six-variable PCA presented above and shows that most of their variance (roughly 70%) is accounted by the first factor. Except *Credits/Deposits*, and, to a lesser extent, *Bank ratio*, each variable is strongly correlated with the first factor. A small share of the variance remains unexplained, except for *Bank ratio*. This confirms the relevance of using a composite index based on a PCA to proxy SBS before banking crises. As a result, our SBS index (*SBSindex*) corresponds to the first factor of the PCA presented in Table 1. Table A in Appendix 1 gives the values of *SBSindex* before each banking crisis in our sample and Table B4 in Appendix 2 its descriptive statistics. Consequently, by using *SBSindex*, our goal in this paper is not to assess what precise components of SBS influence the redistributive effect of banking crises, but rather to determine if a global and synthetic measure of SBS before banking crises can explain it. Finally, to reduce the influence of potential outliers in *SBSindex*, with the same sample size, we follow Kumar *et al.* (2003), and transformed this variable x into $\tilde{x} \equiv sign\{x\}\log(1+|x|)$. Compared with a logarithmic transformation, the use of $\tilde{x}$ mitigates potential extreme values of x, and preserves the negative x values.

[14] Especially in DCs (representing a large proportion of our sample) where central banks can play an important role in savings allocation.
[15] Table B2 in Appendix 2 reports descriptive statistics for each of these six variables.

Table 1. Computing a composite index of the size of the banking sector (SBSindex) using Principal Component Analysis (PCA)

PCA SBSindex		
Factor	**Eigenvalue**	**Extracted variance proportion**
Factor 1	4.11	0.69
Factor 2	1.07	0.18
Factor 3	0.67	0.11
Factor 4	0.10	0.02
Factor 5	0.03	0.01
Factor 6	0.01	0.00
Variables	**Factor loadings**	**Uniqueness**
Liquid liabilities	0.93	0.09
Bank assets	0.98	0.05
Bank deposits	0.92	0.05
Bank ratio	0.61	0.58
Credits	0.95	0.03
Credits/Deposits	0.41	0.02
Obs.	69	

Note: SBS variables are measured the year preceding banking crisis outbreak. *Factor* corresponds to all common factors shared by SBS variables. *Eigenvalue* represents the explanatory power of each estimated factor. *Extracted variance proportion* is the share of the total variance of SBS variables captured by each factor. *Factor loadings* gives the correlation coefficients between the first factor and SBS variables. *Uniqueness* is the share of the variance of each variable not accounted by the first factor.

IV. Econometric methodology

4.1 Model specification

In order to estimate the effect of SBS on the redistributive effect of banking crises, we use the following econometric specification:

$$\text{Diff.Gini}_j = \alpha + \beta\text{SBSindex}_j + \delta\text{GDPcap}_j + \gamma\text{Gini}_{\text{pre-crisis}\,j} + \sum_{k=1}^{8}\varphi_k X_{jk} + \sum_{n=1}^{19}\lambda_n Z_{jn} + \varepsilon_j \quad \text{eq. 1}$$

Where *Diff.Gini* is the dependent variable measuring the IncI dynamics following banking crisis *j*. *SBSindex* is our composite SBS index. *GDPcap*, *Ginipre-crisis*, *X* and *Z* are different sets of control variables. α and *ε* respectively correspond to the intercept and to the error term. Due to cross-sectional dataset, continuous dependent variable, and use of *SBSindex* pre-crisis values, we have chosen to rely on Ordinary least squares (OLS) to estimate the parameters of the model.

Since there are a large number of potential determinants competing to explain the redistributive effect of banking crises, we have decided to subdivide our control variables into three broad sets. Table B3 in Appendix 2 gives their definitions and sources.[16] The first set of control variables is associated with the *GDPcap* and *Ginipre-crisis* variables. They account for both the level of economic development and IncI prior to a banking crisis. These two control variables are found in all our econometric estimates. The level of economic development is indeed essential to explain the long-term dynamics of IncI (Demirguc-Kunt & Levine, 2009) and to understand the recessive consequences banking crises may have (Laeven & Valencia, 2010). On the other hand, given the detrimental consequences – at political and at social level – associated

[16] To take into account potential outliers for these variables, while keeping the sample size unchanged, as for *SBSindex*, we applied the transformation of Kumar *et al.* (2003) to all quantitative variables.

with a high level of income inequality (Atkinson, 2015), it is likely that a post-crisis increase in IncI is made more difficult if the pre-crisis level of IncI was already high. This is due to the pressure governments may face to implement policies that favor a more egalitarian distribution of wealth.

The two sets of control variables X and Z respectively account for the long-term determinants of IncI and for the recessionary impact of banking crises. Based on the empirical literature on the effect of financial development on IncI and following Clarke *et al.* (2006), Beck *et al.* (2007), Demirguc-Kunt & Levine (2009), Kim & Lin (2011), Law *et al.* (2014), we have selected 8 variables considered as key determinants of IncI. Similarly, based on the researches of Cecchetti *et al.* (2009) and Wilms *et al.* (2014), we have chosen 19 variables which all are essential explanatory factors to account for the recessionary impact of banking crises.[17]

Finally, among the 54 countries in our sample, 13 experienced several banking crises over the 1977-2013 period and even sometimes at very narrow intervals (see Table A in Appendix 1). In this case, banking crises occurring in a given country may be correlated and may thus affect their respective redistributive effect. Therefore it is necessary to take into account these potential correlations in the time dimension. For this, we use two econometric strategies. First, we systematically calculate a variance-covariance matrix of estimated coefficients robust to the presence of within-country correlations. Second, among our set of control variables Z, we have defined a binary variable (*Multiple crises*) taking the value 1 if the banking crisis j occurs in a country i experiencing several banking crises over the period 1977-2013 and the value 0 otherwise.

4.2 Selecting the control variables with a Bayesian Model Averaging

The limited number of available observations we have does not allow us to simultaneously take into account the 29 control variables presented in section 4.1. In order to specify a parsimonious model accounting for the most relevant control variables, we first estimate a Bayesian Model Averaging (BMA). This allows us to determinate the variable having the higher explanatory power to describe the redistributive effect of banking crises.

The "*model averaging*" approach allows accounting for the uncertainty related to the specification of an econometric model. The aim is to ensure the robustness of the estimates associated with the key explanatory variables we consider in our model (Hoeting *et al.*, 1999). In the presence of q potential explanatory variables, the objective is to estimate the set of 2^q candidate models, then to calculate a weighted average of the different estimates associated with each of the q explanatory variables, and that in order to deduce the effect of each on the dependent variable (Moral-Benito, 2015).

In the empirical literature, the BMA is the most commonly used method to implement this strategy. The general approach of a BMA is to postulate an *ex ante* distribution for the different models and on the coefficients associated with each explanatory variable. The estimates are then obtained based on the empirical likelihood of each fitted model. Based on the different candidate models, the objective is to assess the *ex post* distribution for the parameters of each

[17] Table B4 in Appendix 2 provides descriptive statistics for the control variables.

explanatory variable. That objective shall be achieved by combining the *ex-ante* (theoretical) dimension – the one relative to the *a priori* specification of both distribution of candidate models and coefficients of each explanatory variable –, and the *ex-post* (empirical) dimension deriving from the likelihood associated with each estimated model. As an outcome of the BMA, we finally obtain the posterior inclusion probability (hereafter PIP) for each explanatory variable. In other words, the PIP is the probability for a variable to be significant among the 2^q estimated candidate models. The explanatory variables we select for our model are those with the highest probability of inclusion.

We have chosen the BMA specification proposed by De Luca & Magnus (2011) since it allows us to distinguish between a category of explanatory variables of primary interest –the "*focus regressors*" (denoted as X_1)– which are always taken into account in the specification and a category of explanatory variables of secondary interest – the "*doubtful regressors"* (denoted as X_2).[18] In this case, the formulation of our model (eq.1) for the estimate of the BMA is as follows:

$$\text{Diff.Gini}_j = \alpha + \sum_{p=1}^{3} \beta_p \text{X1}_{jp} + \sum_{m=1}^{27} \delta_m \text{X2}_{jm} + \varepsilon_j \qquad \text{eq. 2}$$

X_1 is the set of variables always used in the candidate models, namely *SBSindex*, *GDPcap*, and *Ginipre-crisis*. X_2 is a set of 27 additional control variables proxying the determinants of IncI and the recessionary impact of banking crises. Regarding the risk of losing too many degrees of freedom, it is not possible to include the 27 additional control variables in our BMA. Consequently, we have splitted X_2 in two subsets. A first subset of X_2 comprises the 8 variables associated with the effect of financial development on IncI and a second subset of X_2 comprises the 19 variables related to the recessionary impact of banking crises. The estimates of our two BMAs are presented in Table 2.[19]

For all the estimated models, the probability of inclusion appears to be quite low, since it is systematically below 50%. It illustrates the difficulty to *a priori* define what the most relevant variable are to account for the redistributive effect of banking crises. It also emphasizes the relevance of BMA to select the control variables to be put in the model. The results presented in Table 2 indicate that only 7 variables appear to be relevant to capture the IncI dynamics following banking crises. These variables constitute our set of initial control variables.[20]

Concerning the BMA applied to the determinants of IncI, two demographic variables (*Population* and *Dependency ratio*) clearly stand out in terms of PIP. The total population of countries (*Population*), which is positively correlated, exhibits a PIP of 25%. In countries with a large population, the Government may have difficulties to stabilize both employment and income after the outbreak of a banking crisis, leading thus to a rise in IncI caused by the weakening of the poorest households. The share of the population under 15 years old and over 65 years old relative to the working-age population (*Dependency ratio*), which is negatively correlated, has a PIP

[18] Eicher *et al.* (2009) demonstrate that the choice of an *ex-ante* Zellner distribution for the coefficients with a value for the hyper-parameter *g* given by the Fernandez *et al.* (2001) criterion – i.e. $g = \max(N, q^2)$ – and associated with a uniform distribution for model size, leads to better performances when estimating a BMA. It is even better than any other combination of *ex-ante* distributions for both coefficients and models space. As a consequence, we have chosen to base our BMA estimate on such an *ex-ante* setting.

[19] At this stage, the objective is not to precisely quantify the effect of each candidate control variable on the dependent variable, but rather to know the sign and the probability of inclusion of each of them. In order to avoid burdening the result presentation with the estimates of the different BMAs, we have decided to only report the sign and the probability of inclusion of each candidate control variable.

[20] The control variables not retained at this stage will be taken into account in section VI for the robustness checks.

of 23%. Contrary to the working-age population which may experiment a declining income as a result of a contraction in economic activity following a banking crisis, the stability of pensions paid to retirees may lead to a reduction in IncI between seniors and the working-age population.

Table 2. Results of BMA estimates used to select the variables controlling for the redistributive effect of banking crises

	Diff.Gini	
Controls for IncI	Sign of coef.	PIP
Pop (t-1)	+	0.25
Pop growth (t-1)	+	0.14
Dependency ratio (t-1)	-	0.23
GDP growth (t-1)	-	0.11
Trade openness (t-1)	-	0.12
Public spendings (t-1)	+	0.17
Inflation (t-1)	-	0.11
Polity2 (t-1)	-	0.18
Crises	60	
Countries	46	
Number of models	256	
Controls for banking crises	Sign of coef.	PIP
Systemic	-	0.06
Subprime	-	0.07
Multiple crises	+	0.15
Credit boom	-	0.05
Currency crisis	-	0.09
Debt crisis	-	0.05
World crisis (t-1)	-	0.08
Regional crisis (t-1)	+	0.15
World crisis (t)	+	0.26
Regional crisis (t)	-	0.36
FDI (t-1)	-	0.09
Investment (t-1)	-	0.08
Liquidity	+	0.46
Public debt	-	0.20
World crisis post	+	0.06
Regional crisis post	-	0.08
World GDP growth post	+	0.12
Regional GDP growth post	+	0.32
FMI prog	-	0.06
Crises	61	
Countries	47	
Number of models	524 288	

Note: estimated models all include the following variables, *SBSindex*, *GDPcap*, and *Ginipre-crisis*. *PIP* is the probability for a control variable to be significant among all the estimated candidate models. *Sign of coef.* is the sign of the mean value for the coefficient of the control variable, it is calculated based on all the estimated candidate models.

Concerning the BMA applied to the determinants of the recessionary impact of banking crises, five variables exhibit a PIP significantly above the others.

Three variables are positively correlated with the redistributive effect of banking crises. First, the number of banking crises worldwide during the year a crisis occurs in a given country (*World crisis*) has a PIP of 26%. When financial instability increases at an international level, the magnitude of the shock leads to a greater economic downturn that may lead to an increase in IncI. Second, the liquidity provided by public authorities to financial institutions (*Liquidity*) has a PIP of 46%. These interventions appear to have a pro-cyclical effect on IncI. It can be explained by an increase in moral hazard that encourages banks to take more risks, which in turn may increases losses and causes more severe credit contraction and a more important economic downturn. Third, the three-year post-crisis average GDP growth rate of the countries belonging to the same region than the one experiencing a banking crisis (*Regional GDP growth post*) has a PIP of 32%. It can be interpreted as a macroeconomic crowding-out effect at a regional level. If a country experiences a banking crisis in a region having strong economic performance, investors may withdraw capital funds from it with the purpose of investing in the neighboring countries with more favorable conditions. This liquidity contraction in the country facing a crisis may thus foster the recessionary dynamics and increase the upward pressure on IncI.

On the other hand, two variables are negatively correlated with the redistributive effect of banking crises. The increase in public debt following a banking crisis (*Public debt*, 20%) is in part a consequence of counter-cyclical economic policies. They are implemented to mitigate the economic slowdown and as a result can limit the rise in IncI. The number of banking crises at a regional level during the year a crisis starts in a given country (*Regional crisis*, 36%) is contrasting with the result obtained for *Global crisis*. As regional financial instability increases, contagion dynamics between financial systems located in the same region may sharply increase. Each country is thus exposed to a higher risk of banking crisis. This prompts the authorities to implement preventive measures designed to mitigate this risk and therefore limit consequences of a potential banking crisis.

Finally, an interesting point to note is that the *Multiple crises* variable has a low probability of inclusion, which equals 15%. Capturing the occurrence of multiple banking crises in a given country – and therefore their potential correlations – is not a robust and relevant issue to determinate the post-crisis IncI dynamics.

V. Results

5.1 SBS and the redistributive effect of banking crises

Table 3 presents the results of our OLS estimates. They gradually introduce the control variables selected in section IV. We first regress *Diff.Gini* on *SBSindex*, we then introduced the two control variables which were not selected based on the BMA (*GDPcap* and *Ginipre-crisis*). The following estimates introduce – first separately and then jointly – the two sets of control variables selected with the BMA. Finally, we only use the significant BMA control variables.[21]

For all the specifications, *SBSindex* is significantly and positively correlated with *Diff.Gini*. These results mean that the higher the SBS before the outbreak of a crisis, the higher the increase of IncI in the medium term. Both level and significance of correlation between SBS and the redistributive impact of banking crises are robust to a broad range of control variables based on the BMA selection process – see columns (4) and (5). The suppression of the insignificant control variables – see column (6) – does not modify the effect of SBS on IncI dynamics. It brings the evidence that this specification is the relevant one to discuss our results. Based on this, it means that a 1% increase in *SBSindex* leads three years latter to an increase of 0.03 units in the Gini coefficient. This effect is significant: the doubling of *SBSindex* would cause in the medium

[21] Column (6) of Table 3 represents the basic specification of our econometric model. It will be used for the following estimates in this article. It may leads to a slight decrease in the explanatory power of our model compared with the specification presented in column 5 which includes all the control variables. However, given our limited sample size, the inclusion in the reference model of the only significant control variables allows us to ensure a greater accuracy for our estimates and also sufficient degrees of freedom.

term an increase of 3 units for *Diff.Gini*. This scenario is also likely to occur during the upward phase of the financial cycle preceding the outbreak of banking crises.

Table 3. Size of the banking sector and the redistributive effect of banking crises

	Diff.Gini					
	(1)	(2)	(3)	(4)	(5)	(6)
SBSindex	0.927**	1.375*	1.224*	2.862***	2.725***	3.021***
	[0.384]	[0.703]	[0.623]	[0.899]	[0.721]	[0.835]
GDPcap (t-1)		-0.822**	-0.831*	-0.666	-0.575	-0.772**
		[0.409]	[0.459]	[0.400]	[0.391]	[0.339]
Ginipre-crisis		-4.272***	-4.311***	-4.395***	-4.709***	-4.434***
		[1.430]	[1.594]	[1.415]	[1.552]	[1.508]
Population (t-1)			0.212		0.346	
			[0.192]		[0.226]	
Dependency ratio (t-1)			-1.879		1.149	
			[4.824]		[4.317]	
World crisis (t)				0.179***	0.196***	0.191***
				[0.0573]	[0.0730]	[0.0532]
Regional crisis (t)				-0.406***	-0.403***	-0.442***
				[0.118]	[0.109]	[0.105]
Liquidity				0.708**	0.780***	0.711**
				[0.296]	[0.287]	[0.281]
Public debt				-0.0973	-0.0945	
				[0.114]	[0.122]	
Regional GDP growth post				0.265	0.252	
				[0.428]	[0.420]	
Crises	69	69	68	68	67	68
Countries	54	54	53	53	52	53
R^2	0.07	0.19	0.22	0.38	0.42	0.36
SCR	2.26	2.14	2.14	1.96	1.93	1.95
Fisher stat.	5.82	4.59	3.08	3.80	4.57	4.45
Fisher p-value	0.02	0.01	0.02	0.00	0.00	0.00
AIC	310.13	304.57	302.40	292.88	288.23	290.63
BIC	314.60	313.51	315.72	312.86	312.48	306.16

Note: The coefficients represent the marginal effects. The standard deviations associated with each estimated coefficient are given in square brackets and are robust to within-country correlations. R^2 and SCR respectively correspond to the coefficient of determination and the sum of the squared residuals. Fisher stat. and Fisher p-value correspond to Fisher's overall significance test of explanatory variables. AIC and BIC are the Akaike and Bayesian information criteria. ***p<0.01, **p<0.05, *p<0.1.

The results shown in Table 3 seem to confirm the analysis made earlier in Section II. SBS amplifies the recessive dynamics of banking crises since it fosters the pro-cyclicity of the financial sector – real economy relationship. Considering that crisis mainly impact the poorest households, the result is an increase in IncI which is due to difficulty in accessing credit, an increase in unemployment rate, a weakening of the exchange rate, and the implementation of strict fiscal austerity policies. Instead of having a counter-cyclical effect on IncI, our results suggest that SBS tends to strengthen income concentration after the outbreak of a banking crisis.

5.2 Accounting for potential sources of endogeneity

In order to capture different potential sources of endogeneity, three methods are implemented: we account for regional unobservable heterogeneity, we remove the control variables that might be responsible for simultaneity bias, and we estimate the model using Two-Stage Least Squares (TSLS). The results of these estimates are presented in Table 4.

To capture the regional unobservable heterogeneity, we introduce dummy variables associated with the six main regions the countries in our sample belong to.[22] They differ in terms of economic development, quality of institutions, redistributive policy, political stability and degree of financial liberalization. These factors may influence both the redistributive impact of banking crises and SBS. The results in Table 4 column (1) shows that the regional unobservable heterogeneity does not affect the effect of *SBSindex*, that is still significant, positive and with a magnitude very close to that obtained in Table 3.

We also control for a potential simultaneity bias related to the *Liquidity* control variable. Indeed banking crises of high recessive intensity, which potentially strongly impact IncI, usually lead to public interventions targeting financial institutions, in order to provide them with liquidity. In our sample, the correlation between *Liquidity* and *SBSindex* equals -0.29 and is significant at 5%. This simultaneity bias could cause the endogeneity of the *SBSindex* variable. In column (2) of Table 4, we have re-estimated the model by removing the *Liquidity* variable. The results show that the effect of *SBSindex* remains significant, positive and with a magnitude very close to that obtained in Table 3. It suggests the absence of a simultaneity bias in the *Liquidity* variable.

We finally control for the potential endogeneity of *SBSindex* based on TSLS. Many elements *a priori* suggest that this variable may suffer from endogeneity. First, due to the limited size of our sample, the parsimony of our model may lead to the omission of relevant explanatory variables. If the latter are correlated with *SBSindex* it would be a source of endogeneity. Second, due to the relative inertia in income distribution, the *Diff.Gini* variable at time *t* may be correlated with *SBSindex*. As pinpointed by Bazillier & Héricourt (2017), several recent researches show that IncI are one of the factors contributing to explain SBS dynamics in developed countries and in some emerging ones. In this case, there is a risk of simultaneity bias between *Diff.Gini* and *SBSindex*. Third, since *SBSindex* is assessed through a PCA, it may be a biased measurement of SBS, and thus could be correlated with the error term in the model.

Following the empirical literature on both determinants and macroeconomic effects of financial development, our instrumentation strategy is based on the long-term institutional determinants of financial development. We use 7 candidate instrument variables, grouped in 4 categories: quality of economic institutions, legal origin, religion, and geographical location. Table C1 in Appendix 3 gives the definition and source of these variables.[23] We now must determinate the two instrumental variables having the highest explanatory power for our model to be

[22] Starting from World Bank's classification, the six regions we consider are: Eastern and Pacific Asia, Central and Eastern Europe & Central Asia, Northern Africa & Middle East, Sub-Saharan Africa, Latin America & Caribbean, and Western Europe & North America. Western Europe & North America were grouped because of their economic development and institutional proximity, and because of their strong exposure to the subprime mortgage crisis.

[23] For the sake of brevity, for a thorough discussion about the theoretical background of these different categories of instrumental variables, see in particular the work of Levine (2005), McCaig & Stengos (2005), Beck (2011), Jacquet & Pollin (2012).

overidentified. Table C2 in Appendix 3 indicates that *Latitude* has the highest correlation with *SBSindex* (0.60, significant at 1%). It means that the greater the distance to the equator, the higher SBS is. The *Cred. Right* variable has a correlation of 0.27 which is significant at 5%. This means that better creditor protection is associated with higher SBS. Finally, to a lesser extent, *Civil Law* has a correlation of -0.22 which is significant at 5%. This indicates that countries with a French legal origin (*Civil Law*) have on average a lower SBS. The other instrumental variables are not significantly correlated with *SBSindex*.

Given these results and in order to rigorously select the two variables used to instrument *SBSindex* we apply the BMA methodology developed by De Luca & Magnus (2011) presented above in section IV. Since the *Latitude* variable stands out in terms of correlation, it is the only one included in the "*focus regressors*" category. The other variables, which are weakly or not significantly correlated with *SBSindex*, belong to "*doubtful regressors*" category. Column (1) of Table C3 in Appendix 3 gives the results of the BMA used to select instrumental variables. The *Cred. Rights* variable has a higher PIP (41%) than the other ones. The PIPs of the *Protestant* and *Civil Law* variables respectively equal 34% and 32%. The other variables exhibit lower PIPs below 20%. Given these results, the only two instrumental variables we use to account for a potential endogeneity of *SBSindex* are *Latitude* and *Cred. Rights*.[24]

Columns (3) and (4) of Table 4 give the results of our TSLS estimates.[25] The first point to note is that, according to the Hausman test, *SBSindex* is exogenous. Thus the effects of *SBSindex* on the redistributive impact of banking crises (Table 3) does not seem to be subject to endogeneity. We also note that our instrumentation strategy is relevant since the Sargan and Hansen tests both validate the exogeneity of the instrumental variables. Finally, we notice that the instrumentation of *SBSindex* leads to a slight increase in its estimated coefficient compared with the one reported in Table 3. This increased effect of *SBSindex* obtained with TSLS does not come from the sample downsizing caused due to use of both *Latitude* and *Cred. Rights* variables. Indeed, in column (5) of Table 4, we have re-estimated the reference model associated with column (6) of Table 3 and that based on sample of 60 observations of our TSLS estimates. We clearly notice that the estimated effect of *SBSindex* remains unchanged.

[24] Column (2) of Table C3 (Appendix 3) presents the results of the OLS regression of *SBSindex* on *Latitude* and *Cred. Rights*. The explanatory power of these two variables is satisfactory, since its captures nearly 40% of the *SBSindex* variance.
[25] In Table 4, estimates in columns (3) and (4) are respectively made under the assumption of error homoscedasticity and error heteroskedasticity.

Table 4. Accounting for different potential sources of endogeneity

	Diff.Gini				
	(1)	(2)	(3)	(4)	(5)
SBSindex	2.793***	2.321***	4.470**	4.470**	3.144***
	[0.707]	[0.781]	[2.272]	[2.262]	[0.828]
GDPcap (t-1)	-0.784*	-0.711**	-1.043***	-1.043**	-0.860**
	[0.419]	[0.348]	[0.405]	[0.443]	[0.332]
Gini pre-crisis	-4.690***	-3.639**	-3.845**	-3.845**	-4.364***
	[1.591]	[1.397]	[1.727]	[1.728]	[1.530]
World crisis (t)	0.280***	0.156***	0.333***	0.333***	0.274***
	[0.0829]	[0.0521]	[0.129]	[0.123]	[0.0774]
Regional crisis (t)	-0.541***	-0.335***	-0.643**	-0.643***	-0.514***
	[0.141]	[0.0972]	[0.250]	[0.245]	[0.127]
Liquidity	0.721*		0.936**	0.936***	0.766***
	[0.363]		[0.385]	[0.336]	[0.278]
Regional dummies	Yes	No	No	No	No
Crises	68	69	60	60	60
Countries	53	54	46	46	46
R^2	0.41	0.28	0.38	0.38	0.42
SCR	1.98	2.05	1.83	1.83	1.9
Fisher stat.		4.17			4.78
Fisher p-value		0.00			0.00
Wald stat.			25.62	22.45	
Wald stat. p-value			0.00	0.00	
AIC	295.44	300.59			253.58
BIC	322.08	314			268.24
Hausman test			0.56	0.55	
Sargan test			0.89		
Hansen test				0.9	

Note: The coefficients represent the marginal effects. The standard deviations associated with each estimated coefficient are given in square brackets and are robust to within-country correlations. R^2 and SCR respectively correspond to the coefficient of determination and the sum of the squared residuals. Fisher stat. and Fisher p-value correspond to Fisher's overall significance test of explanatory variables. Wald stat. and Wald p-value correspond to the Wald significance test for the explanatory variables in the model estimated with the TSLS. AIC and BIC are the Akaike and Bayesian information criteria. Hausman test corresponds to the p-value of the Hausman endogeneity test for the *SBSindex* variable. Sargan test (Hansen test) reports the p-value of the Sargan (Hansen) test of the exogeneity for the instrumental variables included in a model estimated with the TSLS with homoscedastic (heteroscedastic) errors. ***p<0.01, **p<0.05, *p<0.1.

VI. Robustness

We now check the robustness of the results presented in Table 3 and that following three methods. First, we introduce alternative measures for both the redistributive impact of banking crises and SBS. Second, we take into account two additional characteristics of financial systems, namely the degree of liberalization and the level of development of the stock market. We also introduce all the control variables that were not included in our estimates presented in section IV. Third, we use two alternative estimation methods and modify the sample structure to account for potential measurement errors about the dependent variable and outliers.

6.1 Alternative measures for dependent and interest variables

The measurement of the post crisis increase in IncI (*Diff.Gini*) may be overstated if IncI start to grow before the crisis. It was the case, for instance, in the United States and Europe during the years preceding the subprime mortgage crisis. To capture this, we define a *Diff.Gini2* variable equal to the difference between the Gini coefficients observed at $t + 3$ and $t - 1$.[26] On

[26] *Diff.Gini2* increases the risk of a simultaneity bias since *SBSindex* is also assessed the year before a banking crisis.

the other hand, when mechanisms increasing IncI come into play, limiting the window of observation at $t + 3$ may lead to underestimate the redistributive impact of banking crises. For instance it can be the implementation of more strict fiscal austerity policies due to a prolonged economic crisis. To capture this, we define a *Diff.Gini3* variable equal to the difference between the Gini coefficients observed at $t + 5$ and t.[27] Finally, to simultaneously take into account the former issues, we define a *Diff.Gini4* variable equal to the difference between the Gini coefficients at $t + 5$ and $t - 1$.

Concerning *SBSindex*, as we saw above in section 2.2, the structure of correlation of the *Credit-to-Deposits* variable is different from that of the other five variables used to assess SBS. To ensure robustness, we calculate *SBSindex2* as the first factor derived from a PCA based on all the SBS candidate variables apart from the *Credits-to-Deposits* variable. The results shown in Table D1 of Appendix 4 confirm the interest of this alternative approach since the explanatory power of the new composite indicator is greater, 79% of the total variance is explained by the first factor. On the other hand, the measurement of *SBSindex* the year before the crisis may lead to an overstatement of SBS, since it relates to the pre-crisis upward phase of the financial cycle which may be a source of speculative bubble. We therefore calculate *SBSindex3* based on the average value of all SBS variables over the three years before the outbreak of the crisis. Table D1 in Appendix 4 reports the results of this new PCA and confirms the relevance of using a SBS composite indicator.[28]

The results presented in Table D3 (Appendix 4) clearly show that taking into account alternative measures for both the redistributive impact of banking crises and SBS does not modify the findings reported in Table 3. SBS still induces a significant increase in IncI following banking crises and the magnitude of the effect is quite similar.

6.2 Accounting for additional control variables

This section first takes into account two additional characteristics of financial systems that may be correlated with both SBS and the redistributive impact of banking crises, namely the degree of liberalization and stock market development. Financial systems characterized by a high degree of liberalization are associated with strong competition among financial institutions. This may encourage risk-taking and thus lead, during the upward phase of the financial cycle, to a rapid growth in both credit and asset prices (Kaminsky & Reinhart, 1999, Reinhart & Rogoff, 2009). The subsequent financial fragility may cause banking crises with severe recessionary consequences and an increase in IncI. Similarly, in financial systems with developed stock markets the wealth of economic agent is more sensitive to asset prices fluctuations (Rajan 2005, IMF 2006). This strongly influence the conditions of access to credit and may strengthen the recessionary impact of banking crises due to greater instability in credit supply and also to broad deleveraging operations. This again may increase the effects of banking crises on IncI.

[27] In the following countries the Solt's (2014) SWIID data is only available until 2012: Germany, Belgium, France, Greece, Ireland, Kazakhstan, Luxembourg, the Netherlands, Portugal, Sweden, and Switzerland. To include these countries in the sample, the Gini coefficient at $t + 5$ (2013) is extrapolated from the one observed at $t + 4$ (2012), based on the average growth rate of the Gini coefficient between t and $t + 4$.
[28] Table D2 in Appendix 4 provides the descriptive statistics for these alternative measures of both dependent and independent variables.

More than SBS itself, financial liberalization and stock market development can thus play an important role in the amplification of the redistributive effect of banking crises. To capture that, we select three variables measured the year before crisis starts (as for *SBSindex*).[29]

The *Financial lib.* variable measuring the degree of financial liberalization is based on the Abiad *et al.* (2008) index. It accounts for the internal dimension of financial liberalization policies. The *Financial open.* variable measures the *de jure* opening of the capital account provided by Chinn & Ito (2011). It captures the external dimension of financial liberalization policies. Stock market development is assessed through the *SMindex* composite index. It is based on the first factor derived from a PCA applied to three variables taken from the GFDD World Bank database (2016). They proxy both size and activity of stock markets: *Capitalization* (stock market capitalization-to-GDP), *Liquidity* (stock market total value traded-to-GDP) and *Turnover ratio* (*Liquidity/Capitalization*).[30]

The results in Table D8 (Appendix 4) show that the *Financial lib.*, *Financial open.*, and *SMindex* variables do not have a significant influence on the redistributive impact of banking crises.[31] On the other hand, for all the specifications *SBSindex* is still significantly and positively correlated with the redistributive impact of banking crises. For *SMindex* the magnitude is slightly smaller. It is important to notice that the estimates related to the financial liberalization variables suggest that the size of the banking system plays a greater redistributive role than the financial system organization (liberalization versus financial repression).

We then sequentially introduce all the control variables reported in Table 2 that were not included in the reference model based on the BMA estimates (section 4.2). The results presented in Tables D9a-D9b (Appendix 4) bring the empirical evidence that, unless rare exceptions, they do not have a significant effect on IncI dynamics. Whatever the specification, we also note that a rise in *SBSindex* still leads to a significant increase in the redistributive impact of banking crises. The estimated magnitude is very similar to that of the results given in Table 3.[32]

6.3 Alternative estimation methods and database structure

As previously mentioned, SWIID Gini coefficients are estimated. Although we accounted for the uncertainty associated with their calculation when we designed our sample, we now go one step further and use Weighted Least Square (WLS) based on the methodology employed by Furceri & Loungani (2015). Following the selection procedure presented earlier in section 3.1, the observations are weighted on the basis of the standard deviation of Gini coefficients between $t-3$ to $t+3$, where t is the year the crisis starts. Additionally, despite we have carefully assessed the

[29] Table D4 in Appendix 4 gives the definition of these variables and Table D7 their descriptive statistics.

[30] Tables D5 and D6 in Appendix 4 show that the use of a PCA to calculate a composite indicator of stock market development is particularly appropriate since these variables are significantly correlated and also because the first factor captures 75 % of their variance.

[31] As for *SBSindex*, to take into account potential outliers for both *Financial open.* and *SMindex* variables, we apply the Kumar *et al.* (2003) transformation presented above in section 2.2.

[32] Column (3) in Table D9b (Appendix 4) suggests that, contrary to the estimates made with the BMA in Table 2, the *Multiple Crises* variable is significantly and positively correlated with the redistributive impact of banking crises. Countries experiencing several banking crises exhibit a greater increase in IncI than countries experiencing a single one. This result seems logical since countries (especially developing countries such as Latin America ones) which, over the last three decades, have suffered several banking crises, have macroeconomic and institutional characteristics that expose them to financial instability and to a severe recessive dynamics following banking crises. These factors are likely to increase IncI.

impact of extreme values in explanatory variables –using the Kumar *et al.* (2003) transformation–, we also check our findings with the implementation of a *Robust Regression*.[33]

The results of these estimates are given in columns (1) and (2) of Table D10 (Appendix 4). We notice that *SBSindex* is still significantly and positively correlated with *Diff.Gini*. However the magnitude is lower than the one obtained in our first results.

Finally, the sample is modified through consideration of SWIID Gini coefficients with lower uncertainty associated with their calculation. In reference to the methodology used in section 3.1, the sample now only includes banking crises associated with a Gini coefficient having standard deviations below 2.5 between $t-3$ to $t+3$.[34] The results associated with this new sample are presented in the column (3) of Table D10 (Appendix 4). They clearly show that *SBSindex* significantly increases IncI dynamics. The magnitude is very similar to that obtained in the regressions presented in Table 3.

VII. Heterogeneities in the effect of SBS on the redistributive consequences of banking crises

In this section, we extend our econometric analysis to investigate a potential non-linear dynamics between SBS and the redistributive consequences of banking crises, as well as a possible heterogeneity depending on the level of economic development.

7.1 Accounting for non-linearity in the effect of SBS

Several econometric studies, such as that of Kim & Lin (2011), highlight a nonlinear effect of SBS on IncI. We now consider this potential nonlinear effect of SBS on the dynamics of IncI following banking crises.

On the one hand, above a given size threshold, the banking system benefits from less information asymmetries on the credit market and from better risk diversification (Levine, 2005). This would ease the access to the credit market for the poorest household, whose revenues are particularly affected by the economic slowdown accompanying banking crises. It can contribute as a result to the reduction of IncI.

On the other hand, a significant increase in SBS can tend to make credit allocation less productive and more speculative (Beck, 2011). This leads to an increase in the risk taking behavior of financial intermediaries and as a consequence to an increase in their financial fragility in case of financial downturn. This leads to a less resilient banking system following crisis. In this situation, the credit supply may sharply contract, causing a severe decrease in activity, as well as a lower capacity for the poorest households to borrow in order to mitigate reduced incomes. This would in turn cause an increase in IncI.

The existence of a nonlinear effect of SBS on the redistributive impact of banking crises is not clear and we therefore need to investigate it empirically. For this, we introduce in our

[33] It is thus necessary to make a WLS estimate where observations are weighted on the basis of the absolute value of the predicted standardized errors taken from our model.

[34] This leads us to drop the nine following banking crises: Central African Republic (1995), Cape Verde (1993), Egypt (1980), Guinea Bissau (1995), Indonesia (1997), Mexico (1981,) Nigeria (1991), Turkey (1982), and Zambia (1995).

model a quadratic form for our composite SBS indicator (*SBSindex*^{2}).[35] The results are given in column (1) of Table 5 and it clearly appears that *SBSindex*^{2} is not significant. The estimated coefficient of *SBSindex* remains significantly positive. Its magnitude is slightly higher than that obtained in Table 3. These results therefore suggest that the effect of SBS on the IncI dynamics is linear.

7.2 Accounting for economic development heterogeneity

According to Greenwood & Jovanovic (1990), the level of economic development leads to an heterogeneity in the link between banking sector development and IncI. We therefore need to know if the effect of SBS on IncI dynamics is different depending on the level of economic development.

For developing countries (DCs), some characteristics of financial system may increase the recessionary impact of banking crises and thus foster IncI. The first characteristic is a greater dependency of agents on the banking sector in obtaining financing. It is due to a less developed capital market (Levine, 2005). The second characteristic is a rapid and late implementation of financial liberalization policies and that in an institutional context of weak regulation and weak supervision of financial systems (Demirguc-Kunt & Detragiache, 1998, 2005, Kaminsky & Reinhart, 1999, Reinhart & Rogoff, 2009). The third characteristic is a greater pro-cyclicality in the access to external financing (Eichengreen *et al.*, 2003, Reinhart & Rogoff, 2011). It strengthens the contraction in credit supply following a banking crisis. These characteristics all argue in favor of more stringent effects of banking crises on IncI in DCs, especially since governments have lesser prerogatives in terms of redistributive policies and social insurance (Atkinson, 2015).

In developed countries (DVs), financial systems are larger, more complex and more interconnected (Rajan, 2005, Laeven, 2011). They also have prudential regulation standards leading to more pro-cyclicality and they also are characterized by an increased interdependence between markets and financial intermediaries. The characteristics of financial systems in DVs may thus increase the recessionary impact of banking crises on IncI. However, compared with DCs, DVs governments have additional competencies in the areas of redistributive policies and social insurance. This allows them to mitigate more efficiently the effect of banking crises on IncI.

We notice that the institutional and macroeconomic characteristics of DCs may lead to a greater effect of SBS on the redistributive impact of banking crises. To empirically test this assumption, we define a *SBSindexDC* dummy variable taking the values of *SBSindex* if a banking crisis occurs in a DC (46 countries following the World Bank classification) and the value 0 otherwise, and a variable *SBSindexDV* taking the values of *SBSindex* if a banking crisis occurs in a DV (23 countries following the World Bank classification) and the value 0 otherwise. These variables replace *SBSindex* in the model.[36] In column (2) of Table 5, we first notice that a rise in SBS causes a significant increase in IncI in both DCs and DVs. However, the effect of *SBSindex*

[35] We are aware that a more precise approach of non-linearity would have required the estimation of a threshold regression model as formulated for instance by Hansen (1996, 2000). However, given the limited size of the sample, the estimates of this model are not convergent.

[36] Given the limited size of our sample, we have decided not to make sub-sample estimates based on the level of economic development. The advantage of our approach is that we take into account the effect of economic development in the relationship between SBS and the redistributive impact of banking crises, while keeping the size of our sample unchanged.

on the redistributive impact of banking crises is clearly greater in DC. This confirms the earlier hypothesis that both the institutional and macroeconomic characteristics of DCs lead to a stronger effect of SBS on IncI dynamics.

Table 5. Accounting for heterogeneities in the effect of SBS on the redistributive consequence of banking crises

	Diff.Gini	
	(1)	(2)
SBSindex	3.455***	
	[0.980]	
SBSindex²	-0.665	
	[0.553]	
SBSindexDC		3.729***
		[1.098]
SBSindexDV		2.250***
		[0.799]
Controls	Yes	Yes
Crises	68	68
Countries	53	53
R^2	0.37	0.38
SCR	1.95	1.94
Fisher stat.	4.04	3.94
Fisher p-value	0.00	0
AIC	291.13	290.92
BIC	308.88	308.67

Note: The coefficients represent the marginal effects. The standard deviations associated with each estimated coefficient are given in square brackets and are robust to within-country correlations. R^2 and SCR respectively correspond to the coefficient of determination and the sum of the squared residuals. Fisher stat. and Fisher p-value correspond to Fisher's overall significance test. AIC and BIC are the Akaike and Bayesian information criteria. ***p<0.01, **p<0.05, *p<0.1.

VIII. Conclusion

Several empirical studies stress the central role played by both SBS and banking crises in the dynamics of IncI. To our knowledge, no study has linked these three elements with the objective of investigating the amplifying effect of SBS on IncI following banking crises. This is a particularly important issue given the significant expansion in the size of financial institutions which preceded the subprime mortgage crisis, a constant phenomenon accompanying the increase in IncI.

Based on a set of 69 banking crises that occurred in 54 countries over the period from 1977 to 2013, the objective of this article was to assess the effect of SBS on IncI dynamics following banking crises. Using Gini coefficients, we have defined an indicator to measure the effect of banking crises on the distribution of income over the three years following their outbreak. Our metrics for SBS is a composite indicator based on a six-variable PCA that allow us to approximate the pre-crisis size of the banking sector. Given the relatively limited number of observations and in order to develop a parsimonious econometric model, the selection of control variables relies on a BMA. The estimates are made with the OLS estimator.

Our findings highlight that SBS significantly increases IncI following banking crises. This result is robust to sensitivity analyses including: control for endogeneity, alternative metrics for SBS, alternative methods of estimation, effects of outliers, and introduction of a large number of additional determinants explaining the redistributive impact of banking crises. We also show that the effect of SBS remains unchanged when introducing variables capturing the level of financial liberalization and the development of stock markets. Finally further estimates bring the evidence that the relationship between SBS and the redistributive impact of banking crises is nonlinear and stronger in developing countries.

The results obtained in our article are insightful since they show that beyond the amplifying effect of SBS on the real economy cost of banking crises, SBS can also leads to an increase in IncI after their outbreak. In this regard, by reinforcing the pro-cyclical nature of the relationship between the financial sector and the real economy, SBS amplifies the recessive dynamics subsequent to banking crises. They mainly impact the poorest households, notably through deterioration in the conditions of access to the credit market, rise in the unemployment rate, weakening of the exchange rate, and implementation of policies of strict fiscal austerity. Instead of playing a useful counter-cyclical role, SBS results in an increase in IncI.

Over the last three decades, many DVs and DCs have been experiencing significant growth in their financial sector, higher risk exposure to financial crises, and expansion of IncI. Given the strong interdependence between these three factors (Bazillier & Héricourt, 2017), one major implication of our work is to emphasize the risk related to the amplifying effect of SBS. It can lead to a vicious circle ranging from a rise in IncI to an increase in the frequency of financial crises, through a development of the size of the banking sector. Such a dynamics has negative consequences for political and social stability, and long-term economic growth. Therefore, if governments are prone to mitigate the effects of banking crises on income distribution, our findings suggest that the banking sector need tougher regulations aimed at reducing its size during the upward phase of the financial cycle.

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