Does more finance mean more inequality in times of crisis ?

Clément Mathonnat, Benjamin Williams

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Clément Mathonnat[#] and Benjamin Williams[*]

Abstract

Many recent empirical studies show that both banking crises and financial development (FD) play an important role to understand the dynamics of income inequality (IncI) over the last decades. However, no study has so far investigated the role of FD in the amplification of IncI following 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 suggests that FD is associated with a significant increase in IncI in the aftermath of banking crises. This result is robust to a broad range of alternative specifications and is unaffected by various potential sources of endogeneity. We also show that the relationship between FD and the redistributive consequences of banking crises is not subject to a threshold effect and is stronger for developing countries.

Keywords: financial development; banking crises; income inequality

JEL codes: F30; G01; E25

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I. Introduction

In its 2013 report, "*Crisis squeezes income and puts pressure on inequality and poverty*", OECD shows that, between 2007 and 2010, the subprime crisis caused a sharp increase in income inequality (IncI) in most developed and emerging countries. This crisis has spread in an international context characterized by an important surge in financial development (FD), especially in developed countries. This was notably due to the rise of financial innovation and the implementation of financial liberalization policies beginning in the 1980s (Claessens *et al.*, 2010; Pomfret, 2010). This has led to a sharp increase in loans and financial assets held by banks, as well as a surge in the debt level. Far from supporting financial stability, the deepening of financial systems has been associated with large bubbles in the real estate market of several developed countries, whose bursting generated large losses for banks and triggered an unprecedented banking crisis with adverse recessive and redistributive consequences. Given the increase in IncI following the subprime crisis, the question arises of the role played by FD in this phenomenon. For now, the empirical literature underlines the key influence of FD and banking crises in the dynamics of IncI (Bazillier & Héricourt, 2017) but, to our knowledge, no study has so far linked these three elements together to get a better insight on the determinants of the redistributive consequences of banking crises. This is the objective of this paper, which proposes a new empirical approach that aims to assess the role played by FD in the dynamics of IncI following banking crises.

FD may influence the redistributive impact of banking crises both positively and negatively. On the one hand, FD can increase the resilience of an economy to shocks by alleviating firms' cash constraints and reducing the dependence of financial contracts on borrowers' net worth (Beck *et al.*, 2014). In times of crisis, this can mitigate the rise in unemployment and enable households to smooth their income. This in turn may limit the rise in IncI, since the poorest households are more vulnerable to cyclical downturn and more financially constraints. On the other hand, by reinforcing the interdependence between the financial sector and the real economy, FD may entail a greater sensitivity of financial intermediaries to shocks (Rajan, 2005). This can lead to banking crises with important recessive consequences that can increase IncI due to a worsening in the access to credit and higher unemployment risk for the most fragile population categories.

To evaluate the role played by FD in the dynamics of IncI in times of crises, we use a dataset covering 69 banking crises in 54 countries over the 1977-2013 period. Since the effect of banking crises on IncI could operate rapidly, we have defined an indicator assessing the dynamics of IncI during the three years following their outbreak using Gini coefficients on household disposable income. Given the limited size of our sample, due to constrains relative to the availability of IncI data at international level, we carefully select the baseline control variables to be included in a parsimonious specification of our econometric model using a Bayesian Model Averaging. Then, we estimate the relationship between FD and IncI with OLS estimator.

Regarding FD, we account for its multidimensional nature using a composite indicator based on a principal component analysis applied to a set of variables assessing both the pre-crisis size and activity of the banking sector. When it comes to measuring FD at a macroeconomic level, most of the empirical literature has focused so far on the banking sector, using primarily the bank credit-to-GDP variable (Beck *et al.*, 2014). In our case, this approach is relevant to assess FD in an international perspective, since the banking sector still occupies a central place in the financial system of both developed and developing countries, and is also essential to explain the origins and consequences of banking crises due to the procyclical interaction between credit supply and asset prices. However, following Mathonnat & Minea (2018), instead of a single credit measure, like the bank credit-to-GDP ratio, we assess the depth of the banking sector by additionally accounting for the overall size of assets and liabilities of the banking industry, and for the liquidity risk associated with an increase in the credit supply.

Our results are as follows. First, we show that a higher level of FD is associated with a significant increase in IncI following banking crises. Our estimates thus indicate that instead of having a stabilizing effect, more developed financial systems tend to amplify IncI in the aftermath of banking crises. Second, this result remains unchanged when taking into account several potential sources of endogeneity and a large set of robustness checks. This suggests that despite a limited sample size, our estimates are particularly stable and do not depend on whether the specification considered for our econometric model or the number of observations included in each regression. Third, further estimates accounting for potential sources of heterogeneity in the effect of FD on the redistributive consequences of banking crises show that this relationship is not subject to a threshold effect and is stronger for developing countries.

In an international environment characterized by an increase in both financial instability and IncI since the subprime crisis, this paper contributes to the public debate on the role played by financial systems in the amplification of IncI. Indeed, our results suggest that FD is robustly associated with a higher wealth concentration in the aftermath of banking crises. The remainder of the paper is organized as follows. Section II reviews the literature related to the effects of banking crises on IncI and then analyzes how FD could influence IncI following banking crises. Sections III and IV describe our data and econometric methodology. Section V presents our main results and those taking into account different potential sources of endogeneity. Section VI focuses on robustness checks. Section VII extends our analysis by considering potential sources of heterogeneity in the relationship between FD and the redistributive consequences of banking crises. Section VIII concludes.

II. Literature review

2.1 From banking crises to income inequality

So far, the literature has documented five main channels explaining the effects of banking crises on IncI (Bazillier & Héricourt 2017). Three channels relates to a contraction of the financial sector's activity: 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: an increase in unemployment and the implementation of fiscal austerity policies.[1] We first consider the effects of banking crises on IncI through the dynamics of the financial sector.

First, following banking crises, asset prices (both financial assets and real estates) tend to drop due to expectations reversals and heavy asset selling made by strongly indebted agents needing liquidity (Minsky, 1986; Kindleberger, 2000). Since securities and real estates are mainly held by wealthy households, banking crises may lead to a reduction of IncI (Meyer & Sullivan, 2013; Morelli, 2014).

Second, solvency problems and liquidity shocks banks undergo may lead to a significant contraction of the credit supply (Claessens & Kose, 2013). This can particularly hurt the poorest households since they lack sufficient resources to meet banks' requirements to access credit (Demirguc-Kunt & Levine, 2009). Because the poorest households are more vulnerable to economic downturns, a significant reduction in credit supply is 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 larger will be the expansionary monetary policy implemented by the central bank to provide financial institutions with liquidity (Laeven & Valencia, 2010). This can exert downward pressure on the exchange rate and thus raises the cost of imports. In this case, and especially

[1] Some of the studies quoted in this section relate to the effect of currency crises on IncI. However, the mechanisms they highlight can also account for the effect of banking crises on IncI.

for developing countries, when this effect impacts essential goods price, like food, it can lead to significant losses for the poorest households and may increase IncI (Baldacci *et al.*, 2002).

We now consider the effects of banking crises on IncI through the real sector. First, the reduction in credit supply, accompanied by a severe decline in asset prices and a contraction of private spending, can cause a sharp decrease in aggregate demand. This might lead to an important slowdown in production and therefore to an increase in unemployment (Reinhart & Rogoff, 2009). The poorest households facing a higher risk to lose their job, due to lower skills, will be more prone to experience a decrease in their labor market income. Therefore, the upward trend in unemployment caused banking crises may entail an increase in IncI (Elsby *et al.*, 2010).

Second, the recessive effect of banking crises can lead to an increase in public spending, through the use of countercyclical fiscal policies, and to a decrease in tax revenues (Reinhart & Rogoff, 2011). In this situation, governments facing a significant increase in public debt may implement fiscal austerity policies (Reinhart, 2012). Lewis & Verhoeven (2010) show that to rebalance their budget, governments mainly target spending cuts in the social protection system. This principally impact the poorest households which are the main beneficiaries of social insurance mechanisms (Ball et al., 2013; Woo *et al.*, 2013) and represents another source of growing IncI following banking crises (Jenkins *et al*, 2013).

These mechanisms suggest that banking crises might lead on average to an increase in IncI. Only the channel of asset prices goes in the opposite direction. However, for now, there is no consensus in the empirical literature regarding the overall effect of banking crises on IncI. For example, based on a panel of 62 developed and developing countries 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 after banking crises. However, Denk & Cournede (2015) invalidate this result and show with a sample of 33 countries over the 1970-2011 period that banking crises are not a source of a significant increase in IncI.

2.2 From financial development to the redistributive effect of banking crises

Given the central role played by the dynamics of the financial sector in strengthening the recessive consequences of banking crises (Claessens & Kose, 2013), we now investigate how FD may influence the effect of banking crises on IncI. The influence FD could have on the redistributive effect of banking crises is twofold. We can distinguish *a priori* between a *stabilizing* and an *amplifying effect*.

Regarding the *stabilizing effect*, previous studies on the macroeconomic consequences of FD report that a higher level of FD is associated with an increase in the supply of loanable funds, but also to a better risk management by the banking industry (Levine, 2005). In this regard, a vast literature underlines that FD fosters a more equitable income distribution. Based on the extensive survey of Demirguc-Kunt & Levine (2009), it can be first a direct effect due to increased opportunities for the poorest households to accumulate human capital, for entrepreneurship, and to smooth shocks affecting their income. It can also be an indirect effect due to higher economic growth rate and demand for low-skilled workers. In this perspective, FD could mitigate the rise in IncI following banking crises by enabling the poorest households to stabilize their income. Regarding empirical analysis, there is no clear consensus for now about the relationship between FD and IncI (see e.g., Bazillier & Héricourt, 2017; De Haan & Sturm, 2017).

However, for this stabilizing effect to work, the banking sector must be able to ensure a stable allocation of loans, which is not the case in the aftermath of banking crises (Mishkin, 1996). Banks massively reduce their risk exposure and their credit supply, thus reinforcing the recessive impact of banking crises (Laeven, 2011). This particularly hurts the poorest households, whose incomes are more sensitive to economic turnarounds (Bazillier & Héricourt, 2017).

This leads to consider the *amplifying effect* of FD on the redistributive consequences of banking crises. The history of financial crises underlines that the procyclical dynamics of the banking sector is central to understand both the origins and consequences of banking crises.[2] The accumulation of risk relates to a self-sustaining dynamic linking credit supply and asset prices (Kindleberger, 2000). The more the size and the activity of the banking sector rise during the upward phase of the cycle, the more the increase in indebtedness feeds a surge in asset prices. A strong expansion of the banking sector may thus weaken the ability of financial intermediaries to manage information asymmetries, reduce risks, and allocate funds efficiently (Beck, 2012). When asset prices collapse, this amplifies losses incurred by banks, leads to a credit contraction, and causes a significant decline in private demand. In this context, banking crises have greater recessive consequences that in turn amplify the adverse effect of the financial accelerator and debt deflation mechanisms on both the financial sector and the real economy.

[2] For recent surveys on the empirical literature dealing with the determinants of banking crises and their economic consequences see Kauko (2014) and Wilms *et al.* (2018) respectively.

When the credit market suffers from information asymmetries, the financial accelerator theory (see e.g., Bernanke & Gertler, 1989; Kiyotaki & Moore, 1997; Bernanke *et al.*, 1999) highlights that the financial position of agents generates a procyclical dynamic in access to credit that enables to account for the depth and persistence of adverse shocks affecting their wealth. Regarding the debt deflation theory (see e.g., Fisher, 1933; Minsky, 1986), it indicates that in times of crisis, the contraction of the credit supply forces highly indebted investors to massively sell their assets to pay back their debts, leading to a significant decrease in the aggregate demand that in turn amplifies the recessive impact of the initial shock.

In this perspective, after a collapse in asset prices that significantly raises the number of defaulting borrowers, banks' balance sheet is adversely impacted. They have more difficulties to finance their activity, whether in the form of deposits or on the interbank market, which increase their financial fragility. To meet their liquidity requirements, and to deleverage, banks sell significant amounts of assets (Laeven, 2011). This reinforces the decline in asset prices and thus weakens financial intermediaries, leading to a significant contraction in the credit supply.

Due to both reduction in the credit supply and decline in asset prices, firms encounter difficulties to obtain financing. Households also have troubles in accessing credit due to a drop in real estate prices, which is the main collateral they use to obtain loans (Iacoviello, 2005). Therefore, a significant contraction in aggregate demand arises. This latter is even greater if agents are highly indebted, since they will have to cut their spending to repay their loans (Minsky, 1986). 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 affecting the health of the financial sector then begins. The growing number of defaulting borrowers and the fall in asset prices negatively affect banks' balance sheets and consequently the credit supply declines. This amplifies the recessionary spiral in which the real economy is stuck (Kindleberger, 2000). At this stage, the implementation of expansionary economic policies is necessary to limit the recessionary impact of banking crises (Claessens & Kose, 2013). This is likely to result in an increase in public debt and a weakening of the exchange rate.

Therefore, we can notice the potential role played by FD in amplifying the adverse consequences of banking crises. In light of the financial accelerator and the debt deflation theories, it may come from the strengthening of the procyclical variations affecting the credit supply caused by both the downturn of the financial cycle and the transmission to the real economy of the initial fall in asset prices. A rise in FD, in terms of size and activity of the banking sector, during the upward phase of the financial cycle, by exposing more banks to significant shocks due to asset prices decline, may thus play a role in fostering the adverse effects of banking crises. This is confirmed by several empirical analyses showing that FD, usually measured as bank credit-to-GDP, is an important determinant of the output cost of banking crises (e.g., Boyd *et al.*, 2005; Furceri & Zdzienicka, 2012 and Pesic, 2012).

As a result, a higher level of FD may lead to an amplification of the five transmission channels documented in section 2.1 explaining the effect of banking crises on IncI. Since only the asset prices channel leads to a reduction in IncI, it derives from our previous discussion the following testable hypothesis: the higher FD prior to a banking crisis, the higher the ensuing increase in IncI. The remainder of the paper aims to test this hypothesis.

III. Data

To estimate the relationship between FD and the redistributive effect of banking crises we use a sample of 69 banking crises in 54 countries over the 1977-2013 period.[3] Since the deepening of financial systems and the surge in both banking crises and IncI over the last decades concern both developed and developing countries, we decide to account for the widest possible number of countries in our analysis. Although the structure of the financial system varies significantly depending on the level of economic development, this approach can be considered as appropriate for our study since the procyclical dynamics of financial intermediaries is a key mechanism explaining the origins and consequences of banking crises in developed and developing countries. Moreover, instead of panel data, we choose to rely on a cross-section analysis, where our unit of observation is at the crisis level (not at the country level), since only 13 countries in our sample experienced more than one banking crisis over the 1977-2013 period. Indeed, we thus lack repeated crisis observations in the time dimension to consider a panel data analysis. The relevance of a cross-sectional approach is also justified by the very nature of data on income distribution, which vary slowly over time but significantly across countries.

3.1 Measuring the redistributive effect of banking crises

To assess the redistributive effect of banking crises, we first document the year of crisis outbreak using Laeven & Valencia (2013) database. To account for the counter-cyclical effect of redistributive government policies on IncI following banking crises (OECD, 2013), we measure IncI in terms of household disposable income (i.e., net IncI). In addition, following the recommendations of the Canberra group (2011), our IncI measure accounts for

[3] Table A in the Online Appendix lists countries and banking crises in our sample.

the size of households. As mentioned in section II, banking crises affect the whole distribution of income. Therefore, to capture the overall change in IncI following banking crises, we choose the Gini coefficient, which is more appropriate in this case than top-income metrics used e.g., by Atkinson & Morelli (2010) and Bordo & Meissner (2012). Using the Gini coefficient is also relevant since it is available for many countries and because it is widely used in the empirical literature studying the effect of FD on IncI (Bazillier & Héricourt, 2017).

Based on Gini coefficients, various databases measure IncI correcting for the size of households: *Luxembourg Income Study*, OECD, *Eurostat*, *Chartbook of Economic Inequality* (Atkinson & Morelli, 2014), the World Bank's *World Income Inequality Database* (WIID) and the *Standardized World Income Inequality Database* (SWIID) from Solt (2014). However, for the purpose of our analysis, Solt's SWIID is the only database including Gini coefficients based on household disposable income for a significant number of countries and periods: it includes 174 countries observed at 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 we compare the SWIID data with the crises documented by Laeven & Valencia (2013), we still get Gini coefficients based on household disposable income for 96 banking crises episodes. To obtain this high coverage, the SWIID database imputes data from the *Luxembourg Income Study* mainly based on other sources available from the WIID. Thus, the database provides a significant international coverage for Gini coefficients over a long period of time. This is the reason why our study relies on the SWIID from Solt (2014).[4]

We implement five steps to proxy for the redistributive effect of banking crises. First, we determine a time window to measure the dynamics of IncI after each banking crisis. In section II, we underlined that the channels affecting income concentration following the outbreak of banking crises tend to operate in both short and medium terms. Therefore, to try to isolate the direct consequences of banking crises on income distribution, we consider a four-year interval from the year of occurrence of each crisis (t) to the third year following its outbreak (t+3).[5] Second, we convert the 100 estimated series of Gini coefficients from the SWIID into a single serie. To this end, we compute for each country and each year the average value of these 100 series. Third, based on this new set of Gini coefficients, we drop banking crises lacking IncI data on the (t–3, t+3) interval. 21 banking crises, out of the 96

[4] The availability of the Gini coefficients in the other cited database is discussed in the Online Appendix.
[5] To account for the dynamics of IncI before banking crises, we define a pre-crisis interval, which for the sake of symmetry covers the three years preceding each crisis.

mentioned above, are thus removed from our sample. Fourth, since the SWIID data are estimated, we additionally drop the remaining banking crises with a high degree of uncertainty in the imputation process. For each country and for each year, we calculate the standard deviation of the 100 estimated series of Gini coefficients. Based on this proxy for coefficient uncertainty, we compute the average standard deviation for each period surrounding a crisis (i.e., from t–3 to t+3). To comply with a sufficient number of observations, banking crises with an average standard deviation above 3 are dropped.[6] This step results in eliminating 6 more crises, leading to a final sample that includes 69 banking crises observed in 54 countries between 1977 and 2013. Fifth, we define our measure that proxies for the effect of banking crises on IncI. Given the strong inertia of income distribution, it is important to compare two years sufficiently distant for the channels of transmission linking banking crises to IncI to operate. Thus, for each banking crisis, we measure its redistributive effect as the difference between the Gini coefficients observed in t+3 and t (hereafter *Diff.Gini*).

In the Online Appendix (OA), Table A gives the values of *Diff.Gini* for the 69 banking crises in our sample and Table B5 its descriptive statistics. Note that we do not use the average annual growth rate of the Gini coefficient between t and t+3. The strong short-term inertia in income distribution could lead to underestimate the redistributive impact of banking crises. Similarly, we do not use the cumulative annual growth rate of the Gini coefficient between t and t+3 since we want to measure IncI after being affected by the different transmission channels linking banking crises to income distribution. 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.

3.2 Measuring financial development

As outlined earlier, FD, considered through the size and the activity of the banking sector, might play a potential role in amplifying the redistributive effect of banking crises. Therefore, based on e.g., Samargandi *et al.* (2015) and Mathonnat & Minea (2018), we measure FD in a multidimensional way using 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) that aim to proxy the size and the activity of the banking industry. Each variable is measured in

[6] The choice of this value appears to be appropriate since after using different threshold values (2.5, 3, 3.5, 4 and 4.5), our results show that the majority of banking crises with a high level of uncertainty on IncI are above an average standard deviation of 3.

the year preceding the outbreak of banking crises.[7] First, *Liquid liabilities* (ratio of M3-to-GDP) captures the size of financial intermediaries' liabilities, and proxies the liquidity in the economy. Second, *Bank assets* (ratio of deposit bank assets-to-GDP) measures the size of financial intermediaries' assets, and assesses the importance of commercial banks for saving allocation and risk taking before banking crises. Third, *Bank deposits* (ratio of bank deposits-to-GDP) captures banking sector capacity to mobilize available saving. Fourth, *Assets ratio* (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 the central bank. Fifth, *Credits* (ratio of credits to the private sector by banks-to-GDP) captures the activity of financial intermediaries in their central task of channeling saving towards investment. It also proxies the effect of credit risk and captures the procyclical dynamics of the credit supply in the upward phase of the financial cycle. Sixth, *Credits/Deposits* (ratio of credits to the private sector by banks-to-deposits) measures the intermediation capacity of the banking sector, and the risk-taking behavior of financial intermediaries that may lead to an increase in liquidity risk in case of a bank panic. Table B2 in the OA reports descriptive statistics for each of these variables.

Using a PCA to compute a composite index of FD seems to be relevant in our case since Table B1 in the OA shows that, except *Credits/Deposits*, the variables used to proxy FD are highly correlated. Thus, a PCA allows not only to extract a large proportion of the variability shared by these variables, but also to avoid multicollinearity issues in our econometric analysis. Moreover, given the limited size of our sample, a PCA enables to keep the specification of our econometric model parsimonious when estimating the relationship between FD and the redistributive effect of banking crises. Table B3 in the OA gives the results of the six-variable PCA 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*, variables are highly correlated with the first factor. A small share of their variance remains unexplained, except for *Bank ratio*. This suggests the relevance of considering a composite index based on a PCA to proxy FD before banking crises.[8] Consequently, by using *FDindex*, our goal in this paper is not to assess what precise components of FD are significantly associated with the redistributive effect of banking crises. We rather want to bring preliminary insights on the relationship between the overall size and activity of the banking sector and the

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[7] As mentioned in the introduction, given the importance of the banking sector in the functioning of financial systems in both developed and developing countries, our FD measure relies on bank-based data. However, in section 6.1, we assess the robustness of our results when controlling for other features associated with the development of financial systems.

[8] In the OA, Table A gives the values of *FDindex* before each banking crisis in our sample and Table B5 its descriptive statistics.

dynamics of IncI in times of crisis. Finally, since our estimates may be highly sensitive to outliers, due to a limited sample size, we follow Kumar *et al.* (2003), and transformed our composite FD 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, while preserving its negative values and thus the size of our sample.

IV. Econometric Methodology

4.1 Model specification

To estimate the relationship between FD and the redistributive consequences of banking crises, we use the following econometric specification:

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

where *Diff.Gini* measures the dynamics of IncI following the outbreak of banking crisis *j*. *FDindex* is our composite measure of FD. *GDPcap*, *Ginipre-crisis*, *X* and *Z* are different sets of control variables. α and ε correspond respectively to the intercept and to the error term. Because we use cross-section data, a continuous dependent variable, and pre-crisis values of *FDindex*, we choose to rely primarily on OLS to estimate this model.

Since there are a large number of potential determinants competing to explain the redistributive effect of banking crises, we decide to subdivide our control variables into three broad sets.[9] The first set of control variables is associated with the *GDPcap* and *Ginipre-crisis* variables. They account for the level of economic development and IncI before banking crises. We account for these two control variables in all our estimates. The level of economic development is essential to explain the long-term dynamics of IncI (Demirguc-Kunt & Levine, 2009) and to understand the recessive consequences of banking crises (Laeven & Valencia, 2010). Moreover, given the negative consequences, at a political and social level, associated with a high level of IncI (Atkinson, 2015), it is likely that an increase in IncI following the outbreak of banking crises is made more difficult if the pre-crisis level of IncI is

[9] Table B4 in the OA gives their definitions and sources. To take into account potential outliers for these variables given the limited size of our sample, like *FDindex*, we apply the transformation of Kumar *et al.* (2003) presented in section 3.2 to all quantitative variables.

already high. This might be due to the pressures governments face to implement policies that favor a more egalitarian wealth distribution.[10]

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 FD on IncI and following e.g., Beck *et al*. (2007), Kim & Lin (2011), and Law *et al*. (2014), we select 8 variables considered as important determinants of IncI. Similarly, based on Cecchetti *et al*. (2009) and Wilms *et al*. (2018), we choose 19 variables that account for the recessive consequences of banking crises. This set includes : (i) macroeconomic, financial and institutional conditions preceding banking crises, (ii) crisis severity (e.g., is it systemic or associated with currency or sovereign debt crises?), (iii) economic policies implemented to fight banking crises, and (iv) international macroeconomic and financial conditions during each crisis ("post-crisis" variables). We do not account for macroeconomic and financial domestic conditions in the aftermath of banking crises to avoid potential simultaneity bias with IncI. Table B5 in the OA gives their descriptive statistics.

Finally, among the 54 countries in our sample, 13 experienced several banking crises over the 1977-2013 period and sometimes at narrow intervals (see Table A in the OA). Since banking crises occurring in a given country may be correlated, it is necessary to account for this effect. To this end, we use two econometric strategies. First, we systematically compute a variance-covariance matrix of estimated coefficients robust to within-country correlations. Second, among our set of control variables *Z*, we define a binary variable (*Multiple crises*) equals 1 if banking crisis *j* occurs in a country *i* with more than one banking crisis over the 1977-2013 period, and 0 otherwise.

4.2 Selecting the control variables with a Bayesian Model Averaging

Given the limited number of observations in our sample, we cannot account simultaneously for the 29 control variables presented in section 4.1. In order to specify a parsimonious model that only includes the most relevant control variables, we first resort to the Bayesian Model Averaging (BMA) econometric methodology. This allows us to determinate which variables have the highest explanatory power to account for the redistributive consequences of banking crises.

The "*model averaging*" approach allows us to take into account uncertainty associated with the specification of our econometric model. In the presence of q potential explanatory variables, the objective is to estimate the 2^q candidate models, then to calculate a weighted

[10] An alternative explanation could be that when pre-crises IncI are high, the poorest households have less to lose, and as a result, IncI would increase less following banking crises.

average of the different estimates associated with each of the q explanatory variables, and this in order to compute the effect of each of these variables on the dependent variable (Moral-Benito, 2015). In the empirical literature, BMA is widely used to implement this strategy. The logic of BMA is to set an *ex ante* (theoretical) distribution for both the different models and coefficients associated with each explanatory variable. The estimates are obtained by combining this *ex-ante* dimension with an *ex-post* (empirical) one derived from the likelihood coming from each estimated model. One key outcome of BMA is the *posterior inclusion probability* (hereafter PIP) for each explanatory variable. This is the probability of a variable to be significant among the 2^q estimated candidate models. The explanatory variables selected are those with the highest probability of inclusion.

We chose 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 included in the specification of our econometric model, and a category of explanatory variables of secondary interest (the "*doubtful regressors*" denoted as X_2).[11] Thus, the model specification for the BMA estimate is the following:

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

X_1 is the set of variables always included in the candidate models, namely *FDindex*, *GDPcap*, and *Gini$_{pre\text{-}crisis}$*. X_2 is a set of 27 additional control variables accounting for the determinants of IncI and the recessive consequences of banking crises. To avoid losing too many degrees of freedom, we split X_2 into two subsets. The first subset of X_2 includes the 8 variables associated with the FD - IncI literature and the second subset of X_2 includes the 19 variables related to the recessive consequences of banking crises. Table 1 presents the results associated with the estimates of the two BMA. At this stage, our objective is not to quantify the effect of these candidate control variables, but rather to know their sign and their probability of inclusion. To avoid burdening the presentation of the results coming from the BMA estimates, we thus only report the sign and the probability of inclusion of the candidate control variables.

Across all fitted models, we notice that their probabilities of inclusion are low (below 50%). This illustrates the difficulty to *a priori* define the most relevant variables accounting for the redistributive effect of banking crises. Table 1 shows that only 7 variables stand out

[11] Eicher *et al*. (2009) show that the choice of an *ex-ante* Zellner distribution for the coefficients with a value for the hyper-parameter g given by Fernandez *et al.* (2001) criterion, i.e., $g = \max(N, q^2)$, combined with a uniform distribution for models size, leads to better performances when implementing BMA. Therefore, we have chosen to base our BMA estimates on this *ex-ante* setting.

with a PIP ≥ 20%. They represent our initial set of control variables.[12] Among them, 4 are positively correlated with the redistributive effect of banking crisis (*Liquidity*, PIP = 0.46; *Regional GDP Growth post-crisis*, PIP = 0.32; *World Crisis (t)*, PIP = 0.26; *Pop (t–1)*, PIP = 0.25) and 3 have a negative correlation (*Regional Crisis (t)*, PIP = 0.36; *Dependency ratio (t–1)*, PIP = 0.23; *Public Debt*, PIP = 0.20).

[12] The control variables not retained at this stage are taken into account in section VI when dealing with robustness checks.

Table 1. BMA estimates to select control variables

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

Note: estimated models all include the following variables: *FDindex*, *GDPcap*, and $Gini_{pre\text{-}crisis}$. *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 average value of the coefficient associated with a given control variable, it is calculated based on all the estimated candidate models.

V. Results

5.1 Financial development and the redistributive effect of banking crises

Table 2 presents the results of our OLS estimates. They gradually introduce the control variables selected in section IV. We first regress *Diff.Gini* on *FDindex*, and then introduce the two control variables not coming from BMA estimates (*GDPcap* and $Gini_{pre\text{-}crisis}$). The following estimates introduce, first separately and then jointly, the two sets of control variables selected with BMA estimates. Finally, we only use the significant BMA control variables.

Table 2. Financial development and the redistributive effect of banking crises

	Diff.Gini					
	(1)	(2)	(3)	(4)	(5)	(6)
FDindex	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-crisis				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
RMSE	2.26	2.14	2.14	1.96	1.93	1.95
Fisher stat.	5.82	4.59	3.08	3.8	4.57	4.45
Fisher p-value	0.02	0.01	0.02	0.00	0.00	0.00
AIC	310.13	304.57	302.4	292.88	288.23	290.63
BIC	314.6	313.51	315.72	312.86	312.48	306.16

Note: coefficients displayed are marginal effects. Standard errors robust to within-country correlations are reported in brackets. R^2 and RMSE respectively correspond to the coefficient of determination and the root mean square error. Fisher stat. and Fisher p-value refer to a Fisher test of joint significance of explanatory variables. AIC and BIC are the Akaike and Bayesian information criteria. ***p<0.01, **p<0.05, *p<0.1.

Regarding control variables, results in Table 2 show that both *GDPcap* and *Ginipre-crisis* variables are significantly correlated with the redistributive impact of banking crises (except in columns (4)-(5) for *GDPcap*) and have the expected sign, suggesting that they are important to characterize the dynamics of IncI following banking crises. We also notice that the *Population* and *Dependency ratio* variables are not significant. Regarding the determinants of the recessive consequences of banking crises, 3 variables are always significantly correlated with *Diff.Gini*: *World crisis*, *Regional crisis* and *Liquidity*. The positive coefficient of *World Crisis* suggests that when financial instability materializes at an international level, the resulting economic downturn may increase IncI. Regarding *Regional crisis,* results contrast with those associated with *World crisis*, since the number of banking crises at a regional level during the year of occurrence of a banking crisis in a given country seems to be associated with a decrease in IncI. One possible interpretation is that 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 can prompt public authorities to implement preventive economic policies designed to mitigate this risk, which in turn may limit the adverse consequences of a potential banking crisis.[13] More generally, results associated with both *World crisis* and *Regional crisis* variables underline the role played by regional and international contagion in the dynamics of IncI in times of crisis. As for *Liquidity*, results suggest that the amount of liquidity provided by public authorities to financial institutions during banking crises appears to have a pro-cyclical effect on IncI. This may indicate an increase in moral hazard that encourages banks to take more risks, which ultimately could increase their losses and cause a more severe contraction of the credit supply and a deeper economic downturn. Finally, both *Public debt* and *Regional GDP growth post-crisis* are not significant regardless of the specification considered.

When dealing with the effect of FD on the redistributive consequences of banking crises, we notice that for all specifications *FDindex* is significant and positively correlated with *Diff.Gini*. These results suggest that the higher the size and the activity of the banking sector before the outbreak of a crisis, the higher the increase in IncI during the following three years. Both the magnitude and the significance of the correlation between FD and the redistributive impact of banking crises are robust to different sets of control variables coming from BMA estimates, as shown in columns (4) and (5). The suppression of the insignificant control variables in column (6) does not modify the estimated effect of FD on IncI. This suggests that this specification can be considered as the relevant one to discuss our results.[14] Based on this, a 1% increase in *FDindex* leads three years later to an increase of 0.03 units in the Gini coefficient. This effect is significant: the doubling of *FDindex* would cause in the medium term an increase of 3 units for *Diff.Gini*. This scenario is likely to occur during the upward phase of the financial cycle preceding the outbreak of banking crises. For instance, Table A in the OA shows that a 3 units increase in *Diff.Gini* corresponds to the situation experienced by Japan in the aftermath of the 1997 crisis.

Results in Table 2 seem to confirm our hypothesis of an amplifying effect of FD on the dynamics of IncI in the aftermath of banking crises. In line with the analysis presented in

[13] Despite *World crisis* and *Regional crisis* variables are highly correlated (at roughly 80%), their opposite sign effect on *Diff.Gini* is not due to a multicollinearity issue since the standard errors associated with their coefficients suggest that they are estimated in a rather precise way throughout the different specifications there are accounted for.

[14] We thus consider column (6) of Table 2 as the baseline specification of our econometric model that will be considered for the estimates presented in the rest of this paper. This specification is associated with a slight decrease in the explanatory power of our model compared with the specification presented in column 5 that includes all the control variables. However, given our limited sample size, accounting only for the significant control variables in the baseline specification allows us to ensure a greater accuracy of our estimates and sufficient degrees of freedom to estimate our model.

section II, one possible interpretation could be that an increase in the pre-crisis size and activity of the banking sector, by strengthening the pro-cyclicality of the financial sector and its relationship with the real economy, might expose more banks to significant shocks due to asset prices decline and amplify the adverse consequences of banking crises. Considering that banking crises mainly hurt the poorest households, through a worsening in the access conditions to the credit market, an increase in the unemployment rate, a weakening of the exchange rate, and the implementation of fiscal austerity policies, this might result in an increase in IncI. In this perspective, instead of having a counter-cyclical effect on IncI, our results suggest that FD could tend to magnify income concentration following banking crises.

5.2 Accounting for potential sources of endogeneity

To capture different potential sources of endogeneity, we used three methods: we account for regional unobservable heterogeneity, we remove a control variable that might be responsible for a potential simultaneity bias, and we estimate our model using Two-Stage Least Squares (TSLS). Table 3 presents the results.

To capture regional unobservable heterogeneity, we introduce dummy variables associated with the six main regions countries in our sample belong to.[15] They differ e.g., in terms of economic development, quality of institutions, redistributive policies, political stability, and degree of financial liberalization. These factors may influence both the redistributive impact of banking crises and FD. Column (1) in Table 3 shows that accounting for regional unobservable heterogeneity does not influence the estimated coefficient of *FDindex*, which is still significant, positive and with a magnitude very close to the one obtained in Table 2.

We also control for a potential simultaneity bias related to the *Liquidity* control variable. Indeed banking crises of high recessive intensity, which could strongly influence IncI, usually lead to public interventions aiming to provide financial institutions with liquidity. Since in our sample, the correlation between *Liquidity* and *FDindex* equals -0.29 and is significant at 5%, this simultaneity bias could cause the endogeneity of the *FDindex* variable. In column (2) of Table 3, we have thus re-estimated our model by removing the *Liquidity* variable. The results show that the effect of *FDindex* remains comparable with that obtained in Table 2. This suggests that any potential simultaneity bias in the *Liquidity* variable is not large enough to drive our results.

[15] Using 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.

Table 3. Accounting for different potential sources of endogeneity

	Diff.Gini				
	(1)	(2)	(3)	(4)	(5)
FDindex	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]
Ginipre-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
R²	0.41	0.28	0.38	0.38	0.42
RMSE	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				0.90	

Note: coefficients displayed are marginal effects. Standard errors robust to within-country correlations are reported in brackets. R² and RMSE respectively correspond to the coefficient of determination and the root mean square error. Fisher stat. and Fisher p-value refer to a Fisher test of joint significance of explanatory variables. AIC and BIC are the Akaike and Bayesian information criteria. Wald stat. and Wald p-value correspond to a Wald test of joint significance of explanatory variables in the model estimated by TSLS. Hausman test refers to the p-value of the Hausman endogeneity test for the *FDindex* variable. Sargan test (Hansen test) reports the p-value of the Sargan (Hansen) test of exogeneity for the instrumental variables included in the model estimated by TSLS with homoscedastic (heteroscedastic) errors. ***p<0.01, **p<0.05, *p<0.1.

Finally, we control for the potential endogeneity of *FDindex* based on TSLS. Many elements suggest *a priori* that this variable may suffer from endogeneity. First, due to the limited size of our sample, the parsimony of our econometric model may lead to the omission of relevant explanatory variables. If the latter are correlated with *FDindex*, this would be a source of endogeneity. Second, given relative inertia in income distribution, the *Diff.Gini* variable at time *t* may be correlated with *FDindex*. As pointed out by Bazillier & Héricourt (2017), several recent studies show that IncI is an important factor explaining the deepening of financial systems over the last decades in developed countries and in some emerging ones. In this case, there is a risk of simultaneity bias between *Diff.Gini* and *FDindex*. Third, since *FDindex* proxies FD through a composite indicator derived from a PCA, this may lead to a biased measurement of FD, and thus could induce a correlation between *FDindex* and the error term of our model. Following the empirical literature on both the determinants and the macroeconomic effects of FD, our instrumentation strategy relies on the long-term institutional determinants of the development of financial systems. We use 7 candidate instrumental variables, grouped in 4 categories: quality of economic institutions, legal origin, religion, and geographical location.[16] Then, we determine the two instrumental variables with the highest explanatory power for our model to be over-identified. Table C2 in the OA indicates that *Latitude* has the highest correlation with *FDindex* (60%, significant at 1%). This suggests that the greater the distance to the equator, the higher FD is, which is consistent with Beck *et al*. (2003a) stressing the importance of climate conditions in the design of institutions. The *Cred. Right* variable has a correlation of 27% (significant at 5%). Following Levine (1998), this means that better creditor protection is associated with higher levels of FD. Finally, to a lesser extent, *Civil Law* has a correlation of -22% (significant at 5%). This indicates that countries with a French legal origin (*Civil Law*) have on average a lower level of FD, which is in line with e.g., Beck *et al*. (2003b). The other instrumental variables are not significantly correlated with *FDindex*.

Based on these results, and to make a relevant selection of the two variables used to instrument *FDindex*, we resort to the BMA specification from De Luca & Magnus (2011) that we have already estimated in section IV to select our initial set of control variables. Since the *Latitude* variable stands out in terms of correlation with *FDindex*, it is the only variable included in the "*focus regressors*" category. The other variables that are weakly or not significantly correlated with *FDindex* belong to the "*doubtful regressors*" category. Column (1) of Table C3 in the OA gives the results of the BMA used to select our instrumental variables. The *Cred. Rights* variable has a higher PIP (41%) than the other ones. The PIPs of the *Protestant* and *Civil Law* variables equal 34% and 32% respectively. The other variables exhibit lower PIPs (below 20%). Given these results, the two instrumental variables we use to account for the potential endogeneity of *FDindex* are *Latitude* and *Cred. Rights*.[17]

Columns (3) and (4) in Table 3 display the results of the TSLS estimates.[18] First, based on the Hausman test, we notice that the *FDindex* variable can be considered as exogenous. Thus, the estimated relationship between *FDindex* and the redistributive impact of banking crises presented in Table 2 does not seem to be subject to endogeneity. In addition, our instrumentation strategy seems to be relevant since the Sargan and Hansen tests both validate the exogeneity of the instrumental variables. Finally, the instrumentation of *FDindex* leads to

[16] Table C1 in the OA gives the definition and source of these variables. For the sake of brevity, an in-depth discussion regarding the theoretical background of these different categories of instrumental variables can be found e.g., in Levine (2005), McCaig & Stengos (2005) and Beck (2011).

[17] Column (2) of Table C3 in the OA presents the results of the OLS regression of *FDindex* on *Latitude* and *Cred. Rights*. The explanatory power of these two variables is satisfactory since they account for nearly 40% of the variance of *FDindex*.

[18] In Table 3, estimates in columns (3) and (4) are made under the assumption of error homoscedasticity and error heteroskedasticity respectively.

a slight increase in its estimated coefficient compared with the one reported in Table 2. Note that this increase in the estimated effect of *FDindex* when using TSLS does not come from the smaller sample size due to the use of the *Latitude* and *Cred. Rights* variables. Indeed, in column (5) of Table 3, we have re-estimated the baseline specification of our model associated with column (6) of Table 2 based on the sample of 60 observations used with the TSLS estimates. We notice that the estimated effect of *FDindex* remains unchanged.

VI. Robustness

6.1 Alternative measures for dependent and interest variables

When using *Diff.Gini,* the redistributive impact of banking crises may be overstated if IncI start to grow before their outbreak.[19] The pre-crisis (*t*-1) values of the Gini coefficients would be thus more relevant to capture this phenomenon.[20] Moreover, considering only the third year following banking crises to assess their redistributive consequences might be considered as arbitrary, since it neglects the effect of banking crises on IncI over shorter (*t*+1 and *t*+2) and longer (*t*+4 and *t*+5) horizons.

To account for these two issues, we re-estimate our model where *Diff.Gini* is computed as the difference between the Gini coefficients observed at either *t*+1, t+2, *t*+3, *t*+4, or *t*+5 and *t*-1 or *t*.[21] Table 4 shows that, except *Diff.Gini t*-1 to *t*+1, accounting for these alternative measures does not modify our main results.[22] When considering the magnitude of the estimated effect of *FDindex*, one interesting result is that we have a clear temporal heterogeneity taking the form of an inverted U-shaped relationship. The effect of FD on IncI is at its minimum in *t*+1, increases in *t*+2, then reach its maximum in *t*+3 and *t*+4, and then decreases in t+5. Hence, results in Table 4 give support to the choice of considering the t to *t*+3 interval in our baseline estimates for the computation of *Diff.Gini* since it represents the time horizon where FD has a high amplification effect on IncI.[23]

Table 4. Alternative measures for the redistributive effect of banking crises

[19] See e.g., Rhee & Kim (2018) for a recent empirical analysis assessing the effect of IncI on the occurrence of banking crises.

[20] However, considering the pre-crisis values of the Gini coefficients increases the risk of simultaneity bias since *FDindex* is also assessed the year before banking crises.

[21] In the first version of this paper, we only used data from the SWIID version 5.0, where Gini coefficients of net IncI are missing for the year 2013 in the following countries: Germany, Belgium, France, Greece, Ireland, Kazakhstan, Luxembourg, Netherlands, Portugal, Russia, Sweden, and Switzerland. We now account for these countries when computing *Diff.Gini* at the *t*+5 horizon using the updated SWIID version 8.0. To keep consistent estimates of IncI within each of these countries, we used Gini coefficients of net IncI from the SWIID version 8.0 not only for the year 2013, but for all years corresponding to the time interval surrounding banking crises (including the pre-crisis *t*-3 to *t*-1 interval associated with the computation of the *Ginipre-crisis* variable).

[22] Values and descriptive statistics associated with these alternative measures of the redistributive impact of banking crises are available upon request.

[23] As an alternative dependent variable, we also test if *FDindex* influences the probability of banking crises. Based on an annual panel covering the 1973-2013 period for the 54 countries in our sample, we estimate a Panel Logit model where a dummy variable of banking crises occurrence is regressed on the one-year lag of *FDindex*, together with country and time fixed-effects. Results (available upon request) indicate that FD is associated with a significant increase in the probability of banking crises, which is in line with results obtained so far in the empirical literature emphasizing the important role of FD variables in explaining the outbreak of banking crises (see Kauko, 2014).

	Diff.Gini									
	t to t+1	**t to t+2**	**t to t+3 (baseline)**	**t to t+4**	**t to t+5**	**t-1 to t+1**	**t-1 to t+2**	**t-1 to t+3**	**t-1 to t+4**	**t-1 to t+5**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
FDindex	0.731**	1.861***	3.021***	3.103**	2.634**	0.73	1.859***	3.019***	3.101**	2.888**
	[0.358]	[0.613]	[0.835]	[1.260]	[1.191]	[0.564]	[0.695]	[0.953]	[1.298]	[1.279]
GDPcap (t-1)	-0.112	-0.423	-0.772**	-0.956*	-0.841*	-0.0345	-0.345	-0.694*	-0.879	-0.753
	[0.129]	[0.276]	[0.339]	[0.502]	[0.500]	[0.225]	[0.344]	[0.403]	[0.531]	[0.544]
Ginipre-crise	-1.775*	-2.724**	-4.434***	-5.847***	-6.548***	-1.741	-2.69	-4.400**	-5.813***	-5.647**
	[0.941]	[1.295]	[1.508]	[1.918]	[2.166]	[1.565]	[1.743]	[1.940]	[2.148]	[2.408]
World crisis (t)	0.0496*	0.114**	0.191***	0.226***	0.148*	0.05	0.114	0.192**	0.226***	0.167*
	[0.0267]	[0.0483]	[0.0532]	[0.0690]	[0.0833]	[0.0588]	[0.0688]	[0.0775]	[0.0835]	[0.0968]
Regional crisis (t)	-0.144***	-0.268***	-0.442***	-0.497***	-0.384**	-0.195**	-0.318***	-0.492***	-0.547***	-0.446**
	[0.0424]	[0.0824]	[0.105]	[0.151]	[0.166]	[0.0963]	[0.119]	[0.144]	[0.173]	[0.189]
Liquidity	0.297	0.53	0.711**	0.581	0.239	0.0736	0.306	0.487*	0.357	0.0803
	[0.179]	[0.325]	[0.281]	[0.368]	[0.348]	[0.226]	[0.256]	[0.285]	[0.339]	[0.457]
Crises	68	68	68	68	68	68	68	68	68	68
Countries	53	53	53	53	53	53	53	53	53	53
R^2	0.25	0.25	0.36	0.33	0.30	0.15	0.19	0.29	0.29	0.24
RMSE	0.85	1.60	1.95	2.44	2.57	1.46	1.98	2.39	2.78	3.04
Fisher stat.	3.63	3.24	4.45	3.57	3.24	2.39	2.69	3.43	2.85	2.51
Fisher p-value	0.00	0.00	0.00	0.00	0.00	0.04	0.02	0.01	0.02	0.03
AIC	178.19	263.92	290.63	320.77	328.14	251.12	292.25	317.87	338.65	350.97
BIC	193.73	279.46	306.16	336.31	343.68	266.66	307.79	333.41	354.18	366.51

Note: *baseline* in column (3) corresponds to the baseline estimate associated with column (6) of Table 2. Coefficients displayed are marginal effects. Standard errors robust to within-country correlations are reported in brackets. R^2 and RMSE respectively correspond to the coefficient of determination and the root mean square error. Fisher stat. and Fisher p-value refer to a Fisher test of joint significance of explanatory variables. AIC and BIC are the Akaike and Bayesian information criteria. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Regarding FD, using a composite indicator coming from a PCA to proxy for the overall size and activity of the banking sector prevents us from assessing the potential effect on IncI of each of the six FD variables we use to compute *FDindex*. In Table 5, instead of *FDindex*, we re-estimate our model by introducing these six FD variables sequentially. Variables related to both the size and the activity of the banking sector are significant and positively correlated with *Diff.Gini*, except *Credits/Deposits* and *Assets ratio* (the two variables the least correlated with *FDindex* and the other four FD variables, see section 3.2). These results do not suggest a specific correlation pattern between either the size or the activity of the banking sector and IncI following crises. This supports the relevance of considering an aggregated approach based on a PCA when estimating the relationship between FD and IncI in times of crisis. Moreover, given the non-significance of *Credits/Deposits* and *Assets ratio*, and since these variables display a smaller correlation with other FD variables, we compute *FDindex2* as the first factor derived from a PCA based only on *Liquid liabilities, Bank assets*, *Bank deposits*, and *Credits*. Column 7 of Table 5 shows that altering the composition of our aggregated FD indicator leaves our results unchanged. Besides, relying on bank credit to the private sector (*Credits*) to measure the credit supply before banking crises leads to underestimate the overall amount of credit in the economy. It does not account for non-bank credit from other financial institutions, such as e.g., insurers, pension funds and finance companies. Since non-bank credit represents an increasing proportion of the credit supply, especially in developed countries, this might influence the relationship between the financial sector and the redistributive effect of banking crises. Thus, we re-estimate our model with *FDindex3*, which corresponds to the first factor derived from a PCA based on the same set of FD variables presented in section 3.2, except we replace *Credits* by the ratio of credit to the private sector by banks and other financial institutions-to-GDP from the GFDD (2016) database. Results in column 8 of Table 5 indicate that accounting for non-bank credit does not change the estimated relationship between FD and IncI following banking crises.[24]

Table 5. Individual financial development variables and alternative FDindex measures

	Diff.Gini								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Liquid liabilities	2.127***								
	[0.669]								
Bank assets		1.737**							
		[0.653]							
Bank deposits			1.713***						
			[0.490]						
Bank ratio				0.992					
				[1.289]					
Credits					1.323**				
					[0.500]				
Credits/Deposits						0.428			
						[0.798]			
FDindex2							3.001***		
							[0.951]		
FDindex3								3.124***	
								[0.858]	
FDindex4									2.709***
									[0.856]
Controls	Yes								
Crises	68	68	68	64	68	67	68	68	68
Countries	53	53	53	50	53	53	53	53	53
R²	0.34	0.32	0.3	0.19	0.3	0.18	0.33	0.37	0.32
RMSE	1.99	2.01	2.04	2.27	2.04	2.22	1.99	1.95	2.01
Fisher stat.	4.24	3.35	4.34	2.20	3.00	1.90	4.03	4.61	3.84
Fisher p-value	0.00	0.01	0.00	0.05	0.01	0.09	0.00	0.00	0.00
AIC	292.90	294.74	296.43	293.22	296.83	303.76	293.52	290.11	294.25
BIC	308.43	310.28	311.97	308.33	312.37	319.20	309.06	305.64	309.79

Note: coefficients displayed are marginal effects. Standard errors robust to within-country correlations are reported in brackets. R² and RMSE respectively correspond to the coefficient of determination and the root mean square error. Fisher stat. and Fisher p-value refer to a Fisher test of joint significance of explanatory variables. AIC and BIC are the Akaike and Bayesian information criteria. ***p<0.01, **p<0.05, *p<0.1.

Finally, measuring *FDindex* the year before banking crises outbreak may lead to an overestimation of FD, since it relates to the pre-crisis upward phase of the financial cycle that

[24] In addition, instead of *FDindex*, we re-estimate our model by introducing only the ratio of credit to the private sector by banks and other financial institutions-to-GDP. Results (available upon request) are identical to those obtained in column (5) of Table 5 with the *Credits* variable. This result comes from the fact that the correlation between these two credit variables is very high (95%), suggesting that focusing on the banking sector is relevant to proxy for the overall credit supply before banking crises.

may be associated speculative bubble. We therefore calculate *FDindex4* based on the average value of all our baseline FD variables during the three years before banking crises. Results in column 9 of Table 5 suggest that our main results are unchanged when accounting for this additional alternative measure of the pre-crisis level of FD.[25]

6.2 Accounting for additional control variables

We begin by accounting for several other characteristics of financial systems that may be correlated with both the size and the activity of the banking sector and the redistributive impact of banking crises.

First, highly liberalized financial systems are associated with strong competition among financial institutions. This may encourage risk-taking and lead to a rapid growth in credit and asset prices during the upward phase of the financial cycle (Kaminsky & Reinhart, 1999, Reinhart & Rogoff, 2009), with a subsequent increase in financial fragility that may cause banking crises with severe recessive and redistributive consequences. To account for this, we use the *Financial lib.* variable for the internal dimension of financial liberalization policies (i.e., the extent of liberalization of the domestic financial system) based on the Abiad *et al.* (2008) index, and the *Financial open.* variable for the external dimension of financial liberalization policies (i.e., the openness of an economy to foreign capital flows) based on the *de jure* measure of capital account openness from Chinn & Ito (2011).

Second, the bank-based approach of FD we use may appear restrictive to capture the overall level of development of financial systems. Especially, in developed countries, where institutional investors and financial markets experienced an important expansion over the last decades (Beck *et al.*, 2014). Due to their key role in the functioning of modern financial systems, the overall size of financial institutions and financial markets may play a potential role in explaining IncI following banking crises. Based on the IMF's *Financial Development Index Database* (Svirydzenka, 2016), we use two composite indicators that proxy for the overall size of financial institutions (*Size financial institutions*) and financial markets (*Size financial markets*). We also account for the overall size of financial systems with the variable *Size financial systems*, which corresponds to the sum of *Size financial institutions* and *Size financial markets*.

Third, as pointed out by Gambacorta *et al.* (2014), bank-based financial systems are associated with a higher output cost of financial crises compared to market-based ones. Given that *FDindex* focuses on the banking sector, we have to make sure that our main results do not

[25] Results from the PCA used to compute *FDindex2*, *FDindex3*, and *FDindex4* are available upon request.

reflect a potential amplifying effect of bank-based financial systems on IncI following crises. To proxy for the structure of financial systems, we define the *Financial structure* variable equals (*Size financial institutions*) / (*Size financial institutions* + *Size financial markets*). Higher values of the *Financial structure* variable are associated with more bank-oriented financial systems.

Fourth, Cerutti *et al.* (2017a) show that financial crises often lead to important changes in macroprudential policies, with an effectiveness in curbing the financial cycle that depends on several countries' characteristics, including their level of financial development. Besides, Frost & van Stralen (2018) highlight a significant and positive relationship between several macroprudential policies and IncI in a sample of 69 countries over the 2000-2013 period. Therefore, since FD might influence the type of macroprudential policies implemented following banking crises, with potential important redistributive consequences, we account for changes in macroprudential policies in the aftermath of banking crises when assessing the relationship between FD and IncI dynamics following crises. To this end, we compute the *Macroprudential policies* variable, which corresponds to the average between t and t+3 of the Macroprudential Index coming from the Cerutti *et al.* (2017b) database.[26]

Results in Table 6 show that, except the *Macroprudential policies* variable, these additional characteristics of financial systems are not significantly correlated with the redistributive effect of banking crises. However, in all specifications, *FDindex* still has a significant effect, with an estimated coefficient very similar to our baseline results. Besides, estimates in Table 6 suggest some interesting implications. First, columns (1) and (2) indicate that the size and the activity of the banking sector play a greater redistributive role compared to the degree of liberalization of the financial system and thus the number of restrictions places on its functioning (liberalization versus financial repression). Second, columns (3)-(5) suggest that the size and the activity of the banking sector represent an independent and significant factor to understand the dynamics of IncI in times of crisis. Thus, our results do not seem to reflect the effect of the overall size of financial institutions, financial markets or financial systems, but instead highlight the specific contribution of the size and the activity of the banking sector in explaining IncI. This supports the interpretation of the FD-IncI relationship we suggest in section II, but also the choice to focus on the banking sector when

[26] Note that except the *Macroprudential policies* variable, all the variables used to proxy for these additional characteristics of financial systems are measured the year before the outbreak of banking crises. In the OA, Table D1 provides more information on the definition of these variables and Table D2 gives their descriptive statistics.

measuring FD.[27] Third, column (6) suggests that whether a financial system is bank-based or market-based do not appear as a critical factor explaining the redistributive consequences of banking crises compared with the pre-crisis size and activity reached by the banking sector. Fourth, despite a very limited sample size due to strong constrains on the availability of macroprudential policies data, column (7) indicates that, while *FDindex* still has a significant effect, the implementation of macroprudential policies in the aftermath of banking crises is significantly associated with an increase in IncI, which echoes the results of Frost and van Stralen (2018) previously mentioned.

Table 6. Additional characteristics of financial systems and output cost of banking crises

	Diff.Gini							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FDindex	3.013***	3.242***	2.772***	2.766***	2.672***	2.846***	3.245**	2.946***
	[0.935]	[0.856]	[0.795]	[0.833]	[0.800]	[0.857]	[1.293]	[0.759]
Financial lib.	0.0863							
	[0.0899]							
Financial open.		0.197						
		[0.376]						
Size financial institutions			1.638					
			[1.547]					
Size financial markets				1.500				
				[1.298]				
Size financial systems					1.068			
					[0.812]			
Financial structure						-1.898		
						[1.532]		
Macroprudential policies							0.413*	
							[0.222]	
Diff.GDP								5.064*
								[2.914]
Controls	Yes							
Crises	62	67	67	67	67	67	36	68
Countries	47	52	53	53	53	53	35	53
R²	0.42	0.38	0.367	0.369	0.371	0.380	0.389	0.396
RMSE	1.86	1.95	1.97	1.97	1.97	1.95	1.67	1.91
Fisher stat.	3.88	4.09	3.92	3.87	3.94	3.83	1.36	4.44
Fisher p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00
AIC	260.35	287.38	288.73	288.47	288.25	287.36	146.27	288.65
BIC	277.36	305.02	306.36	306.10	305.89	304.99	158.93	306.41

Note: coefficients displayed are marginal effects. Standard errors robust to within-country correlations are reported in brackets. R² and RMSE respectively correspond to the coefficient of determination and the root mean square error. Fisher stat. and Fisher p-value refer to a Fisher test of joint significance of explanatory variables. AIC and BIC are the Akaike and Bayesian information criteria. ***p<0.01, **p<0.05, *p<0.1.

In addition, as mentioned earlier, FD play an important role in explaining the output cost of banking crises. Since the recessive consequences of banking crises may lead to an increase in IncI (see section II), it is important to ensure that our results do not only reflect the

[27] Further estimates (available upon request) show that our main results are also robust when accounting for the other dimensions of FD included in the IMF's *Financial Development Index Database*, i.e., the efficiency and the access dimensions associated with both financial institutions and financial markets.

effect of FD on the output cost of banking crises. To this end, in column (8) of Table 6, we re-estimate our model with the introduction of the *Diff.GDP* variable that proxies the output cost of banking crises. To be consistent with the *Diff.Gini* variable, *Diff.GDP* corresponds to the difference between GDP *per capita* observed in t+3 and t.[28] We account for GDP *per capita* instead of real GDP since it enables to account for differences in economic development between countries when measuring the output cost of banking crises.[29] In line with the discussion in section II, results show that *Diff.GDP* is significantly associated with an increase in IncI following banking crises. More importantly, *FDindex* has a significant and positive correlation with *Diff.Gini* that is very similar to our baseline results. This supports our analysis and confirms that FD can have a significant and independent effect on the redistributive consequences of banking crises.[30]

Finally, we introduce sequentially all the control variables reported in Table 1 that were not included in the reference model based on the BMA estimates (see section 4.2). Results presented in Tables D3a-D3b of the OA show that, with only a few exceptions, these variables do not have a significant effect on IncI. Whatever the specification, *FDindex* is still associated with a significant increase in IncI, with an estimated effect very similar to our baseline results. Importantly, in column (4) of Table D3b, the specification including the *Credit boom* variable (not significant), which accounts for the presence of a credit boom before banking crises, indicates that our baseline results are not driven by an abnormally high pre-crisis growth of the credit supply. This suggests once again that FD could represents an independent and significant factor explaining the redistributive impact of banking crises.

6.3 Alternative estimation methods and sample structure

As previously mentioned, Gini coefficients from the SWIID are estimated. Although we account for the uncertainty associated with their calculation when designing our sample, we now go one-step further and use Weighted Least Squares (WLS) based on the methodology employed by Furceri & Loungani (2015). Following the selection procedure presented in section 3.1, observations are weighted according to the standard deviation of the estimated Gini coefficients observed between *t*–3 to *t*+3. Moreover, despite the fact that we carefully control for potential outliers in our set of explanatory variables using the Kumar *et al*. (2003) transformation, we also check for the robustness of our results using a *Robust*

[28] Like the *GDPcap* control variable, data used to compute *Diff.GDP* come from the World Bank's WDI (2016) database. In the OA, Table D2 gives the descriptive statistics of this variable.
[29] Besides, to get an estimate of the output cost of banking crises that does not only reflect the strong heterogeneity in GDP *per capita* among countries in our sample when banking crises occur, all observations of the *Diff.GDP* variable are divided by the level of *GDP* per capita in t.
[30] In addition, following the approach presented in Table 4, we re-estimate the relationship between FD and IncI for different time horizons following banking crises with the introduction of the *Diff.GDP* variable. Results (available upon request) are the same to those obtained in Table 4 regarding *FDindex*. However, the *Diff. GDP* variable is no longer significant.

Regression.[31] Results of these estimates are given in columns (1) and (2) of Table D4 in the OA. *FDindex* is still significant and positively correlated with *Diff.Gini*, although with a magnitude slightly lower compared to our main results.

Finally, we modify our sample by keeping only Gini coefficients from the SWIID associated with lower uncertainty in their computation. Compared with the methodology used in section 3.1, our sample now only includes banking crises associated with a standard deviation of the estimated Gini coefficients observed between t-3 and t+3 below 2.5.[32] Column (3) in Table D4 of the OA presents the results obtained with this new sample. They show that *FDindex* is significantly associated with an increase in IncI following banking crises, and the magnitude of its estimated coefficient is similar to our baseline results.

VII. Heterogeneity

7.1 Accounting for non-linearity in the effect of financial development

Several econometric studies, such as e.g., Kim & Lin (2011), highlight a nonlinear effect of FD on IncI. Here, we look for a potential nonlinear effect of FD on the dynamics of IncI in the aftermath of 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 a better risk diversification (Levine, 2005). This would facilitate the access to the credit market for the poorest households, whose revenues are particularly impacted by economic slowdowns associated with banking crises. This can thus contribute to a decrease in IncI. On the other hand, higher level of FD may be associated with a less productive and more speculative credit allocation (Beck, 2012). This can increase the risk taken by financial intermediaries, leading to an increase in financial fragility in case of a financial downturn. This can make the banking sector less resilient following crisis, with a sharp contraction of the credit supply causing a severe decrease in economic activity, as well as a lower ability for the poorest households to borrow in order to offset the decrease in their labor market income. This can ultimately entail an increase in IncI.

In our set-up, to deal with potential nonlinearities in the relationship between FD and IncI in times of crises, we introduce in our model the squared term of the *FDindex* variable ($SBSindex^2$).[33] Column (1) in Table 7 shows that $FDindex^2$ is not

[31] A *Robust regression* corresponds to a WLS estimate where observations are weighted according to the absolute value of the predicted standardized errors taken from our model.

[32] This leads to drop the following nine 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).

[33] We acknowledge that a more precise approach to account for the nonlinear effect of FD would have required the estimation of a threshold regression model, like the one proposed by Hansen (2000). However, given the limited size of our sample, we could not obtain convergent estimates with this model. Note that the same apply when considering in section 7.2 the heterogeneity in the effect of FD on IncI depending on the level of economic development.

significant, while the effect of *FDindex* remains significant and positive, with a magnitude slightly higher compared with our baseline estimates. These results suggest that the relationship between FD and IncI dynamics following banking crises is not subject to a threshold effect.

7.2 Accounting for economic development heterogeneity

According to Greenwood & Jovanovic (1990), the level of economic development leads to heterogeneity in the relationship between FD and IncI. In this perspective, we investigate if the effect of FD on the redistributive consequences of banking crises depends on the level of economic development.

Regarding developing countries, some characteristics of their financial systems may amplify the recessive impact of banking crises and as a result could foster IncI. Indeed, developing countries are characterized by a greater dependency of agents on the banking sector to obtain external financing due to less developed capital markets (Levine, 2005), a rapid and late implementation of financial liberalization policies in a weak institutional context (Demirguc-Kunt & Detragiache, 2005), and more pro-cyclicality in access to external financing (Eichengreen *et al.*, 2003, Reinhart & Rogoff, 2011). These characteristics suggest a more stringent effect of banking crises in developing countries, especially since governments have fewer prerogatives in terms of redistributive policies and social insurance (Atkinson, 2015).

As for developed countries, their financial systems are larger, more complex and more interconnected (Rajan, 2005), and are also characterized by stronger interdependence between financial markets and financial intermediaries (Laeven, 2011). These features may thus amplify the recessive and the redistributive consequences of banking crises. However, compared with developing countries, governments in developed countries have more prerogatives in terms of redistributive policies and social insurance that could in turn mitigate the effect of banking crises on IncI more efficiently.

As a result, the institutional and macroeconomic characteristics of developing countries may be associated with a greater amplifying effect of FD on IncI following banking crises. To test this assumption, we replace in our model *FDindex* by the following two dummy variables.

The *FDindex developing* variable equals *FDindex* if banking crises occur in developing countries (46 countries following the World Bank classification), and 0 otherwise. The *FDindex developed* variable equals *FDindex* if banking crises occurs in developed countries

(23 countries following the World Bank classification), and 0 otherwise. The advantage of this approach is to account for the effect of economic development in the relationship between FD and IncI, while keeping the size of our sample unchanged. Indeed, given the limited size of our sample, we do not carry out subsample estimates for developing and developed countries. Results in column (2) of Table 7 indicate that for both developing and developed countries, a higher level of FD is associated with an increase in IncI following banking crises. However, the estimated effect of FD on the redistributive consequences of banking crises seems to be more important in developing countries. In line with our earlier assumption, these results could suggest that due to their institutional and macroeconomic characteristics, the amplifying effect of FD on IncI in times of crisis may be stronger in developing countries.

Table 7. Heterogeneity in the effect of financial development on the redistributive consequences of banking crises

	Diff.Gini	
	(1)	(2)
FDindex	3.455***	
	[0.980]	
FDindex²	-0.665	
	[0.553]	
FDindex developing		3.729***
		[1.098]
FDindex developed		2.250***
		[0.799]
Controls	Yes	Yes
Crises	68	68
Countries	53	53
R²	0.37	0.38
RMSE	1.95	1.94
Fisher stat.	4.04	3.94
Fisher p-value	0.00	0.00
AIC	291.13	290.92
BIC	308.88	308.67

Note: coefficients displayed are marginal effects. Standard errors robust to within-country correlations are reported in brackets. R² and RMSE respectively correspond to the coefficient of determination and the root mean square error. Fisher stat. and Fisher p-value refer to a Fisher test of joint significance of explanatory variables. 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 important role played by both FD and banking crises in the dynamics of IncI. To our knowledge, no study has so far linked these three elements with the objective of investigating the effect of FD on IncI following banking crises. This is an important issue since the significant expansion of financial systems before the subprime crisis has been associated with an increase in IncI in its aftermath.

Based on a sample of 69 banking crises in 54 countries over the 1977-2013 period, this paper sought to assess the relationship between FD and the redistributive consequences of banking crises. Using Gini coefficients, we have defined an indicator measuring the effect of banking crises on the distribution of income over the three years following their outbreak. Our metric for FD is a composite indicator based on a six-variable PCA that allows us to proxy for the pre-crisis size and activity of the banking sector. Given the limited size of our sample and in order to estimate a parsimonious econometric model, the selection of control variables relies on BMA. The estimates are then made using OLS.

Our results highlight that FD is significantly associated with an increase in IncI following the outbreak of banking crises. This result is robust when controlling for endogeneity, using alternative metrics for FD and estimation methods, accounting for outliers, and introducing a large number of additional determinants of the redistributive impact of banking crises. We also show that the effect of FD remains unchanged when introducing variables capturing several other key features of financial systems. The robustness of our results indicate that despite a limited sample size, the estimated effect of FD is particularly stable and does not rely on whether the specification considered for our econometric model or the number of observations included in each regression. Finally, further estimates suggest that the relationship between FD and the redistributive consequences of banking crises is not subject to a threshold effect and is stronger for developing countries.

The results obtained in our study show that beyond the amplifying effect of FD on the output cost of banking crises, FD might also lead to an increase in IncI after their outbreak. In this regard, one interpretation could be that, by reinforcing the procyclical relationship between the financial sector and the real economy, FD can amplify the recessive consequences of banking crises. These latter may mainly affect the poorest households, notably through a deterioration in the access conditions to the credit market, a rise in the unemployment rate, a weakening of the exchange rate, and the implementation of fiscal austerity policies. Therefore, instead of having a counter-cyclical role, a higher level of FD may be associated with an increase in IncI in the aftermath of banking crises.

Over the last decades, many developed and developing countries have experienced a significant deepening of their financial system, a higher exposure to financial crises, and an increase in IncI. Given the strong interdependence between these three factors (Bazillier & Héricourt, 2017), one potential implication of our paper is to emphasize the redistributive risk resulting from a higher level of FD. In the aftermath of crises, this may lead to a vicious circle ranging from a rise in IncI to higher financial instability, through an increase in the size and the activity of the banking sector. Such a dynamic could have negative consequences for political and social stability, and long-term economic growth. Thus, in line with the recent trends in macro-prudential policies implemented in developed countries, our results suggest that regulations that aim at limiting the pro-cyclicity of the financial sector during the upward phase of the cycle, through more constrains on the size and the activity of the banking sector, may potentially reduce the adverse effect of banking crises on IncI.

Finally, our study could motivate further research on the relationship between FD and the dynamics of IncI following banking crises. First, it would be interesting to investigate the precise transmission channels explaining the effect of FD on IncI in times of crises. This could help to highlight the relevant public policies aimed at mitigating the redistributive consequences of banking crises. Second, based on a panel data analysis, one could extend our sample to account for the counterfactual dynamics of IncI in countries that did not experience banking crises. This would enable to characterize the relationship between FD and IncI in crisis and non-crisis periods, thus broadening the scope of our paper. Third, it would be relevant to consider the effect of FD on the redistributive consequences of other types of financial crises, such as currency, debt, and stock market crises.

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