

Research article

The inequality-credit linkage

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Abstract: In this paper, I analyzed the underlying mechanisms of the interaction between credit expansion and income inequality—inequality-credit interaction—and its influence on the economy. For this purpose, System and Difference GMM models were applied to assess the influence of the interaction on the triggering of banking crises in 212 economies between 1970 and 2017. Furthermore, a Granger-Causality panel data test was applied, employing a maximum sample size of 216 world countries for the 1960–2021 period and balanced subsamples. The interaction was negatively related with risk of unchaining banking crises and led to economic growth. Robustness checks were applied, confirming the results.

Keywords: income inequality; credit expansion; banking crises; monetary policy; Granger Causality

JEL Codes: G21, D63, G01, E52

Abbreviations: GMM: Generalized Method of Moments; SYS: System; DIF: Differences; GDP: Gross Domestic Product; VCEs: Two-step variance-covariance matrix estimators; ATMs: Automatic Teller Machines; ECA: Europe and Central Asia

1. Introduction

The interest on the analysis of the association of income inequality with the development of the financial sector has increased in recent years, especially since the unchaining of the Great Recession and even more after a relatively long period of high inflation exceeded the most adverse economic impacts of the COVID-19 pandemic. Thus, the reason may be the widening of income inequality for most developed and developing economies. In this paper, I deal with the question about how the

inequality-credit interaction influences the risk of triggering banking crises. Many researchers have analyzed this interaction (of, inter alia, Galor and Zeira 1993, Benabou 2000; Easterly 2007; Kavya and Shijin, 2020) and the relationships between the inequality of income and different measures of the development of the financial sector, and most have studied its correlation with the growth rates of the economies. Thus, the question of how this link influences economic activity is a subject of much debate. For instance, Braun et al. (2019) studied the influence of the interaction between inequality and credit on economic growth. However, to my knowledge, there is a lack of research that involves empirically testing the effects on banking crises of the explicit interaction between credit expansions and income inequality (inequality-credit linkage), and I contribute to this topic by filling the gap. Therefore, the key new contribution of this paper is adapting the empirical exercise of Braun et al. (2019) to banking crises instead of economic growth. This is done by employing dynamic panel data models. Furthermore, another novelty is the completion of the results of the other authors who made on income inequality by adding a new result by studying the Granger-causality of the above-mentioned inequality-credit linkage on per capita income. Finally, the third main contribution, in contrast to other papers, such as Fischer et al. (2019) Chang et al. (2020), and Magwedere (2023), is the proposal of a new theoretical framework where the influence of the linkage on the likelihood of a banking crisis can be observed. This is also used for discussing the empirical results.

Empirical results are developed for the above purpose. A model is estimated explaining the risk of banking crises by inequality–credit interaction and controlling by the major determinants of the literature for the 212 worldwide countries in the 1970–2017 period, according to the widest available data of banking crises. The analysis is performed using System and Difference panel data models of Generalized Method of Moments (GMM) since the former models are strongly advised for the high degree of persistence in the explained variable and the avoidance of endogeneity (Roodman, 2009), and the last models are employed as a robustness check. There is no need to focus on potential endogenous variables, since, as Ullah et al. (2018) state, the two-step System GMM (employed in this paper) “relies on internal instruments (lagged values, internal transformation) to address the different sources of endogeneity” (p.4). Two additional robustness checks are performed: Providing different specifications of the inequality and credit variables and incorporating a temporal dummy that includes the five immediate years before the Global Financial Crisis (GFC) that occurred on 2007–2009, so 2002–2006, denominated the “lax period”, including two economic and geographical dummy variables.

A significant and beneficial negative effect of the interaction—measured as a combination, i.e., the product of both variables—on the probability of unchaining banking crises is found, smoothing an individual positive influence on the banking crisis of income inequality (Mo, 2000) and financial development (Cecchetti and Kharroubi, 2021), separately. The interaction negatively alleviates the individual effect on the risk of triggering banking crises; therefore, a beneficial-collateral consequence of the raise in the inequality of income and development of the financial institutions emerges. On the other hand, if policy-makers seek to reduce income inequality and a possible excessive size of the financial sector, this interaction would collaborate on triggering banking crises. These results are also consistent with theoretical expectations. To my knowledge, nobody has directly studied the joint-interacted-impact of credit booms and income inequality on banking activity. Last, it is checked that the interaction leads to Gross Domestic Product per capita (GDPpc) by employing a novel technique of Granger Causality for panel datasets, found by the econometricians Juodis et al. (2021). Additionally, a robustness check is provided where a country-by-country test is applied to different measures of the nexus.

Therefore, I seek to shed further light on the inequality-credit interaction. This paper is divided as follows. In Sections 2 and 3, I show a brief literature review of the inequality-credit interaction and the determinants of the crises in the banking sector, jointly with theoretical expectations of the effects of the interaction on the of banking crisis triggering. In Section 4, I explain the data and methodology applied in this paper and expose the econometric results and checks of robustness. Finally, in Section 5, I discuss results and provide some policy measures as well as concluding remarks.

2. The literature review

2.1. A Linkage

Much debate has arisen about the linkage between the development of the financial system and economic inequality measured by income, and overall, its relation with economic activity, such as the Braun's et al. (2019) paper. If we focus on whether income inequality slows or accelerates economic growth, there are arguments for both directions at the theoretical level. While there is a tradition in modeling saving rates as a function positively correlated with wealth, leading to a positive relationship (Bourguignon, 1981; Kaldor, 1957; Keynes, 1919; Lewis, 1954; Smith, 1776), other researchers consider loan restrictions in investment on human capital lead to a link through which income equality would improve the growth of GDP (Benabou 2000; Galor and Zeira 1993). At the empirical level, there is neither consensus. On the one side, several studies support a negative association between the inequality of income and economic growth variables (Alesina and Rodrick 1994; Easterly 2007; Panizza 2002). On the other side, other authors suggest a positive effect (Forbes, 2000; Li and Zou, 1998).

Regarding the previous expected linear influences, it is worth mentioning that Kuznets (1955) suggested an inverted "U" shape linkage between the development of the economies and inequality of income, since inequality seemed to be positively correlated with development but until a maximum, and the relationship would become negative. Tan and Law (2012) empirically observed a U-shape relationship in the inequality-credit nexus. In fact, there is literature suggesting the nonlinearity in the relation inequality-growth (Barro, 2000; Castelló-Climent, 2010; Kim and Lin, 2011 and Brueckner and Lederman, 2015, Kavya and Shijin, 2020, Ghosh et al., 2022). Kruger (2008) reviewed the literature in which high inequality might not be good for an economy. On the other hand, there are arguments for a positive and a negative correlation of the development of the financial sector variable with the inequality one. The key is the way in which the increase of financial services provided by an expansion of financial development may benefit low-income households.

Among the literature of the association of the interaction with growth, Braun et al. (2019) is the closest one to this paper, since they have the same target variables (credit, income inequality, and the interaction) but on a different dependent variable; economic growth instead of the banking crisis probability in this paper. They show the theoretical expectations by an analytical model and empirically analyze the expectations by estimating System GMM models with those variables and controlled by other factors. They obtain that several of the prejudicial influences of income inequality over economic growth may be reduced by enhancing access and entry to loans.

The previous expectations for economic growth can be easily adapted for banking crises. As will be seen later, our results on banking crises will be similar to those on reducing economic growth but for the case of triggering these crises (opposite sign). Other researchers have dealt with the topic of the

influence of income inequality and financial development on triggering banking crises. Nonetheless, this interaction has never, to my knowledge, directly considered the interacted effects of both variables on banking crises as Braun et al. (2019) performed for growth of income as a dependent variable.

2.2. The nexus and its association with economic growth and banking crises

According to authors, such as as Büyükkarabacak and Valev (2010), private loan booms are a relevant prelude to later banking crises. They argue that the household credit growth raises liability levels without a significant impact on the income in the long-run. While fast household loan expansions may exacerbate vulnerabilities, probably unchaining banking crises and rising business loans can hold similar influences; those vulnerabilities are tempered by the related income increase. Mathonnat and Minea (2018) delved on this issue by analyzing different disaggregation levels, finding by a panel of more than one hundred of crises in the banking sector and 112 economies where the M3/GDP growth and the ratio of the credits/deposits from the financial institutions trigger banking crises, and sometimes varying bank asset ratios over the total assets from the banking sector and the Central Bank are factors that reduce it. Finally, they did not empirically observe any significant influence of credits/GDP from financial institutions. Furthermore, Binici and Ganioglu (2021) found that net external position and financial development significantly affect the economy's risk of a banking crisis. We show that influence on the latter appears when interacted effects are considered.

Rhee and Kin (2018) used data for 68 economies for the 1973–2010 period. They found that developing economies holding a higher level of income inequality usually have a greater amount of domestic loan capital and that excessive domestic credit expansions raise the unchaining of a banking crisis. Finally, their results also showed that these countries display direct mechanisms from income inequality to the likelihood of a banking crisis with no underlying linkage with credit booms. In this paper, I show that this does not occur for middle-income countries where this channel is relevant. Regarding this direct effect, El Herradi and Leroy (2022) quantified distributional effects of the triggering of a crisis in the banking sector for a panel with 132 economies during 1970–2017. Their results provide evidence on the risk of a banking crisis steadily decreasing the share of income from rich households and positively impacting middle-income families. Finally, they obtained that the inequality of income rises prior to triggering banking crises.

Regarding the inequality-credit interaction, Rajan (2010) and Kumhof et al. (2015) proposed that a higher level of inequality leads to an excessive credit expansion and eventually to a banking crisis in the US at the beginning of the 21st century as well as in the 1920s. Moreover, Bordo and Meissner (2012) employed a dataset from 14 developed economies for the 1920–2000 period, finding that these are not significant general relationships. They suggest that excessive credit expansions intensify the risk of banking crises, but they do not find any evidence that rising top income proportions trigger loan booms. Nonetheless, Gu and Huangre (2014) observed evidence of an inequality-leverage-crisis interaction for financialized countries using a similar database. Their implications point back that credit can hardly be maintainable under a rising income inequality.

Some authors have also found an econometric association between credit and income inequality correlated with crises in the financial sector (Perugini et al., 2015). These authors analyze, sequentially, the effects of loan growth on financial crises and then the influence of income inequality on the credit expansion. However, the consequences of the interaction between credit growth and inequality on banking crises is not investigated by these authors. On the one hand, Perugini et al. (2015) studied a

panel data of 18 OECD economies during 1970–2007, and they found a positive association of income distribution with private sector leverage and income inequality. The major implications of their results are refusing the traditional view of considering that income inequality is irrelevant to macroeconomic stability and suggest taking into account the effects on income distribution as an instrument to strengthen the financial system, not only using monetary policy and regulatory reforms as instruments.

Regarding the determinants on GDP growth, additional ones are analyzed. Chirwa and Odhiambo (2016) performed a literature review of the topic. The major facts are that the determinants depend on the degree of development of the country. While there are common factors as fiscal and monetary policy, trade, and financial factors, there are others that are specific for developed or developing countries as natural resources for developing countries and technological factors for developed economies. Here, I consider the common factors mainly concerning policy. Nonetheless, the differences in economic growth are not only a matter of space but also of time, as Bruns and Ioannidis (2020) suggest after dividing a dataset of developed and developing economies in different periods, showing, through a Bayesian model, that the most important factors are demography and education. Additionally, Pal et al. (2021) found that inflows of remittances spur income growth in both developed and developing countries.

The rural areas have less access to financial services (Schreiner and Colombet, 2001), and this fact increases the income and population inequalities in countries such as China (Song et al., 2020). The authors proposed to improve the access to digital finance as a way to promote consumption with larger effects in rural areas. Nonetheless, a greater financial access could also lead to detrimental effects, overall, when low-income families have access to the services from financial institutions. A reason is the possible excessive indebtedness, higher interests, and possible defaults. Even if I focus on the inequality-credit linkage and its association with banking crises, and the determinants of banking crises in general are not my target, the key determinants are collected in the next section. Previously, the linkage between income inequality and financial development is dealt briefly with enough depth.

2.3. The debate

In the last decades, it is well known that the inequality of income has risen in many developed countries. Some authors have pointed out financial causes to this origin. Xu et al. (2018) used state-level data from the United States during 1970–2000, two state-level indicators of income inequality, and applied a System GMM dynamic panel data analysis. They found that branching deregulation in the United States has increased inequality. Other authors have empirically found that financial liberalization increases income inequality and poverty. Zhang and Naceur (2019) and Dabla-Norris et al. (2015) highlight financial globalization as one of the causes. Globalization leads to a more efficient international allocation on capital and promotes risk sharing among countries. In particular, portfolio flows and foreign direct investment (FDI) have led to an increase in inequality in developed and developing countries (Freeman, 2010). Another cause suggested by Dabla-Norris et al. (2015) is financial deepening because it can facilitate higher-income households to meet their financial needs. Financial deepening with inclusive financial systems might reduce inequality by allocating the resources better. Nonetheless, other authors consider that financial development could help high-income households to progress more in the early steps of financial deepening (Greenwood and Javanovic, 1990) or increase the inequality since high-income households have improved their access to a higher return to capital (Claessens and Perotti, 2007).

Furthermore, authors recognize the need for a reform of the financial sector in order to reduce income inequality and then promote economic growth. It is worth mentioning Claessens and Perotti (2005, p. 3) when they state that:

“The lack of success of financial reform may be the consequence itself of a highly skewed distribution of wealth and power. Inequality itself can be a hinder to productive financial reform and financial development when powerful interests block or manipulate reforms so as to capture the benefits and avoid the costs.”

They also affirm on p. 6 that there is a link for the interaction between financial development and income inequality as a factor for economic growth:

“So a central role for a financial system, and thus financial reform, should be helping the diffusion of economic opportunities and thereby reducing inequality. Lack of financial access can be both a direct and an indirect entry barrier to growth.”

Despite the emerging interest and debate on the inequality-credit interaction, the empirical research is limited, as Perugini et al. (2015) state. In order to clarify the topic, it is important to consider the major determinants of financial instability. The authors highlight the role of government, deregulation of the financial system, accommodative monetary policy (Peña, 2017), fast economic growth, and foreign flows. I consider these factors in this paper.

The main question is whether financial services are extending to poor people after financial development: If low-income consumers can have better access to financial services, then income inequality would improve (Claessens & Perotti, 2007), while if they cannot access these services, income inequality would rise (Clarke et al., 2006). According to Huizinga's (2002, p.520) findings, “higher-income households are seen to be more frequent users of all bank financial instruments”. Furthermore, Demirgüç-Kunt & Levine (2009) consider that financial development can also impact those who are not financial service consumers. The reason is that financial development leads to higher economic development and this would raise the labor demand, may widen income inequality according to the rise in demand of skilled or not skilled labor. Empirically, while some authors obtain that financial development reduces income inequality (Clarke et al., 2006; Beck et al., 2007; Zhang and Naceur, 2019), others find the opposite result (Jauch and Watzka, 2016; De Haan and Sturm, 2017). Finally, it is worth highlighting that Frost et al. (2022) found a positive association between financial development and financial technology with households' financial wealth and returns.

2.4. The determinants of banking crises

Prior to the study of determinants, it is worth asserting a definition of banking crisis that is used in the empirical section of this paper. According to Laeven and Valencia (2020), “we define a banking crisis as an event that meets two conditions: 1) Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or banking liquidations). 2) Significant banking policy intervention measures in response to significant losses in the banking system. We consider the first year that both criteria are met to be the year when the crisis became systemic.”

The major determinants of banking crises are several and can be divided into policy, macroeconomic, banking, and institutional origins. Regarding the policy determinants, Gavin and Hausmann (1996) highlight the sources of banking crises as the volatile fiscal policy or incorrect monetary policy, as mentioned, highlighting the effects of money supply or interest rates (Frankel and

Saravelos, 2012). Large fiscal deficits can precede crises while central bank independency prevents them (Kauko, 2014). Regarding the macroeconomic factor, macroeconomic volatility measured by inflation can be sources of the problem (Frankel and Saravelos, 2012), in addition to the terms of trade or world rates of interest (Gavin and Hausmann, 1996) or in exports (Peña, 2020). Furthermore, low Gross Domestic Product (GDP) and a high level of debt can also be roots of banking crises (Pereira et al., 2018). Finally, high secondary enrollment can reduce poverty, where financial inclusion is associated with lower financial instability (Neaime and Gaysset, 2018).

With respect to the banking factors, significant determinants include excessive lending expansions (Peña, 2017; Bouvatier and Ouardi, 2023) and asset price collapses, and surges in capital flows are (Goldstein and Turner, 1996) serious credit crunches, bank leverage or illiquidity (Gavin and Hausmann, 1996), equity returns or debt composition (Frankel and Saravelos, 2012), excessive banking competition (Kauko, 2014), and, probably, excessively high interest rates (Laeven, 2011). These issues are related to the first point of the definition provided by Laeven and Valencia (2020) when there is financial distress in the banking system. Finally, among the institutional roots, as Goldstein and Turner (1996) state, the incorrect preparation for financial liberalization and financialization or the weaknesses in the bank supervision and regulation are in the accounting and legal frameworks. This is related with the second point of the definition given by Laeven and Valencia (2020) when there are significant banking policy intervention measures.

2.5. Further determinants and other views

As seen, Mathonnat and Minea (2018) found that the raise in M3/GDP and the level of credit/deposit of banks increase the likelihood of banking crises. According to these authors, some measures of financial development could lead to banking crises but not others. Therefore, we can deduct from these results that accommodative monetary policy could be associated with economic crises or recessions. Nonetheless, Lee and Werner (2018) found that official interest rates follow GDP growth, and not the opposite.

Researchers acknowledge the presence of redistributive consequences of monetary policy (Ibrahim, 2020). The consideration that lax monetary policy may raise income and wealth inequality has become extremely popular, and one of the ways is by increasing asset prices (Albert et al., 2021). According to Taylor (2012), years prior to the Global Financial Crisis (GFC) of the 2007–2009 period and after the Great Moderation period, a period of economic growth, financial stability, and certainty dated by Peña (2017) from 1987 to 2001, there was a denominated “lax period” of accommodative monetary policies that ended up following the Taylor’s (1993) rule, which could lead to the GFC, and these policies may continue even during the GFC. The reason may be that, also in this period and according to Cruz-García et al. (2020), Central Banks applied lax monetary policies to reduce the pernicious impact of the crisis.

2.6. The impact of inequality and credit on banking crisis

Rhee and Kim (2018) econometrically explored whether a raising inequality of income leads to banking crises with a panel dataset of 68 economies during 1973–2010. The findings displayed that low-income countries with a greater inequality usually benefit greater amounts of domestic loan capital. Furthermore, domestic loan booms lead to a higher probability of a bank crisis. Low-income

economies show direct channels that go from income inequality to triggering a banking crisis with no linkage with loan booms. On the other hand, for advanced economies, they do not obtain any consistent econometric evidence that this inequality unchains a crisis. In low-income economies, the banking crisis risk raises sharply at the same time that inequality raises.

Destek and Koksel (2019) verified whether the Rajan hypothesis can be confirmed. The hypothesis argues that raising income inequality is crucial in the unchaining of crises on the financial sector. The researchers examined the correlation between 10 developed countries. For that, a procedure of bootstrap rolling-window estimate was applied to find any causality regarding the linkage of inequality with loan booms for several financial crises' sub-sample periods. The findings showed that the Rajan hypothesis is supported for some crises, such as the 1989 crisis in Australia, those of 1991 and 2007 for the United Kingdom, and the 1929 and 2007 crises for the United States. Thus, raising income inequality holds a predictive power on the loan booms for some Anglo-Saxon economies. Nonetheless, there is no confirmation of the hypothesis for some countries in Scandinavian and the continental European ones. The researchers contributed in the use of a procedure rolling-window bootstrapping. This enables us to find potential relationships between income inequality and credit booms for financial crises.

Moreover, Wang (2023) sustains that there is a non-linear nexus between the triggering of banking crises and income inequality. They empirically obtained a U-shaped linkage between these crises and inequality for a dataset of 172 countries over fifty years. Additionally, they found that income inequality maintains a non-linear effect on growth conditioned to the stage of economic development, playing also a non-linear role for crises models. In the next section, I show the expected effects of the inequality-credit linkage on banking crises after providing a new model that illustrates it.

3. Theoretical analysis and development of hypothesis

The theoretical framework starts with the works of López-Laborda and Peña (2018) for introducing the value added of the financial sector, and the work of Peña (2022) for dealing with the risk of a banking crisis. The former authors consider that the value added of the financial sector can be expressed as a proportion ρ of interest receipts and payments, respectively, the lending interest rate r times the loan amounts C and the deposit interest rate R times the deposit amounts D . The pure interests are the pure interest rates ε_0 times the capital, B . The optimal pure interest rate is derived as follows:

$$\left. \begin{aligned} VAC^*: \rho rC &= rC - \varepsilon_0 B \\ VA^D*: \rho rD &= \varepsilon_0 B - RD \end{aligned} \right\} \varepsilon_0 = \frac{2rCRD}{(rC + RD)B} \quad (1)$$

Nonetheless, there can be distortions in the economy, and the financial sector sometimes has to provide extraordinary provisions, $P_0 = P(C)$, measured as a function regarding the probability of default and the credit amounts. In this case, the new pure interest rate is given as follows, with γ^C and γ^D being the shares of provisions for loans and deposits, respectively (Peña, 2022):

$$\left. \begin{aligned} VAC^*: \rho rC &= rC - \varepsilon'_0 B - \gamma^C P(C) \\ VA^D*: \rho rD &= \varepsilon'_0 B - RD - \gamma^D P(C) \end{aligned} \right\} \varepsilon'_0 = \frac{2rCRD + P_0(rC - RD)}{(rC + RD)B} \quad (2)$$

Peña (2022) also identifies a criteria for the occurrence of risk of a banking crisis, Φ . Inspired by this author, the next indicator, Φ , is provided, measuring the risk of a banking crisis as the difference between the current pure interest rate and the optimal one:

$$\varepsilon'_0 \neq \varepsilon_0 \Rightarrow \Phi > 0 \rightarrow \Phi^0 = \varepsilon'_0 - \varepsilon_0 \quad (3)$$

The zero superscript of Φ indicates the period 0. Starting from the previous situations observed in the literature, I go further and propose a new view that checks whether the risk of a banking crisis increases when there is a period 1 after a raise in income inequality (i) or, alternatively, a raise of the size of the financial sector (ii), and a period 2 after when both variables raise at the same time. The raise on income inequality is provided, for instance, after an increase in g in income for higher-income people and, thus, of loans and deposits, and a decrease g_d in the need of extraordinary provisions.

$$i: \Delta Y, \varepsilon_0^{1i} = \frac{2rCRD(1+g)^2 + P_0(rC - RD)(1 - g_P)(1+g)}{(rC + RD)B(1+g)} \quad (4)$$

$$\xrightarrow{\Phi^{1i} = \varepsilon_0^{1i} - \varepsilon_0} \Phi^{1i} - \Phi^0 = \frac{2rCRDg + P_0(rC - RD)(-g_P)}{(rC + RD)B} ? 0$$

The sign can be positive or negative. For the (ii) case, we raise g of the banking sector measured by the increase of capital, B :

$$ii: \Delta B, \varepsilon_0^{1ii} = \frac{2rCRD + P_0(rC - RD)}{(rC + RD)B(1+g)} \xrightarrow{\Phi^{1ii} = \varepsilon_0^{1ii} - \varepsilon_0} \quad (5)$$

$$\Phi^{1ii} - \Phi^0 = \frac{-g[2rCRD + P_0(rC - RD)]}{(rC + RD)B(1+g)} < 0 \text{ if } g > 0$$

The sign is always negative if there is an increase in income of higher-income households. For the period 2, it holds that,

$$2: \Delta Y, \Delta B, \varepsilon_0^2 = \frac{2rCRD(1+g)^2 + P_0(rC - RD)(1 - g_P)(1+g)}{(rC + RD)B(1+g)^2} \quad (6)$$

$$\xrightarrow{\Phi^2 = \varepsilon_0^2 - \varepsilon_0} \left\{ \begin{array}{l} \Phi^2 - \Phi^{1i} = \frac{-g \left[2rCRD + \frac{1 - g_P}{1 + g} P_0(rC - RD) \right]}{(rC + RD)B(1+g)} ? 0 \\ \Phi^2 - \Phi^{1ii} = \frac{g2rCRD - g_P P_0(rC - RD)}{(rC + RD)B(1+g)} ? 0 \end{array} \right.$$

The hypothesis for the effect of the inequality–credit interaction on banking crises is provided:

Hypothesis: *The inequality-credit linkage (target independent variable) hampers the individual separate effect on the risk of triggering a banking crisis (dependent variable).*

The inequality-credit linkage is the interaction between income inequality and financial sector size, measured as a product. The individual effect is the separate effect of each one of those variables. There are, at least, two reasons for the effect proposed in the Hypothesis: One on the demand side and the other on the supply side. First, if I consider only the first-round effects of a raise in the demand of financial services by low-income households, as they pay a higher lending interest rate

than high-income households, this would increase at the same time as income inequality and financial development, leading to higher profits to the banks and a lower probability of a banking crisis in the current period. Second, if the supply side is seen, a joint effect of a change in both income inequality and financial sector size would mitigate the reduction of economic distortions provided by the individual effects, leading to a higher risk of banking crisis.

The second-round effects or possible secondary effects on the demand side could be related to applying higher interest rates to the low-income households than to the other customers, and with the possible defaults associated with those higher interests. There is a reduction in the demand due to both facts since they generate lower available income and a higher awareness of a higher risk of default, respectively. This lower demand would attenuate the above-mentioned first-round effects. The predominant effect is known in the empirical section.

Therefore, the expectations are as follows if there is a raise on the size of the financial sector:

$$\begin{aligned}
 \text{Case 1a: Higher-income raise: } \Phi^{1i} - \Phi^0 &< 0, \Phi^2 - \Phi^1 > 0 \\
 \text{Case 1b: Higher-income decrease: } \Phi^{1i} - \Phi^0 &> 0, \Phi^2 - \Phi^1 < 0 \\
 \text{Case 2a: Lower-income raise: } \Phi^{1i} - \Phi^0 &> 0, \Phi^2 - \Phi^1 < 0 \\
 \text{Case 2b: Lower-income decrease: } \Phi^{1i} - \Phi^0 &< 0, \Phi^2 - \Phi^1 > 0
 \end{aligned} \tag{7}$$

The cases of raising income inequality are 1a and 2b, while the decrease in income inequality appears in cases 1b and 2a. In Equation (7), the opposite inequality can also be found, where the key is that the period 2 effect (the linkage) hampers the period 1 (isolated) effect. Therefore, it is considered that the lower economic distortions and the reduced likelihood of suffering a banking crisis, which is provoked by the isolated higher income inequality and greater financial sector size, are hampered by the opposite effect on the risk of a banking crisis that is led by an increase in both inequality and financial size.

4. Empirical analysis

4.1. Empirical model specification

In this section, I specify the impact of the interaction between credit and income inequality on the probability of banking crises. An unbalanced data sample with 108 world countries for the period between 2002 and 2017 is managed.

I estimate models using the two-step dynamic System and Difference GMM methods (Arellano and Bover, 1995 and Blundell and Bond, 1998) since the instruments in the level regression are efficient predictors for endogenous variables (Blundell and Bond, 1998) and since these models are strongly advised for the high degree of persistence in the explained variable (Roodman, 2009). All models apply a bias-corrected robust estimator used for two-step variance-covariance matrix estimators (VCEs) and the WC-robust estimator of Windmeijer (2005). The specification of the GMM models follows Perugini et al. (2015) and Braun et al. (2019), with some modifications:

$$bcrisis_{i,t} = \beta_0 + \beta_1 bcrisis_{i,t-1} + \beta_2 inter_{i,t} + \beta_3 inequality_{i,t} + \beta_4 credit_{i,t} + X_{i,t} \beta_X + \varepsilon_{i,t} \tag{8}$$

where $i=1, \dots, N$ and, for the panel data estimations, the total of countries is $N=212$, $t=1, \dots, T$, and $T=48$ is the total of temporal periods. The dependent variable is the probability of suffering a systemic

banking crisis, the *interaction* variable is the product between the variables of income inequality (*inequality*), and credit (*credit*) and X are the control variables. In addition, β_0 is the constant, $\beta_1 - \beta_4$ are the coefficients of the temporal lag and target variables, β_X is the vector of coefficients of control variables, and $\varepsilon_{i,t}$ is the error term.

The *bcrisis* variable of systemic banking crises, provided by Laeven and Valencia (2013), takes 1 if there is a banking crisis in the country or 0 otherwise, using the definition of banking crisis from the previous authors. This variable is directly obtained from the World Bank, beginning with data in 1970 and ending in 2017 due to the availability of the variable in the World Bank Development Indicators Database for the dependent variable.

The target variables, in addition to the interaction, are the following depending on the model: The measures of income inequality are the Gini Index from the World Bank for *giniwb*, which reflects the way the distribution of income (or consumption expenditure) among persons within a country deviates from an equal distribution and the top income shares of the 1% richest people by the World Income Inequality Database for *top1*. The credit variable is measured by *cdpv* and *cdb*s and they are the percentage of domestic private credit provided by the financial sector and the banks over total GDP, respectively, which includes all credits to several public and private sectors. The *inter* variable constitutes, depending on the model, the product of the variables *giniwb* and *cdpv*, and *top1* and *cdb*s, respectively. The years and countries of the different samples and subsamples appear in Tables 1–2, using the classification codes developed by the World Bank.

The control variables of this model are the major targets of public policy. The GDP per capita is measured by the *gpc* variable, while in growth rates, it is expressed by *gpcgr* as a percentage. The public expenditure, *ps*, is measured by the expenditure of the public sector over the total of GDP and considers the public sector affairs. The macroeconomic issues are collected, initially, in *tbr*, reflecting the treasure bill rates calculated as the lending rate minus the risk premium. The deviation from the ideal inflation is provided by *dinfl*, which is the deviation between inflation and its optimum, measured as the absolute value of the difference between the inflation rate and the desirable inflation, which is considered to be 2% (OECD database). This variable takes into account the target of monetary policy. The variable *xgdp* considers the international influence and is measured as the quotient between the exports divided by the GDP; and the *atm* variable reflects the number of Automated Teller Machines (ATMs) over 100,000 adults for showing the banking factors.

Concerning the institutional issues, *sec* measures the rate of secondary school enrollment and the percentage of cities over total towns. The *unem* variable measures the unemployment rate. These variables have been constructed from the World Bank. Finally, a set of dummies is included for checking robustness: *Laxity* is a binary dummy used for the robustness check and reflects the period after the Great Moderation, 1987–2001, and previous to the Global Financial Crisis (GFC), 2007–2009; thus, it shows the period of similar lax monetary policy in most countries from 2002 to 2006 (taking 1 for the 2002–2006 period and 0 otherwise) as Peña (2017) points, where most countries began to apply accommodative policies and finished the Great Moderation period of high stability and certainty. There are two additional binary variables concerning economic and geographical issues: *oecd* and *eca*, which measure whether a country belongs to the Organization for Economic Cooperation and Development (OECD) or the Europe and Central Asia (ECA) region according to the World Bank, 1, or 0, otherwise, respectively.

The data sample is based on the countries that appear in Tables 1–2. An unbalanced panel is used, with data from 1970 to 2017 of 212 world countries considered for the panel data estimations,

while data from 1960 to 2021 of the 216 world countries is handled for the country-by-country Granger-causality test, with three different sub-samples for the panel Granger-causality tests since a balanced dataset is required.

Table 1. Countries and territories (216) of the full sample (1960–2021) of the Granger-causality test.

Full sample: 216 countries for 1960–2021							
ABW	BRB	DZA	HKG	LBR	MUS	QAT	THA
AFG	BRN	ECU	HND	LBY	MWI	ROU	TJK
AGO	BTN	EGY	HRV	LCA	MYS	RUS	TKM
ALB	BWA	ERI	HTI	LIE	NAM	RWA	TLS
AND	CAN	ESP	HUN	LKA	NCL	SAU	TON
ARE	CHE	EST	IDN	LSO	NER	SDN	TTO
ARG	CHI	ETH	IMN	LTU	NGA	SEN	TUN
ARM	CHL	FIN	IND	LUX	NIC	SGP	TUR
ASM	CHN	FJI	IRL	LVA	NLD	SLB	TUV
ATG	CIV	FRA	IRN	MAC	NOR	SLE	TZA
AUS	CMR	FRO	IRQ	MAF	NPL	SLV	UGA
AUT	COD	FSM	ISL	MAR	NRU	SMR	UKR
AZE	COG	GAB	ISR	MCO	NZL	SOM	URY
BDI	COL	GBR	ITA	MDA	OMN	SRB	USA
BEL	COM	GEO	JAM	MDG	PAK	SSD	UZB
BEN	CPV	GHA	JOR	MDV	PAN	STP	VCT
BFA	CRI	GIB	JPN	MEX	PER	SUR	VEN
BGD	CUB	GIN	KAZ	MHL	PHL	SVK	VGB
BGR	CUW	GMB	KEN	MKD	PLW	SVN	VIR
BHR	CYM	GNB	KGZ	MLI	PNG	SWE	VNM
BHS	CYP	GNQ	KHM	MLT	POL	SWZ	VUT
BIH	CZE	GRC	KIR	MMR	PRI	SXM	WSM
BLR	DEU	GRD	KNA	MNE	PRK	SYC	XXK
BLZ	DJI	GRL	KOR	MNG	PRT	SYR	YEM
BMU	DMA	GTM	KWT	MNP	PRY	TCA	ZAF
BOL	DNK	GUM	LAO	MOZ	PSE	TCO	ZMB
BRA	DOM	GUY	LBN	MRT	PYF	TGO	ZWE

Note: World Bank country codes, for the panel estimations the sample is constrained by the *bcrisis* variable, so it is for the 1970–2017 period for 212 countries, the previous ones with the exceptions of ATG, MCO, MUS, WSM. All the 212 countries have non-empty data from 1970 to 2017 with the exceptions of 15 countries that ranges from 1971 to 2017: AND, CHI, COD, GRL, GUM, IMN, NRU, PRI, PSE, ROU, SSD, SXM, TCA, TLS, XXK. Note: ABW: Aruba; AFG: Afghanistan; AGO: Angola; ALB: Albania; AND: Andorra; ARE: United Arab Emirates; ARG: Argentina; ARM: Armenia; ASM: American Samoa; ATG: Antigua and Barbuda; AUS: Australia; AUT: Austria; AZE: Azerbaijan; BDI: Burundi; BEL: Belgium; BEN: Benin; BFA: Burkina Faso; BGD: Bangladesh; BGR: Bulgaria; BHR: Bahrain; BHS: Bahamas, The; BIH: Bosnia and Herzegovina; BLR: Belarus; BLZ: Belize; BMU: Bermuda; BOL: Bolivia; BRA: Brazil; BRB: Barbados; BRN: Brunei Darussalam; BTN: Bhutan; BWA: Botswana; CAN: Canada; CHE: Switzerland; CHI: Channel Islands; CHL: Chile; CHN:

China; CIV: Cote d'Ivoire; CMR: Cameroon; COD: Congo, Dem. Rep.; COG: Congo, Rep.; COL: Colombia; COM: Comoros; CPV: Cabo Verde; CRI: Costa Rica; CUB: Cuba; CUW: Curacao; CYM: Cayman Islands; CYP: Cyprus; CZE: Czech Republic; DEU: Germany; DJI: Djibouti; DMA: Dominica; DNK: Denmark; DOM: Dominican Republic; DZA: Algeria; ECU: Ecuador; EGY: Egypt, Arab Rep.; ERI: Eritrea; ESP: Spain; EST: Estonia; ETH: Ethiopia; FIN: Finland; FJI: Fiji; FRA: France; FRO: Faroe Islands; FSM: Micronesia, Fed. Sts.; GAB: Gabon; GBR: United Kingdom; GEO: Georgia; GHA: Ghana; GIB: Gibraltar; GIN: Guinea; GMB: Gambia, The; GNB: Guinea-Bissau; GNQ: Equatorial Guinea; GRC: Greece; GRD: Grenada; GRL: Greenland; GTM: Guatemala; GUM: Guam; GUY: Guyana; HKG: Hong Kong SAR, China; HND: Honduras; HRV: Croatia; HTI: Haiti; HUN: Hungary; IDN: Indonesia; IMN: Isle of Man; IND: India; IRL: Ireland; IRN: Iran, Islamic Rep.; IRQ: Iraq; ISL: Iceland; ISR: Israel; ITA: Italy; JAM: Jamaica; JOR: Jordan; JPN: Japan; KAZ: Kazakhstan; KEN: Kenya; KGZ: Kyrgyz Republic; KHM: Cambodia; KIR: Kiribati; KNA: St. Kitts and Nevis; KOR: Korea, Rep.; KWT: Kuwait; LAO: Lao PDR; LBN: Lebanon; LBR: Liberia; LBY: Libya; LCA: St. Lucia; LIE: Liechtenstein; LKA: Sri Lanka; LSO: Lesotho; LTU: Lithuania; LUX: Luxembourg; LVA: Latvia; MAC: Macao SAR, China; MAF: St. Martin (French part); MAR: Morocco; MCO: Monaco; MDA: Moldova; MDG: Madagascar; MDV: Maldives; MEX: Mexico; MHL: Marshall Islands; MKD: North Macedonia; MLI: Mali; MLT: Malta; MMR: Myanmar; MNE: Montenegro; MNG: Mongolia; MNP: Northern Mariana Islands; MOZ: Mozambique; MRT: Mauritania; MUS: Mauritius; MWI: Malawi; MYS: Malaysia; NAM: Namibia; NCL: New Caledonia; NER: Niger; NGA: Nigeria; NIC: Nicaragua; NLD: Netherlands; NOR: Norway; NPL: Nepal; NRU: Nauru; NZL: New Zealand; OMN: Oman; PAK: Pakistan; PAN: Panama; PER: Peru; PHL: Philippines; PLW: Palau; PNG: Papua New Guinea; POL: Poland; PRI: Puerto Rico; PRK: Korea, Dem. People's Rep.; PRT: Portugal; PRY: Paraguay; PSE: West Bank and Gaza; PYF: French Polynesia; QAT: Qatar; ROU: Romania; RUS: Russian Federation; RWA: Rwanda; SAU: Saudi Arabia; SDN: Sudan; SEN: Senegal; SGP: Singapore; SLB: Solomon Islands; SLE: Sierra Leone; SLV: El Salvador; SMR: San Marino; SOM: Somalia; SRB: Serbia; SSD: South Sudan; STP: Sao Tome and Principe; SUR: Suriname; SVK: Slovak Republic; SVN: Slovenia; SWE: Sweden; SWZ: Eswatini; SXM: Sint Maarten (Dutch part); SYC: Seychelles; SYR: Syrian Arab Republic; TCA: Turks and Caicos Islands; TCD: Chad; TGO: Togo; THA: Thailand; TJK: Tajikistan; TKM: Turkmenistan; TLS: Timor-Leste; TON: Tonga; TTO: Trinidad and Tobago; TUN: Tunisia; TUR: Turkiye; TUV: Tuvalu; TZA: Tanzania; UGA: Uganda; UKR: Ukraine; URY: Uruguay; USA: United States; UZB: Uzbekistan; VCT: St. Vincent and the Grenadines; VEN: Venezuela, RB; VGB: British Virgin Islands; VIR: Virgin Islands (U.S.); VNM: Vietnam; VUT: Vanuatu; WSM: Samoa; XKX: Kosovo; YEM: Yemen, Rep.; ZAF: South Africa; ZMB: Zambia; ZWE: Zimbabwe.

Table 2. Balanced subsamples for the panel Granger-causality test.

Balanced Subsample 1 (2005–2019), H_0 : $giniw*bcdpv$ does not GC gpc					
AUT	BEL	CRI	CYP	CZE	
DNK	DOM	ECU	ESP	EST	
FIN	GRC	HND	HUN	KGZ	
LUX	NLD	NOR	PER	PRT	
PRY	RUS	SLV	SVN	SWE	USA
Balanced Subsample 2 (1960–2021), H_0 : $topl*cdbs$ does not GC gpc					
AUS	IND	JPN	NOR	SWE	USA
Balanced Subsample 3 (2002–2019), H_0 : $topl*cdbs$ does not GC gpc					
AGO	CHN	GHA	KHM	NER	SLV

Continued on next page

Balanced Subsample 3 (2002–2019), H_0 : *topl*cdbs* does not GC *gpc*

AGO	CHN	GHA	KHM	NER	SLV
ALB	CIV	GIN	KOR	NGA	SRB
ARE	CMR	GNB	KWT	NIC	STP
ARG	COD	GNQ	LBR	NLD	SUR
ARM	COG	GRC	LBY	NOR	SWE
AUS	COL	GTM	LKA	NPL	SWZ
AUT	COM	GUY	LSO	OMN	SYC
AZE	CPV	HKG	LUX	PAK	TCO
BDI	CRI	HND	MAC	PAN	TGO
BEL	CYP	HRV	MAR	PER	THA
BEN	CZE	HTI	MDA	PHL	TJK
BFA	DEU	HUN	MDG	PNG	TLS
BGD	DJI	IDN	MDV	POL	TTO
BGR	DNK	IND	MEX	PRT	TUN
BHS	DOM	IRL	MKD	PRY	TUR
BIH	DZA	ISL	MLI	PSE	TZA
BLR	ECU	ISR	MMR	QAT	UGA
BLZ	EGY	ITA	MNE	ROU	UKR
BOL	ESP	JAM	MNG	RUS	URY
BRA	FIN	JOR	MOZ	RWA	USA
BRN	FRA	JPN	MUS	SDN	VNM
BTN	GAB	KAZ	MWI	SEN	ZAF
BWA	GBR	KEN	MYS	SGP	ZMB
CHL	GEO	KGZ	NAM	SLE	

The recent Granger-causality panel data test proposed by Juodis, Karavias, and Sarafidis (2021) and Xiao et al. (2023) follows this function:

$$Y_{i,t} = \phi_{0i} + \sum_{p=1}^P \beta_{pi} x_{it-p} + \varepsilon_{it} \quad (9)$$

Being the X and Y independent and dependent variables, x_{it-p} is a scalar of individual i in time t minus the temporal lag p , and the errors are ε_{it} and β_{pi} for the Granger-causality parameter. The null hypothesis is that x_{it-p} does not Granger-cause (GC) $y_{i,t-p}$, formalized as follows (left), whereas the alternative is (right):

$$H_0: \beta_{pi} = 0 \forall i, p; H_1: \exists i, p | \beta_{pi} \neq 0 \quad (10)$$

Avoidance of the rejection of the null hypothesis shows that x_{it-p} does not GC $y_{i,t-p}$.

The major characteristics of the variables and the expected signs of the explanatory variables are included in Tables 3 and 4. No significant correlation between each couple of variables is found after applying the matrix of correlation and the Variance Inflation Factor (VIF) test¹.

¹ Results available upon request.

Table 3. Major characteristics of the variables.

Variable	Source	Expected sign	Definition. References	Observations	Mean	Standard deviation	Minimum	Maximum
<i>bcrisis</i> (0,1)	World Bank (WB)	N/A	Variable taking 1 if banking crisis, 0 otherwise	10161	0.04	0.21	0.00	1.00
<i>giniwb</i> (0–100)	WB	+	Gini Index/Income share of the 1 st percentile of richest people. Claessens and Perotti (2005) and Braun et al. (2019)	1665	38.46	9.19	20.70	65.80
<i>top1</i> (0–1)	WID			6805	0.16	0.06	0.02	0.64
<i>cdpv</i> (% GDP)	WB	+	Share of private credit. Share of banking sector credit. Claessens and Perotti (2005), Peña (2017), Braun et al. (2019) and Bouvatier and Ouardi (2023)	5609	40.13	38.68	0.01	304.58
<i>cdbs</i> (% GDP)				6659	37.23	40.47	0.00	525.64
<i>inter</i> (interaction)	WB/WID	-	<i>giniwb*cdpv/top1*cdbs</i> . By the authors, based on Claessens and Perotti (2005) and Braun et al. (2019)	<i>giniwb*cdpv, top1*cdbs</i>				
<i>gpcgr</i> (% growth rate)	World Bank	-	Growth rate of GDP per capita. Pereira et al. (2018)	8040	2.00	6.06	-64.99	140.37
<i>ps</i> (% GDP)	World Bank	+	Share of public spending. Demirgüç-Kunt and Detragiache (1998)	3564	26.56	12.59	0.00	210.21
<i>tbr</i> (% rate)	World Bank	+	Treasury bill rate: lending interest rate minus risk spread. Laeven (2011)	2074	9.23	9.81	-0.54	124.03
<i>dinfl</i> (% growth rate)	OECD Database	+	Deviation between inflation and 2% optimum. Demirgüç-Kunt and Detragiache 1998, von Hagen and Ho 2007	6871	26.13	364.23	0.00	23771.13

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Variable	Source	Expected sign	Definition. References	Observations	Mean	Standard deviation	Minimum	Maximum
<i>xgdp</i> (% GDP)	World Bank	+	Share of exports. Peña (2020)	7017	37.25	28.98	0.01	433.84
<i>atms</i> (per 100000 adults)	World Bank	-	Automated Teller Machines per adults. Gavin and Hausmann (1996)	2623	44.60	45.87	0.01	324.17
<i>sec</i> (% gross)	World Bank	-	Secondary school enrollment. Neaime and Gaysset (2018)	6150	64.98	34.08	0.19	166.14
<i>urban</i> (% over total)	World Bank	?	Share of urban population	10122	52.90	25.24	2.85	100.00
<i>unem</i> (% rate)	World Bank	+	Unemployment rate. Pereira et al. (2018)	4076	8.19	6.17	0.05	57.00
<i>lax</i> (0,1)	Own elaboration	+	Lax (discretionary) period: 1, 0 otherwise. Taylor (2012), Peña, 2017)	10176	0.10	0.31	0.00	1.00
<i>oecd</i> (0,1)	Own elaboration	?	OECD member: 1, 0 otherwise	10176	0.18	0.38	0.00	1.00
<i>eca</i> (0,1)	World Bank	?	Europe and Central Asia member: 1, 0 otherwise	10176	0.27	0.45	0.00	1.00

Table 4. Descriptive statistics for the samples used for Granger-causality.

Full sample					
Variable	Obs	Mean	Std. dev.	Min	Max
<i>gpc</i>	10,271	9051.918	17589.54	12.80281	189487.1
<i>top1*cdb</i> s	6,056	6.174511	5.867718	0.0002167	54.85093
<i>giniwb*cdpv</i>	1,457	2259.034	1677.736	4.617013	9446.48
Subsample 1					
Variable	Obs	Mean	Std. dev.	Min	Max
<i>gpc</i>	390	29796.21	27208.48	476.552	123679
<i>giniwb*cdpv</i>	390	2834.955	1786.364	215.3008	9446.48
Subsample 2					
Variable	Obs	Mean	Std. dev.	Min	Max
<i>gpc</i>	372	22919.56	23258.77	82.1886	102913
<i>top1*cdb</i> s	372	7.70555	5.153445	1.052586	25.26913
Subsample 3					
Variable	Obs	Mean	Std. dev.	Min	Max
<i>gpc</i>	2,574	12885.05	19105.91	113.567	123679
<i>top1*cdb</i> s	2,574	7.350831	6.636802	0.0002623	54.85093

4.2. Results

The major results are shown, with the robust standard errors in Tables 5 and 6. These tables show the results of the System GMM models (SYS) and Difference GMM models (DIF). The target variables are *cdpv* and *gini* for Table 5 and *cdb*s and *top1* for Table 6. The estimations are shown with only interaction (INTER, Models 1–2), with both the credit and inequality variables (BOTH, 3–4), the interaction and inequality measures (INTER & INEQ, 5–6), the interaction and inequality measures (INTER & CRED, 7–8), or with all the variables (INTER & BOTH, 9–10). The models achieve accurate econometric properties, which are confirmed by the no significance of the subjection to serial correlation of order two (fulfilling the Arellano-Bond test) and the no significance of the over-identification of the instruments. These instruments are considered valid by the application of the Sargan test, which is the same as the Hansen's for this two-step model (Roodman, 2009).

Table 5. Panel data estimations I.

MODELS\ VARIABLES	(1) SYS	(2) DIF	(3) SYS	(4) DIF	(5) SYS	(6) DIF	(7) SYS	(8) DIF	(9) SYS	(10) DIF
Dependent variable:	ONLY	ONLY	BOTH	BOTH	INTER &	INTER &	INTER &	INTER &	INTER &	INTER&
<i>crisisb</i>	INTER	INTER			INEQ	INEQ	CREDIT	CREDIT	BOTH	BOTH
<i>crisisb_{t-1}</i>	0.690*** (0.226)	0.705** (0.329)	0.694*** (0.182)	0.824*** (0.239)	0.672*** (0.169)	0.797*** (0.225)	0.903*** (0.328)	0.914* (0.487)	0.946*** (0.298)	0.854*** (0.225)
<i>giniwb</i>			0.00707 (0.0164)	0.0632* (0.0356)	0.00625 (0.0162)	0.0588* (0.0346)			−0.0286** (0.0125)	−0.0318 (0.0354)
<i>cdpv</i>			3.30e-05 (0.00160)	−0.00102 (0.00114)			−0.0202** (0.0102)	−0.0310*** (0.0112)	−0.0332*** (0.0118)	−0.0364*** (0.0120)
<i>inter^a</i>	3.70e-06 (7.61e-5)	1.72e-05 (3.79e-05)			2.31e-05 (5.26e-5)	7.28e-06 (4.33e-05)	0.000604* (0.000308)	0.000966*** (0.000322)	0.00102*** (0.000372)	0.00115*** (0.000364)
<i>gpcgr</i>	−0.00684 (0.00959)	−0.00768 (0.00603)	−0.00650 (0.00777)	−0.010*** (0.00362)	−0.00651 (0.00700)	−0.0097** (0.00381)	−0.00915 (0.00664)	−0.00766 (0.00838)	−0.00791 (0.00671)	−0.00513 (0.00819)
<i>ps</i>	0.00546 (0.00400)	0.00962 (0.00775)	0.0105 (0.0156)	0.00599 (0.00480)	0.00999 (0.0150)	0.00637 (0.00507)	0.00540 (0.00904)	0.00214 (0.00239)	0.00156 (0.00320)	0.00226 (0.00240)
<i>tbr</i>	0.00884 (0.0243)	−0.00767 (0.0270)	0.00650 (0.0224)	−0.0184 (0.0206)	0.00610 (0.0209)	−0.0192 (0.0189)	0.00555 (0.0113)	−0.00912 (0.0132)	1.74e-05 (0.0125)	−0.00888 (0.0112)
<i>dinfl</i>	0.0125 (0.0157)	0.0111 (0.0106)	0.0160 (0.0121)	0.00981 (0.00782)	0.0153 (0.0117)	0.00953 (0.00753)	0.00995 (0.00976)	0.00624 (0.00693)	0.00494 (0.00804)	0.00614 (0.00861)
<i>xgdp</i>	0.00123 (0.00376)	0.00492 (0.00415)	0.00102 (0.00266)	0.00219 (0.00426)	0.00133 (0.00293)	0.00292 (0.00434)	0.00242 (0.00332)	0.00113 (0.00454)	0.000668 (0.00289)	0.00120 (0.00448)
<i>atms</i>	0.000427 (0.00208)	0.000837** (0.000424)	0.000601 (0.00108)	0.000423 (0.000445)	0.000392 (0.00140)	0.000368 (0.000464)	0.000503 (0.00104)	0.000211 (0.000547)	−0.00128 (0.00214)	0.000190 (0.000609)
<i>sec</i>	−0.00134 (0.00292)	−0.000319 (0.00197)	−0.00149 (0.00300)	0.000785 (0.00243)	−0.00155 (0.00316)	0.000854 (0.00240)	0.000455 (0.00245)	0.00151 (0.00242)	0.000763 (0.00287)	0.00110 (0.00201)

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MODELS\ VARIABLES	(1) SYS	(2) DIF	(3) SYS	(4) DIF	(5) SYS	(6) DIF	(7) SYS	(8) DIF	(9) SYS	(10) DIF
Dependent variable:	ONLY	ONLY	BOTH	BOTH	INTER &	INTER &	INTER &	INTER &	INTER &	INTER &
<i>crisisb</i>	INTER	INTER			INEQ	INEQ	CREDIT	CREDIT	BOTH	BOTH
<i>urban</i>	−0.00208 (0.00332)	−0.0382 (0.0393)	−0.00217 (0.00561)	−0.00870 (0.0362)	−0.00205 (0.00443)	−0.0123 (0.0351)	0.00193 (0.00569)	−0.00369 (0.0316)	0.00227 (0.00331)	−0.0126 (0.0248)
<i>unem</i>	−0.00714 (0.0171)	−0.0258 (0.0260)	−0.0156 (0.0217)	−0.0412 (0.0275)	−0.0134 (0.0204)	−0.0383 (0.0262)	−0.0284 (0.0248)	−0.0224 (0.0302)	−0.0184 (0.0248)	−0.0142 (0.0224)
<i>constant</i>	0.0370 (0.246)	2.319 (2.744)	−0.251 (0.846)	−1.609 (3.147)	−0.274 (0.768)	−1.357 (3.070)	−0.410 (0.656)	−0.131 (2.153)	0.762 (0.545)	1.508 (2.517)
Observations	197	137	197	137	197	137	197	137	197	137
Number of countries	32	19	32	19	32	19	32	19	32	19
A-B test	0.2575	0.2923	0.2835	0.5148	0.2622	0.4489	0.4285	0.4969	0.4802	0.5079
Sargan test	0.9657	0.5191	0.7627	0.6952	0.7844	0.7081	0.9032	0.6647	0.9648	0.6450

Note: ***, **, and * indicate statistical significance at 1%, 5% and 10% level, respectively. Standard errors are in parenthesis. ^a: *inter* is obtained as *giniwb*cdpv*.

Table 6. Panel data estimations II.

MODELS \ VARIABLES	(1) SYS	(2) DIF	(3) SYS	(4) DIF	(5) SYS	(6) DIF INTER	(7) SYS	(8) DIF	(9) SYS	(10) DIF
Dependent variable:	ONLY	ONLY	BOTH	BOTH	INTER &	& INEQ	INTER &	INTER &	INTER &	INTER &
<i>crisisb</i>	INTER	INTER			INEQ		CREDIT	CREDIT	BOTH	BOTH
<i>crisisb_{t-1}</i>	0.802*** (0.254)	0.767*** (0.0906)	0.806*** (0.170)	0.745*** (0.0770)	0.792*** (0.302)	0.767*** (0.0816)	0.715*** (0.191)	0.679*** (0.108)	0.783*** (0.137)	0.678*** (0.109)
<i>top1</i>			−0.964 (0.995)	−1.032 (0.974)	−0.175 (1.006)	0.308 (1.216)			1.317** (0.542)	1.671*** (0.335)
<i>cdbb</i>			−0.00025 (0.00116)	−0.000397 (0.00192)			0.00289 (0.00196)	0.00325 (0.00474)	0.00417 (0.00303)	0.00482 (0.00484)
<i>inter^a</i>	−0.0163 (0.0152)	−0.022*** (0.00612)			−0.0157 (0.0170)	−0.0233** (0.00946)	−0.0276*** (0.0104)	−0.0331*** (0.00363)	−0.0362*** (0.00681)	−0.0450*** (0.00545)

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MODELS \ VARIABLES	(1) SYS ONLY	(2) DIF ONLY	(3) SYS BOTH	(4) DIF BOTH	(5) SYS INTER & INEQ	(6) DIF INTER & INEQ	(7) SYS INTER & CREDIT	(8) DIF INTER & CREDIT	(9) SYS INTER & BOTH	(10) DIF INTER & BOTH
Dependent variable:	ONLY	ONLY	BOTH	BOTH	INTER & INEQ	& INEQ	INTER & CREDIT	INTER & CREDIT	INTER & BOTH	INTER & BOTH
<i>crisisb</i>	INTER	INTER			INEQ		CREDIT	CREDIT	BOTH	BOTH
<i>gpcgr</i>	−0.00243 (0.00212)	−0.00151 (0.00545)	−0.00044 (0.00193)	0.000177 (0.00309)	−0.00222 (0.00219)	−0.00148 (0.00542)	−0.00150 (0.00584)	0.000231 (0.00598)	−0.000692 (0.00982)	0.000388 (0.00476)
<i>ps</i>	0.00554 (0.00976)	0.00655 (0.00486)	0.00335 (0.00407)	0.00521 (0.00605)	0.00528 (0.00869)	0.00632 (0.00451)	0.00259 (0.00393)	0.00467 (0.00874)	0.00351 (0.00530)	0.00413 (0.00861)
<i>tbr</i>	0.00310 (0.00824)	−0.000930 (0.0179)	−0.00220 (0.00363)	−0.00486 (0.00365)	0.00269 (0.00723)	−0.00114 (0.0171)	0.00145 (0.0186)	−0.00468 (0.0127)	0.000454 (0.0274)	−0.00533 (0.00865)
<i>dinfl</i>	0.00459 (0.00547)	0.00129 (0.00549)	0.00464 (0.00553)	0.00107 (0.00299)	0.00480 (0.00575)	0.00153 (0.00539)	0.00463 (0.00661)	−0.000456 (0.00453)	0.00474 (0.00456)	−0.000980 (0.00336)
<i>xgdp</i>	−0.00165 (0.00261)	−0.00153 (0.00161)	−0.00106 (0.00114)	0.000100 (0.000982)	−0.00166 (0.00250)	−0.00147 (0.00151)	−0.00156 (0.00271)	−0.000940 (0.00188)	−0.00148 (0.00301)	−0.000926 (0.00196)
<i>atms</i>	0.00110 (0.00153)	0.000926 (0.000822)	0.000293 (0.00137)	0.000537 (0.000789)	0.00112 (0.00216)	0.000853 (0.000743)	0.000553 (0.000987)	0.000420 (0.00135)	0.000392 (0.00137)	0.000110 (0.00112)
<i>sec</i>	−0.000975 (0.00259)	−0.000702 (0.00127)	−0.00085 (0.00197)	−0.000445 (0.00123)	−0.00103 (0.00323)	−0.000629 (0.00134)	−0.00120 (0.00166)	−0.000574 (0.00159)	−0.000310 (0.000871)	−0.000400 (0.00158)
<i>urban</i>	−0.00147 (0.00204)	−0.00810 (0.0159)	−0.00061 (0.00258)	−0.0101 (0.00734)	−0.00136 (0.00294)	−0.00823 (0.0159)	−0.000768 (0.00178)	−0.0111 (0.00875)	−0.00401 (0.00346)	−0.0104 (0.00699)
<i>unem</i>	−0.00445 (0.00957)	−0.00617 (0.0111)	−0.00488 (0.00392)	−0.00530 (0.00506)	−0.00480 (0.00893)	−0.00647 (0.0105)	−0.00379 (0.00867)	−0.00629 (0.00516)	−0.00330 (0.00931)	−0.00588 (0.00495)
<i>constant</i>	0.219 (0.302)	0.703 (1.242)	0.292 (0.328)	0.802 (0.503)	0.252 (0.383)	0.684 (1.323)	0.233 (0.382)	0.869 (0.559)	0.127 (0.339)	0.584 (0.447)
Observations	329	261	329	261	329	261	329	261	329	261
Number of countries	40	34	40	34	40	34	40	34	40	34
A-B test	0.3904	0.4551	0.3493	0.3628	0.3950	0.4587	0.3597	0.4052	0.3354	0.3806
Sargan test	0.8286	0.4137	0.7456	0.6236	0.7599	0.4158	0.7894	0.4802	0.7549	0.5167

Note: ***, **, and * indicate statistical significance at 1%, 5% and 10% level, respectively. Standard errors are in parenthesis. “: *inter* is obtained as *top1*cdbs*

The results in Tables 5 and 6 show the robustness for most coefficients of the variables that are significant. In particular, the coefficients of the target variables are hardly always significant. The results of the target variables are depicted. As expected, a negative impact of interaction on the dependent variable is obtained, while the Gini and credit variables have a positive individual effect on the probability of a banking crisis, confirming the proposed Hypothesis of Section 3. Therefore, the first-round effects of a raise in the demand of financial services by low-income households with higher lending interest rates leads to a higher income inequality and financial development that raises banks' profits and reduce the likelihood of a banking crisis in the current period. This first-round effect is in the opposite sign than the second-round effects since those high interest rates lead to a lower demand and less profits to the banks.

The rest of control variables are never significant, except *gpcgr* and *atms*. The presence of interactive terms means that the total effect of one variable (the credit or inequality variable) must be computed using the estimated coefficient of that variable plus the estimated coefficient of the interactive variable multiplied by the other variable. Thus, the positive effect of the non-interacted target variables is reduced by the interaction.

Finally, as it is not possible to identify whether the interaction does not Granger Cause (GC) a binary variable as a dependent variable, as when the risk of a banking crises and Braun et al. (2019) did not check that relationship, I employed the extremely novel technique for checking Granger-causality on GDP per capita in panel data. This was proposed by Juodis et al. (2021) and was developed by Xiao et al. (2023), who solved the so-called 'Neville bias'. As it is useful for balanced panels, I reduced the sample in order to achieve a balanced panel. The results are shown in Table 7.

Table 7. Panel data Granger-causality tests with the three subsamples.

Balanced Subsample 1 (2005–2019, 26 countries), H_0 : <i>gini</i> * <i>cdpv</i> does not GC <i>gpc</i>			
p-value	Units	Obs. per unit	BIC
0	26	14	4982.371
Balanced Subsample 1 (2005–2019, 26 countries), H_0 : <i>gpc</i> does not GC <i>gini</i> * <i>cdpv</i>			
p-value	Units	Obs. per unit	BIC
0.188	26	14	3399.521
Balanced Subsample 2 (1960–2021), H_0 : <i>topl</i> * <i>cdbs</i> does not GC <i>gpc</i>			
p-value	Units	Obs. per unit	BIC
0	62	5	3674.653
Balanced Subsample 2 (1960–2021), H_0 : does <i>gpc</i> not GC <i>topl</i> * <i>cdbs</i>			
p-value	Units	Obs. per unit	BIC
0	62	5	425.4523
Balanced Subsample 3 (2002–2019), H_0 : <i>topl</i> * <i>cdbs</i> does not GC <i>gpc</i>			
p-value	Units	Obs. per unit	BIC
0	143	17	32846.07
Balanced Subsample 3 (2002–2019), H_0 : <i>gpc</i> does not GC <i>topl</i> * <i>cdbs</i>			
p-value	Units	Obs. per unit	BIC
0	143	17	71.53767

Note: Obs. means observations.

Checking the null hypothesis as to whether the interaction, specified in two differentiated alternative ways, does not GC *gpc*, it was found that the null hypothesis is rejected at the 1% level of significance for all the samples and specifications. The opposite direction is non-rejected at the 10% significance level with a p-value of 0.180 for sub-sample 1. Two different additional subsamples have been used with GDP per capita, a different measure of inequality and credit with similar results, and rejecting the null hypothesis for the opposite direction. These results are consistent with the theoretical analysis in Section 3 and follows the Hypothesis developed there.

3.3. Robustness check

The results in Tables 8–10 show the robustness checks for the panel data estimations. Table 10 shows *cdpv* and *gini* (GINI, Models 1–4), and *cdb*s and *top1* (GINI, Models 5–8) as target variables. Different dummy variables are incorporated, such as *lax* (Models 1–2, 5–6), *oecd* (Models 3, 7), and *eca* (Models 4, 8). The results are similar to those in Tables 5–6.

Table 8. Robustness check: Country-by-country Granger-causality test full sample (available tests for 64 countries).

WB CC	p-value	Reject?	WB CC	p-value	Reject?
ALB	0	1	ISR	0.192	0
ARG	0.761	0	ITA	0.013	1
ARM	0.025	1	KGZ	0.325	0
AUT	0.592	0	LTU	0.528	0
BEL	0.828	0	LUX	0.024	1
BGR	0.021	1	LVA	0	1
BLR	0.545	0	MDA	0.095	1
BOL	0.013	1	MKD	0	1
BRA	0.128	0	MLT	0.007	1
CHE	0.239	0	MNE	0.869	0
CHN	0	1	NLD	0.808	0
COL	0.24	0	NOR	0.365	0
CRI	0.074	1	PAN	0	1
CYP	0.005	1	PER	0	1
CZE	0.262	0	POL	0.022	1
DEU	0.014	1	PRT	0.758	0
DNK	0.016	1	PRY	0.038	1
DOM	0.101	0	PSE	0	1
ECU	0	1	ROU	0	1
ESP	0.624	0	RUS	0.504	0
EST	0.262	0	SLV	0.038	1
FIN	0.036	1	SRB	0	1
FRA	0.005	1	SVK	0.593	0
GBR	0.969	0	SVN	0.504	0
GEO	0	1	SWE	0.155	0

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WB CC	p-value	Reject?	WB CC	p-value	Reject?
GRC	0	1	THA	0	1
HND	0.859	0	TUR	0	1
HRV	0	1	UKR	0.011	1
HUN	0.011	1	URY	0.702	0
IDN	0	1	USA	0.062	1
IRL	0	1	VEN	0.803	0
ISL	0.03	1	XKX	0.027	1
			AVG	0.22035938	0.59375

Note: WB CC means World Bank Country Codes, p-value indicates the one of the country-by-country Granger-causality test with H_0 *gini*cdpv* does not GC gpc, Reject? means whether the null hypothesis is rejected for a country (1) or not (0), and AVG means the average. For the meaning of the country codes, see the footnote in Table 2.

Table 9. Robustness check: Country-by-country Granger-causality test full sample (available tests for 176 countries).

WB CC	p-value	Reject?	WB CC	p-value	Reject?	WB CC	p-value	Reject?
AFG	0	1	GMB	0.007	1	NIC	0.045	1
AGO	0.463	0	GNB	0.016	1	NLD	0.034	1
ALB	0.005	1	GNQ	0.467	0	NOR	0.011	1
ARE	0.99	0	GRC	0	1	NPL	0.053	1
ARG	0.287	0	GTM	0	1	NZL	0.001	1
ARM	0.007	1	GUY	0.402	0	OMN	0.244	0
AUS	0.002	1	HKG	0	1	PAK	0.448	0
AUT	0.97	0	HND	0.003	1	PAN	0.13	0
AZE	0.671	0	HRV	0.25	0	PER	0.07	1
BDI	0	1	HTI	0.394	0	PHL	0.1	0
BEL	0.169	0	HUN	0.569	0	PNG	0.004	1
BEN	0	1	IDN	0	1	POL	0.73	0
BFA	0.11	0	IND	0	1	PRT	0.086	1
BGD	0.027	1	IRL	0	1	PRY	0	1
BGR	0.502	0	IRN	0.003	1	PSE	0.092	1
BHR	0.8	0	IRQ	0	1	QAT	0.455	0
BHS	0.112	0	ISL	0.142	0	ROU	0.166	0
BIH	0.118	0	ISR	0.949	0	RUS	0.004	1
BLR	0.003	1	ITA	0.011	1	RWA	0	1
BLZ	0.737	0	JAM	0.251	0	SAU	0	1
BOL	0.621	0	JOR	0	1	SDN	0.369	0
BRA	0.081	1	JPN	0	1	SEN	0.001	1
BRN	0.591	0	KAZ	0	1	SGP	0.051	1
BTN	0.355	0	KEN	0	1	SLE	0	1
BWA	0.002	1	KGZ	0.231	0	SLV	0.501	0
CAN	0	1	KHM	0.002	1	SOM	0.218	0

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WB CC	p-value	Reject?	WB CC	p-value	Reject?	WB CC	p-value	Reject?
CHE	0.209	0	KOR	0	1	SRB	0.307	0
CHL	0.298	0	KWT	0.001	1	STP	0.002	1
CHN	0.78	0	LAO	0.003	1	SUR	0.127	0
CIV	0	1	LBN	0.118	0	SVK	0.001	1
CMR	0.367	0	LBR	0	1	SVN	0.11	0
COD	0.003	1	LBY	0.332	0	SWE	0.08	1
COG	0.017	1	LKA	0.004	1	SWZ	0	1
COL	0.021	1	LSO	0	1	SYC	0.525	0
COM	0.026	1	LTU	0.004	1	SYR	0.056	1
CPV	0.955	0	LUX	0.269	0	TCD	0.376	0
CRI	0.003	1	LVA	0.708	0	TGO	0.521	0
CYP	0.173	0	MAC	0.267	0	THA	0.118	0
CZE	0.46	0	MAR	0.211	0	TJK	0.2	0
DEU	0.246	0	MDA	0.005	1	TLS	0.006	1
DJI	0.001	1	MDG	0.005	1	TTO	0	1
DNK	0.658	0	MDV	0.013	1	TUN	0.361	0
DOM	0.283	0	MEX	0.683	0	TUR	0	1
DZA	0.132	0	MKD	0.848	0	TZA	0.396	0
ECU	0.22	0	MLI	0	1	UGA	0.004	1
EGY	0	1	MLT	0.427	0	UKR	0.748	0
ERI	0.005	1	MMR	0	1	URY	0	1
ESP	0.123	0	MNE	0	1	USA	0.327	0
EST	0.825	0	MNG	0.007	1	UZB	0	1
ETH	0	1	MOZ	0.001	1	VEN	0	1
FIN	0.263	0	MRT	0.004	1	VNM	0	1
FRA	0.055	1	MUS	0	1	XKX	0.459	0
GAB	0.189	0	MWI	0	1	YEM	0.161	0
GBR	0.568	0	MYS	0.973	0	ZAF	0.008	1
GEO	0.455	0	NAM	0.089	1	ZMB	0.039	1
GHA	0.278	0	NER	0.089	1	ZWE	0.064	1
GIN	0.162	0	NGA	0.396	0	AVG	0.19624118	0.53529412

Note: WB CC means World Bank Country Codes, p-value indicates the one of the country-by-country Granger-causality test with H_0 *top1*cdbs* does not GC *gpc*, Reject? means whether the null hypothesis is rejected for a country (1) or not (0), and AVG means the average. For the meaning of the country codes, see the footnote in Table 2.

Table 10. Robustness of the panel data estimations.

VARIABLES	(1) SYS GINI	(2) DIF GINI	(3) SYS GINI	(4) SYS GINI	(5) SYS TOP1	(6) DIF TOP1	(7) SYS TOP1	(8) SYS TOP1
Dependent variable: <i>crisisb</i>	LAX	LAX	OECD	ECA	LAX	LAX	OECD	ECA
<i>crisisb_{t-1}</i>	0.947*** (0.295)	0.854*** (0.225)	0.937*** (0.271)	0.707*** (0.229)	0.722*** (0.164)	0.665*** (0.118)	0.768*** (0.102)	0.783*** (0.164)
<i>cdpv</i>	0.00103** (0.000418)	0.00114*** (0.000357)	0.000922** (0.000372)	0.000859*** (0.000228)				
<i>giniwb</i>	-0.0286** (0.0125)	-0.0310 (0.0357)	-0.0189 (0.0195)	-0.00132 (0.0253)				
<i>inter</i>	-0.0337*** (0.0130)	-0.0362*** (0.0119)	-0.0305*** (0.0116)	-0.0283*** (0.00706)	-0.0403*** (0.00728)	-0.0462*** (0.00410)	-0.0363*** (0.00625)	-0.0367*** (0.00669)
<i>top1</i>					1.361** (0.598)	1.619*** (0.437)	1.199* (0.679)	1.368** (0.698)
<i>cdbs</i>					0.00408*** (0.00109)	0.00466 (0.00447)	0.00405 (0.00252)	0.00415 (0.00352)
<i>gpcgr</i>	-0.00817 (0.00700)	-0.00519 (0.00838)	-0.00703 (0.00515)	-0.0136* (0.00744)	-0.00149 (0.00180)	-0.000386 (0.00696)	-0.000666 (0.00825)	-0.000694 (0.00893)
<i>ps</i>	0.00133 (0.00313)	0.00216 (0.00254)	0.00123 (0.00186)	0.00284 (0.00233)	0.00506 (0.00488)	0.00447 (0.00747)	0.00438 (0.00623)	0.00388 (0.00617)
<i>tbr</i>	-0.00270 (0.0278)	-0.00912 (0.0112)	0.00378 (0.0139)	-0.0116 (0.0237)	0.000713 (0.00868)	-0.00426 (0.0161)	0.000566 (0.0222)	0.000177 (0.0250)
<i>dinfl</i>	0.00474 (0.00798)	0.00613 (0.00802)	0.00634 (0.00830)	0.00889 (0.00715)	0.00220 (0.00265)	-0.000537 (0.00554)	0.00392 (0.00349)	0.00433 (0.00379)
<i>xgdp</i>	0.000579 (0.00309)	0.00103 (0.00451)	0.000269 (0.00279)	-0.000493 (0.00342)	-0.00156 (0.00181)	-0.00130 (0.00197)	-0.00129 (0.00300)	-0.00156 (0.00264)
<i>atms</i>	-0.00132	0.000161	-0.000525	-0.000480	0.000488	0.000223	0.000462	0.000399

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VARIABLES	(1) SYS GINI	(2) DIF GINI	(3) SYS GINI	(4) SYS GINI	(5) SYS TOP1	(6) DIF TOP1	(7) SYS TOP1	(8) SYS TOP1
Dependent variable: <i>crisisb</i>	LAX	LAX	OECD	ECA	LAX	LAX	OECD	ECA
	(0.00262)	(0.000594)	(0.00234)	(0.00136)	(0.000698)	(0.00145)	(0.00110)	(0.00141)
<i>sec</i>	0.000667	0.00107	0.000912	−0.000323	−0.000855	−0.000520	−0.000396	−0.000328
	(0.00285)	(0.00198)	(0.00264)	(0.00223)	(0.00121)	(0.00132)	(0.000657)	(0.00136)
<i>urban</i>	0.00287	−0.0115	0.00159	0.00240	−0.00456	−0.0141	−0.00365	−0.00426
	(0.00388)	(0.0260)	(0.00278)	(0.00356)	(0.00356)	(0.00961)	(0.00407)	(0.00474)
<i>unem</i>	−0.0199	−0.0142	−0.0151	−0.0146	−0.00337	−0.00575	−0.00318	−0.00374
	(0.0251)	(0.0218)	(0.0231)	(0.0208)	(0.00694)	(0.00620)	(0.00884)	(0.00816)
<i>lax</i>	−0.00225	−0.0107			−0.0564	−0.0667		
	(0.0435)	(0.0753)			(0.0551)	(0.0531)		
<i>oecd</i>			0.143				−0.0372	
			(0.209)				(0.145)	
<i>eca</i>				0.384				−0.00355
				(0.394)				(0.266)
<i>constant</i>	0.765	1.422	0.360	−0.259	0.225	0.868	0.116	0.144
	(0.629)	(2.583)	(0.917)	(1.201)	(0.323)	(0.662)	(0.344)	(0.306)
Observations	197	137	197	197	329	261	329	329
Number of countries	32	19	32	32	40	34	40	40
A-B test	0.4897	0.5140	0.4769	0.5073	0.3930	0.4328	0.3453	0.3397
Sargan test	0.9688	0.6435	0.9774	0.9775	0.8996	0.4759	0.7570	0.6864

Note: ***, **, and * indicate statistical significance at 1%, 5% and 10% level, respectively. Standard errors are in parenthesis. ^a: *inter* is obtained as *giniwb*cdpv* in models (1)–(4) and as *top1*cdb*s in models (5)–(8).

In order to check the results obtained by Braun et al. (2019) of a positive association of the interaction and income, different univariate OLS, pool, and fixed effects have been developed, showing a positive significant sign in all cases. This confirming their findings but with an additional observation: The interaction may lead to higher GDP. In addition, country-by-country Granger causality tests are performed with the three sub-samples, finding that the *inter* variable, which is the inequality-credit linkage measured as the product between the income inequality and financial sector size variables, does not GC *gpc*, so the null hypothesis is rejected in most countries, as shown in Tables 9 and 10 and Figures 1 and 2. Tables 9 and 10 measure the inequality-credit linkage by two alternative ways. Figures 1 and 2 show the results in Tables 9 and 10, respectively.

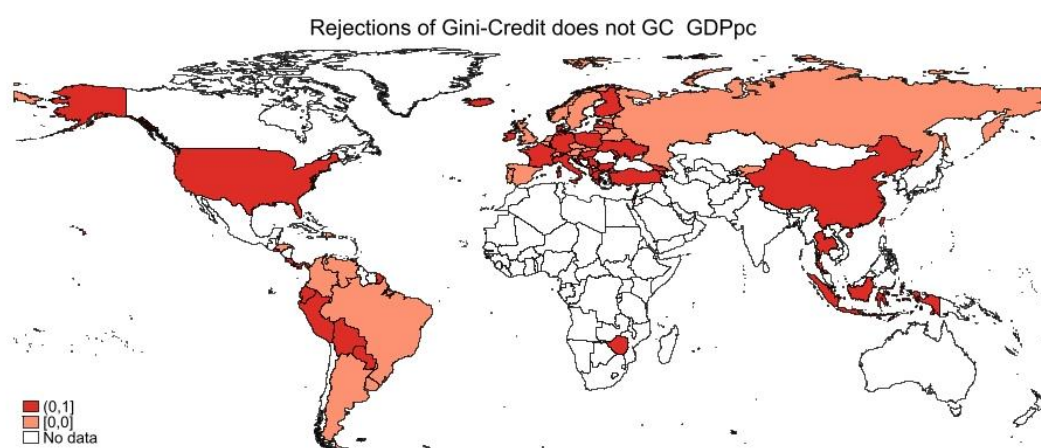


Figure 1. Map showing where the inequality-credit linkage, measured by *gini*cdpv*, may Granger Cause per capita income.

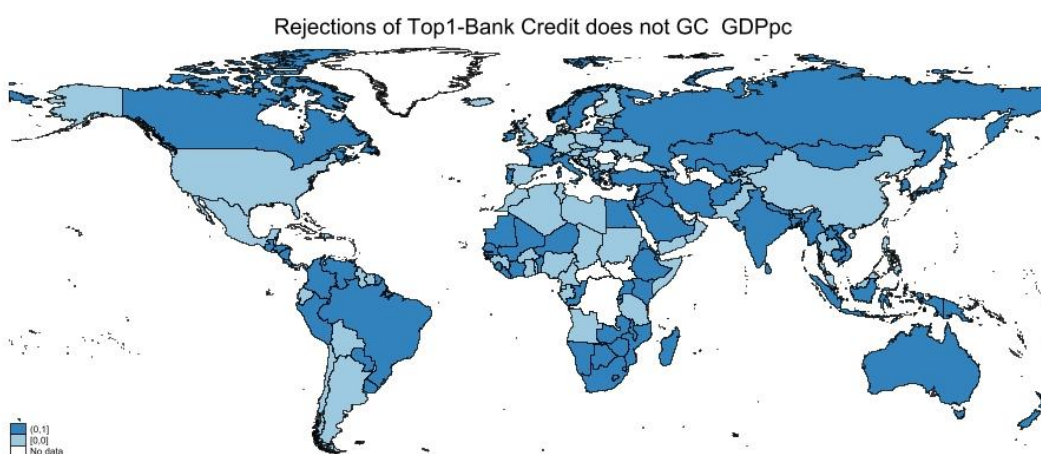


Figure 2. Map showing where the inequality-credit linkage, measured by *top1*cdbv*, may Granger Cause per capita income.

5. Discussion of the results and policy implications

The provided conceptual and empirical results lead to some considerations. An increase on income inequality and on the value added of financial services would unchain banking crises.

Nonetheless, this negative effect is moderated by the interaction. Furthermore, this leads to reductions in the probability of a banking crisis in world countries even if lax monetary policies implemented by Central Banks in the Ad-Hoc Era (Taylor, 2012) are considered, settling unconventional monetary policies that have resulted in a higher income inequality (Ballabriga and Davtyan, 2021). The isolated effects of the financial development and income inequality variables are positive for banking crises since the coefficients of inequality and credit variables from Tables 5 and 6 are positive and statistically significant. Nonetheless, the coefficient of the interaction has the opposite sign. Thus, the isolated effect of reducing income inequality and the size of the financial sector separately would be beneficial for banking activity but harmful considering the joint association of both variables. This is in line with literature regarding economic growth (Braun et al., 2019, Topuz, 2022, Juuti, 2022). These empirical results also agree with the theoretical expectations in Section 3, concretely, as there is a fulfillment of the Hypothesis proposed in addition to the achievement of Equations (4)–(7).

The major originalities of this work are, first, the study of the effects of the inequality-credit interaction on the probability of banking crises and, second, the Granger Causality test for panel data on GDP. The results show the beneficial direct effect on banking crises and GDP of reducing income inequality and having a more reasonable financial sector size, while there is an indirect, detrimental collateral effect that originates from the interaction between inequality and credit variables, that is, the inequality–credit interaction. Concerning GDP, a Granger-causality test is checked. The null hypothesis considers the interaction does not GC the GDP expressed in levels and per capita and is rejected with a p-value lower than 0.01 and a positive correlation, while it is not rejected in the opposite direction.

Therefore, both reasons from the Hypothesis can be valid since the Hypothesis has been empirically checked. The first reason is on the demand side. The inequality-credit linkage could be related with the low-income customers. If there is an increase in the demand of financial services by low-income households, for instance credit, then income inequality rises since these households pay a higher lending rate. Furthermore, and considering only first-round effects, this increase in demand would develop the financial sector more and raise the profits of the financial sector at the current period, reducing the risk of a banking crisis at that time, but maybe not for future periods since there could be a raise on the risk of default from those households. On the other hand, the second-round effects could lead to a reduction in the demand of low-income households due to the high lending interests. The second reason comes from the supply side. While the isolated effects of income inequality and financial sector size may mitigate other economic distortions on the banking sector and reduce the risk of triggering a banking crisis, this effect is hampered by the linkage of both variables, provoking a higher likelihood of unchaining a banking crisis.

A policy measure would be to design and develop a financial reform to avoid that negative collateral influence of the inequality-credit interaction. For instance, promoting financial services in rural areas—even if they have a lower income—by developing more fin-tech applications and online finance for these regions and promoting financial and technological education would reduce the financial costs for low-income customers, and the interest spread with higher-income customers would be mitigated. The negative effects of inequality and credit expansion on banking crises can be mitigated through policy interventions; for instance, the public sector could subsidize the lower-income defaults given determined conditions, or a new imposition of financial services under VAT can be applied as López-Laborda and Peña (2018) propose. This would help mitigate the negative effects on banking crises of an excessive financial sector.

6. Concluding remarks

In this paper, I develop System and Difference GMM models for analyzing the association of the linkage between financial development and income inequality with the probability of triggering banking crises. An unbalanced panel of 212 countries for the years 1970–2017 is handled. In addition, a recent Granger Causality test for panel data is used with a sample size of 216 countries during the 1960–2021 period and different balanced subsamples. The linkage improves the likelihood of a banking crisis and is associated with a higher economic growth. Robustness checks are applied, confirming the results. It is also found that the individual effect of decreasing income inequality and the financial sector size separately would be an improvement for banking crises, but it would worsen it considering the joint association of both variables. A policy measure is the design and development of a financial reform that avoids negative collateral correlation of the inequality–credit linkage. Jointly fighting for income inequality and the potential excessive size of the financial sector would reduce the collateral effects of the interaction on banking crises.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Data availability statement

Peña, Guillermo, 2025, “Replication Data for: The Inequality–Credit Linkage”, <https://doi.org/10.7910/DVN/J6NWK>, Harvard Dataverse, V1.

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Conflict of interest

The author declares no conflicts of interest in this paper.

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