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June 15, 2016

Jan Behringer[1] Sabine Stephan[2] Thomas Theobald[2]

ABSTRACT

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Macroeconomic factors behind financial instability Evidence from Granger causality tests*

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Keywords: income distribution, credit, financial crises, Granger causality tests

JEL Classifications: C32, C33, E51, G01

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1 Introduction

Episodes of excessive credit growth are widely considered to be a contributing factor to financial and macroeconomic instability. Several authors, including Mendoza and Terrones (2008), Elekdag and Wu (2011) and Schularick and Taylor (2012) note that banking crises are typically preceded by credit booms.

Competing theoretical explanations for excessive credit expansion include herding behavior of banks (Kindleberger, 2000), information problems leading to bank-independent lending policies (Rajan, 1994), the underestimation of risks (Borio et al., 2001) and the lowering of lending standards (Dell'Ariccia and Marquez, 2006), the presence of government guarantees (Corsetti et al., 1999), limited commitment on the part of borrowers (Lorenzoni, 2008), and the financial accelerator mechanism (Bernanke et al., 1999; Kiyotaki and Moore, 1997).[1] The empirical literature argues that episodes of credit booms are most likely associated with economic upswings (Mendoza and Terrones, 2008), an overly loose monetary policy (Borio and White, 2004; Mendoza and Terrones, 2008; Elekdag and Wu, 2011), asset price booms (Hofmann, 2004; Mendoza and Terrones, 2008; Elekdag and Wu, 2011), the liberalization of financial markets (Demirguc-Kunt and Detragiache, 1998) or large capital inflows (Decressin and Terrones, 2011; Elekdag and Wu, 2011). However, there is no consensus as to what explains the massive build-up of private sector debt in many countries during the period leading up to the global financial crisis.

Over the last thirty years prior to the Great Recession, overall income inequality has increased dramatically in most industrialized countries (OECD, 2011, 2015). Atkinson et al. (2011) show that the rise of income concentration at the very top of the income distribution during the most recent period has even reached levels similar to those in the pre-Great Depression era, especially in Anglo Saxon countries. The results of the empirical literature on the evolution of top income shares have triggered a lively debate among economists and policymakers about possible implications of changes in income inequality for macroeconomic stability. Several prominent economists now reckon that rising income inequality has been an underlying cause of excessive household indebtedness and the financial crisis in the US starting in 2007 (for surveys of the literature see Atkinson and Morelli, 2010; van Treeck, 2014). There are different variants of the thesis but the main argument is that low and middle income households in the United States have reduced their saving and increased debt as a reaction to rising (permanent) income inequality since the early 1980s. This process was facilitated by government action through credit promotion policies or the deregulation of the financial sector and an accommo-

[1]For a review of the literature see Mendoza and Terrones (2008).

dating monetary policy (e.g. Cynamon and Fazzari, 2008; Fitoussi and Stiglitz, 2009; Rajan, 2010; Palley, 2012; Kumhof et al., 2015).

By contrast, Krugman (2010) and Acemoglu (2011) emphasize the role of the financial industry and its political influence as a potential driver of both income inequality through exorbitant remuneration of executives in the financial industry and financial instability through deregulation of the financial markets. According to this view, the concomitant rise in inequality and the vulnerability of the financial sector may be due to coincidence rather than causality.

One of the first attempts to explore the relationship between income inequality and the occurrence of a financial crisis empirically is the paper by Atkinson and Morelli (2010). Using a window event study, Atkinson and Morelli assess the evolution of inequality around 25 systemic banking crises for a sample of 25 countries over the last 100 years. Generally, they find only limited support that systemic banking crises are preceded by growing inequality. Their results show that inequality increased in ten cases and decreased in seven cases while it remained broadly stable in eight cases prior to a systemic banking crisis. Empirical evidence further shows that banking crises tend to affect inequality, but there is no systematic presumption about the direction of the effect. They identify nine cases in which inequality increases or decreases after the crises, respectively. These findings contradict evidence from Roine et al. (2009) showing that the number of years a country is exposed to a banking crisis has a substantial negative impact on top income shares for a sample of 16 countries over the twentieth century.

Other papers focus more directly on the inequality-credit channel as it is widely recognized that financial crises are typically preceded by credit booms. Bordo and Meissner (2012) analyze a panel of 14 countries over the period 1920-2008 and conclude that inequality only occasionally rises during episodes of credit expansion. Instead, their analysis confirms earlier results of the literature that low interest rates and economic expansion are key determinants of credit booms. Using a similar dataset, Malinen (2014) finds evidence for the existence of a long-run equilibrium relationship between top income shares and debt-to-GDP ratios for a sample of developed economies. Both studies rely on bank loans to the private non-financial sector as proxy for credit due to the absence of more comprehensive data for a longer time period. While, at first sight, this credit measure seems to be warranted in order to analyze the relevance of other potential determinants which are expected to impact the aggregate private sector, rising income inequality is likely to affect credit of the private household sector. The choice of the measure of credit is even more important since evidence by Dembiermont et al. (2013) not only suggests a gradual shift towards more household credit but also shows that non-bank financial institutions have become a more important source of credit in some countries over time.

In the present article, we assess the relationship between income inequality, leverage and financial crises using bivariate Granger causality tests for a sample of 13 European countries and the United States over the period 1975-2013. We also examine the relevance of other potential determinants of credit to income expansions which are frequently discussed in the literature such as economic activity, the monetary policy stance, asset prices and the deregulation of the financial sector. In particular, we analyze whether the causal relationships are sensitive to specific measures of credit. More specifically, we use domestic bank loans to the private non-financial sector which is commonly used in empirical studies, and total credit to the household sector since the credit boom prior to the global financial crisis was associated with a massive over-indebtedness of private households. Our empirical analysis relies on panel causality tests which take into account both the heterogeneity of the causal relationship and the heterogeneity of the regression model. As a robustness check, we also perform time series Granger causality tests.

Our main findings are as follows: Firstly, our results illustrate the relevance of changes in income inequality as a driver of household borrowing. More precisely, top income shares are found to have a significant effect on future household credit to income expansions. Our findings further suggest that the causal impact of changes in top income shares is stronger for total credit to the private household sector than for bank credit to the private non-financial sector. This is broadly consistent with the notion, that rising (top-end) personal inequality may lead to an increase in the demand for credit by low and middle income households in order to maintain their relative standards of consumption. Surprisingly, while changes in top income shares are found to have a causal effect on household borrowing for some European countries, the effect is substantially weaker for Anglo-Saxon countries. Moreover, we find no robust causal relationship between the Gini coefficient of household disposable income and our measures of credit. This might be due to the fact that the Gini coefficient is less sensitive to changes in the tails of the distribution. There is also evidence for feedback relationships which seem to be stronger for top income shares than for the Gini coefficient. This might be explained by cyclical effects on the decomposition of household income, in particular on capital income which is typically concentrated at the top of the income distribution.

Secondly, the Granger causality analysis also points to the importance of other determinants of credit to income expansions. Our results reveal strong evidence for bidirectional causality relationships between economic activity and credit aggregates on the one hand and asset prices and our measures of credit on the other. These findings are broadly consistent with the literature and the observation that credit cycles have often coincided with cycles in economic activity and property markets over the last decades. As noted by Hofmann (2004), these two-way relationships between credit, economic activity, and asset prices may give rise to mutually reinforcing boom-bust cycles which increases the fragility of the financial sector. Moreover, both panel and time series results indicate that the monetary policy stance does not seem to be a strong driver of credit to income expansions. Conversely, evidence for the role of financial liberalization is rather mixed. Although the panel causality analysis reveals no robust link between the financial reform index and credit aggregates, time series evidence suggests that the financial reform index significantly affects future credit to income of the private household sector in the United States and other European countries such as Spain.

The remainder of this paper is structured as follows. In Section 2, we review the literature. Section 3 documents a number of stylized facts on different determinants of credit to income expansions and financial crises for some selected countries. Section 4 presents the empirical strategy. In Section 5, we discuss the results of the Granger causality tests. Section 6 concludes.

2 Related literature

2.1 Traditional determinants of credit expansion

A traditional strand of literature stresses the role of the business cycle and monetary policy for credit expansion. Economic activity may affect the development of credit through credit demand and credit supply channels. In a cyclical upswing, improved profit and income expectations stimulate investment and consumption demand which in turn increase the demand for credit (Mendoza and Terrones, 2008). Economic activity may also determine credit supply: Given informational asymmetry in credit markets, some economic agents are borrowing constrained and can only borrow when they provide collateral. Thus, their ability and the level of borrowing depend on their net worth. The net worth of most borrowers is procyclical, since it depends on the development of firms' cash flow, household income, and the value of assets, which tend to increase in periods of economic expansion and decrease in periods of economic contraction. A rise in borrowers' net worth reduces the credit default risk. As a result, banks are willing to expand lending (Kiyotaki and Moore, 1997; Hofmann, 2004; Iacoviello, 2005).

Monetary policy may influence credit via the interest rate channel as well as via the bank lending and the balance sheet channel of monetary transmission (Mishkin, 1996). If prices are assumed to be sticky in the short-run, a reduction in nominal interest rates is associated with lower real interest rates which provides an incentive for households and firms to increase their purchase of durable goods, residential housing, and investment. As a result, credit demand may rise. Furthermore, expansionary monetary policy may affect credit supply via the balance sheet channel. Lower interest rates can turn bonds into a less attractive investment relative to other assets. Thus, investors' demand for equity and property may increase which leads to higher asset prices. As a consequence, the net worth of capital and home owners and thereby collateral values increase which in turn may augment the willingness of banks to expand lending.

Asset prices may affect credit via wealth effects or Tobin's q effects.[2] An increase in asset prices raises the value of assets. According to the lifecycle model of household consumption, an increase in wealth may lead households to expand spending and borrowing in order to smooth consumption over the lifecycle (Ando and Modigliani, 1963). Thus, credit demand goes up. Since loans are commonly secured with real estate collateral, a rise in the value of assets increases the creditworthiness of households and firms. As a consequence, banks may be willing to enlarge their credit supply. Furthermore, a rise in property prices may foster credit demand by stimulating construction activity. An increase in housing prices raises the market value of houses relative to their construction costs. Thus, Tobin's q for housing goes up, providing an incentive for enlarging construction (Mishkin, 1996).

Financial liberalization and deregulation may ease borrowing restrictions for economic agents previously without access to financial markets. Furthermore, financial innovations may enlarge the scope for banks to increase lending. In either case, credit supply will rise.

There are reasonable arguments how economic growth, expansive monetary policy and asset prices may affect credit expansion. However, it is also clear that this is not a one-way relationship but a feedback process. Since it is well documented in the literature that these variables are positively correlated with credit, the feedback process may accelerate leading to mutually reinforcing dynamics and boom-bust cycles.

Most empirical studies identify economic growth and monetary policy as key determinants of credit booms (Borio and White, 2004; Hofmann, 2004; Mendoza and Terrones, 2008; Elekdag and Wu, 2011). There is also ample evidence that rising asset prices, especially house prices, push credit growth which emphasizes the relevance of the balance sheet channel (Hofmann, 2004; Mendoza and Terrones, 2012; Goodhart and Hofmann, 2008; Iacoviello, 2005). Finally, empirical studies confirm that financial reforms stimulate credit expansion (Demirguc-Kunt and Detragiache, 1998).

[2]Tobin's q is defined as the market value of firms divided by the replacement cost of capital. This concept can also be applied to property. Tobin's q for housing is the market value of houses relative to their construction costs. A high value of Tobin's q means that property prices are high relative to their construction costs which creates an incentive for enlarging construction.

2.2 The role of inequality in the run-up to the recent financial crisis

Recently, a new argument entered the debate, stressing the relevance of the massive increase in income inequality in the US for the emergence of the credit boom that finally led to the US banking crisis. The rise in income inequality caused substantial relative income losses of middle and low income households. Fitoussi and Stiglitz (2009) argue that monetary policy react to the resulting decline in aggregate demand keeping real interest rates low. Rajan (2010), however, emphasizes the reaction of policymakers which were confronted with the call for redistribution. He points out that the government promoted policies to improve access to mortgage loans, in particular for middle and low income households. These households were enabled to purchase residential investment and due to the balance sheet effect to maintain their level of consumption at times when real incomes were stagnating. The resulting lending boom led to a sharp increase in household leverage and fuelled a rise in housing prices. When housing prices dropped in 2007 household leverage proved unsustainable and a surge of defaults caused the subprime mortgage crisis.

Kumhof and Rancière (2010) analyse the link between income concentration and financial instability using a DSGE framework in which a financial crisis can arise endogenously as a result of changes in the income distribution. The model has two groups of households: Investors, who account for the top 5% of the population, are capital owners who save, consume and invest, whereas workers, who account for the remaining 95% of the population, earn wages which they spend completely on consumption. In their model, the crisis emerges as a result of a shock to the relative bargaining powers of the two income groups. Investors use part of their increased income to purchase additional financial assets, which are then channelled by the financial sector to workers in the form of loans, allowing them to maintain their level of consumption. As a result, debt-to-income ratios of workers increase substantially which generates higher financial instability leading to a financial crisis.

It is also possible that reverse causality occurs, i.e. that causality runs from credit to inequality. From a theoretical point of view it is not clear, whether the effect is positive or negative (Denk and Cournede, 2015). On one hand, an increase in credit may reduce income inequality if the provision of credit makes it easier for poor households to invest in viable projects that generate additional income. However, this channel only works if credit is not used to purchase consumption goods but for investment purposes. On the other hand, the intertwined relationship between credit expansion, economicy activity and asset price developments might be correlated with a greater share of income going to capital.

There is growing literature examining the relationship between income inequality and financial instability empirically. Atkinson and Morelli (2011) analyse the evolution of income inequality around economic crises. The empirical analyis relies primarily on overall income inequality, as measured primarily by the Gini coefficient, and consider different types of economic crises (systemic banking crises, GDP and consumption collapses) to detect patterns of changes in inequality in pre-crisis and post-crisis periods for a large data set covering 25 countries over the period 1911-2010. However, they did not obtain clear-cut results: in about one third of cases they observe an increase in inequality before the crisis, whereas in the majority of cases they detect no significant change. Regarding changes in inequality after the crisis results are also mixed: while there is evidence that financial crises are followed by rising inequality, inequality remains rather stable after consumption and GDP collapses. In a recent paper, Morelli and Atkinson (2015) reassess whether rising inequality is systematically associated with the occurence of a banking crisis but do not find conclusive evidence.

Other authors analyze the link between income inequality and credit expansion using panel econometric approaches. Bordo and Meissner (2012) examine the determinants of real credit growth (changes in the log of real domestic bank credit to households and non-financial corporations) including a measure for income inequality (share of pre-tax income accruing to the top 1%) and macroeconomic indicators that account for the business cycle and monetary policy using a panel of 14 advanced economies over the period 1920-2008. They find "strong evidence linking credit booms to banking crises, but no evidence that rising income concentration was a significant determinant of credit booms" (p.20). Rather, their results suggest that credit booms are largely driven by economic expansion and low interest rates. Malinen (2014) finds a long-run steady-state relationship between income inequality (top 1% income share to real GDP) and private sector leverage (domestic bank loans to households and non-financial corporations in percent of GDP) using a panel cointegration framework for a data set of eight developed countries covering the period 1959-2008. Variables that account for economic activity and expansive monetary policy are relevant for the short-run adjustment. Perugini et al. (2015) use a panel of 18 OECD countries over the period 1970-2007 to examine the link between income concentration (top 1% income share) and private sector indebtedness (credit of domestic deposit banks and other financial institutions to the non-financial private sector in percent of GDP). Their results suggest that income concentration contributes significantly to the explanation of private sector indebtedness once other credit drivers such as economic activity, the monetary environment and credit market deregulation are controlled for.

3 Stylized facts

This section documents a number of stylized facts. Firstly, we examine the link between the expansion in household credit to income and episodes of financial instability using auxiliary regressions. Based on the competing explanations of possible drivers of credit to income expansions discussed in the literature review, we then present preliminary descriptive evidence regarding the role of monetary policy, asset prices, financial deregulation and income distribution.

We work with an unbalanced panel dataset which consists of 13 European countries and the United States. More specifically, the following countries are included in the sample: Denmark (1981–2010), Finland (1975–2009), France (1977–2009), Germany (1980–2010), Ireland (1975–2009), Italy (1980–2009), Netherlands (1975–2012), Norway (1980-2011), Portugal (1988–2005), Spain (1981–2012), Sweden (1982–2012), Switzerland (1990–2010), United Kingdom (1975–2011), United States (1975–2013). The country-specific observation periods are selected in a way that ensures a maximum overlap of the variables. Appendix A provides a detailed description of the variable definitions and data sources. It also reports summary statistics of the data.

3.1 Credit expansion and financial crises

The empirical literature on the determinants of excessive credit expansion and financial instability has mostly analyzed the large build-ups of bank credit to the private non-financial sector since these data are available over a long time period. Obviously, this credit measure is highly warranted to examine the relationship between economic activity or monetary policy and credit booms. In the context of income inequality, however, focusing on bank credit to the private non-financial sector has the disadvantage that corporate credit should not be affected by changes in income inequality. In addition, this measure fails to include credit from non-bank financial institutions and foreign lenders. Dembiermont et al. (2013) show that in several countries, domestic banks have become a significantly more important source of credit over time. However, the share of bank credit in total credit varies considerably across countries and over time depending to a large extent on whether the financial system is market-based such as in the United States or heavily bank-based as in Germany.

In the present article, we therefore rely on a recently generated database by the Bank for International Settlements (BIS), which provides detailed information on several characteristics of the credit series. Our key variable measuring credit expansion is total credit to the household sector. This credit variable is defined as loans and debt securities financed by domestic and foreign banks as well as non-bank financial institutions. We also use bank credit to the private non-financial sector to compare our results with the existing literature. In order to measure credit expansion relative to the size of sectoral income, we scale the credit variables by household or private disposable income, respectively. The main reason is that increasing levels of credit do not necessarily translate into higher instability of the financial sector. Whether this is the case also depends on the evolution of income. For instance, a change in credit which is accompanied by a similar change in income should not alter macroeconomic risk, ceteris paribus. Similarly, a drop in income as a result of increased unemployment during a severe recession is expected to amplify financial instability even at unchanged debt levels.[3]

Figure 1 shows the evolution of total credit to the household sector and bank credit to the private non-financial sector for selected countries over the period 1980-2012. In most countries, both household credit to income and private sector credit to income have increased substantially over the past three decades. However, the timing and the extent of the credit to income expansion varied considerably across countries. As shown in Figure 1, in the United States and the United Kingdom household credit to income has grown steadily since the 1980s whereas in Italy, Ireland, Spain and Sweden, household borrowing started to increase sharply in the late 1990s. Germany and France experienced only a moderate increase in household indebtedness. Interestingly, in most countries household credit to income and bank credit to income of the private sector exhibit a similar pattern. However, household borrowing expanded more rapidly than private sector credit in the United States and to a lesser extent also in the United Kingdom. This confirms the notion of Dembiermont et al. (2013) that sectoral breakdowns suggest a gradual shift towards more household borrowing over the last decades including countries where the levels of household credit to income even exceeds corporate sector borrowing. Furthermore, non-bank financial institutions have become important providers of credit mainly for Anglo Saxon countries prior to the global financial crisis.

Recent empirical evidence has broadly confirmed that excessive private sector credit expansion is likely to be associated with episodes of financial instability (see amongst others, Borio and White, 2004; Mendoza and Terrones, 2012; Elekdag and Wu, 2011; Schularick and Taylor, 2012). As is apparent from Figure 1, banking crises tend to be preceded not only by large build-ups of bank credit to the private sector but also by boosts of total credit to the household sector, which is amongst other countries most obvious for the United Kingdom and the United States.

[3]A similar argument has been made by Perugini et al. (2015).

In order to assess the link between household credit to income expansion and financial instability more thoroughly, we use a simple regression framework which allows analyzing whether a country's recent evolution of household leverage helps explain the probability of a financial crisis. Similar to Schularick and Taylor (2012) and Bordo and Meissner (2012), we estimate the probability of a banking crisis as a function of the level of credit to income using the following estimation equation

$$Pr(Banking\ Crisis_{it}) = \sum_{p=1}^{P} \beta_p Credit_{i,t-p} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

where $i = 1, \ldots, N$ and $t = 1, \ldots, T$ denote the cross-sectional and time series dimensions, respectively. The dependent variable is coded as a binary indicator variable equal to one when a banking crisis occurred and zero otherwise. Data are taken from the updated banking crises database compiled by Valencia and Laeven (2012). According to Valencia and Laeven, a systemic banking crisis is defined as an episode when significant signs of financial distress in the banking system (indicated by significant bank runs, losses in the banking system, and/or bank liquidations) emerge and significant policy intervention measures have been taken in response to significant losses in the banking system. $Credit_{it}$ is defined as household credit in percent of disposable income. μ_i is an unobserved country-specific effect, δ_t is a time-specific effect and ε_{it} is an idiosyncratic error term. Equation 1 is estimated with a linear probability model and alternatively with a logit model. The number of lags P is set to 3 as the time series dimension of our dataset is smaller compared to the analysis by Schularick and Taylor (2012) or Bordo and Meissner (2012).

Estimation results for the different specifications are shown in Table 1. Column 1 presents results of an OLS linear probability model with pooled data. In Column 2, country fixed effects are added to the OLS model, which are highly statistically significant. In Column 3, time fixed effects are introduced to account for common global factors, which are also highly statistically significant. The results of the OLS estimations suggest a strong positive link between household leverage and the probability of a banking crisis. The diagnostic tests reveal that the coefficients on the lags of the credit variable are jointly statistically significant at the 1 percent level for all specifications. The estimation results in Column 3 suggest that the sum of these coefficients is 0.35 implying that a 3-year period increase of 10 percentage points in household borrowing is associated with an increase in the probability of a banking crisis by about 3.5 percentage points.

The linear probability model is simple to estimate but at the cost that the fitted probabilities can be less than zero or greater than one. To overcome this limitation, we also estimate different logit models. Column 4 reports results of a pooled logit model, while in Column 5 country fixed effects are added which again are statistically significant. The diagnostic tests also show that the coefficients on the lags of the credit variable are jointly statistically significant at the 1 percent level. The sum of these coefficients is 2.34 (16.25) in Column 4 (Column 5) and statistically significant. Since the magnitudes of the estimated coefficients from the logit model and the linear probability model are not directly comparable, we calculate average marginal effects. The sum of the average marginal effects including all lags is 0.21 (0.74) for the specification reported in Column 4 (Column 5) which is similar compared to estimates of the linear probability model in Column 1 (Column 2).

3.2 Monetary policy

In order to examine how the monetary policy stance affects credit aggregates, we consider the standard Taylor rule which links the level of the policy rate to deviations of inflation from its target level and of output from its potential as suggested by Taylor (1993). We calculate Taylor rule benchmarks using data from the AMECO database of the European Commission. For a detailed description of the methodology see Appendix A. Figure 2 plots credit aggregates and the deviation from the Taylor rule. Positive (negative) values indicate that the policy rate is below (above) the level implied by the Taylor rule and hence the monetary policy stance is considered to be rather loose (tight).

In the early 1980s, policy rates have been below the levels indicated by the Taylor rule in a number of countries followed by a period with policy rates being almost always higher than the Taylor rule benchmarks. Since the early 1990s, the deviations have started to narrow in all countries. Thus, between the early 1980s and the outbreak of the global financial crisis, the deviations seem to have followed a u-shaped pattern in countries such as France, Italy, Ireland, Spain and the United Kingdom, whereas in Germany and Sweden the divergence between the policy rate and the Taylor-rule implied rate has been relatively weak. In Germany, the policy rate has been slightly too high compared to the Taylor rule benchmark between the early 1980s and the early 2000s which could be interpreted as a sign of a minor but persistently restrictive monetary policy. Since the early 2000s, the policy rate has been almost consistent with the level implied by the Taylor rule. In Sweden, the policy rate fluctuates around the Taylor rule rate between the early 1980s and the mid-2000s. Since the late 1990s, policy rates have been systematically below the levels implied by the Taylor rule indicating a loose monetary policy in Ireland and Spain until the global financial crisis. Since the early 2000s, this is also the case in France, Italy, the United States and to a lesser extent in Sweden and the United Kingdom. As is apparent from Figure 2, this period of prolonged monetary accommodation coincides with the build-up of household debt prior to the global financial crisis.

3.3 Asset prices

As pointed out in the literature review, changes in asset prices might affect consumption and investment decisions of households and firms through various channels. Figure 3 plots the evolution of credit aggregates and asset prices for selected countries over the period 1980-2013. Data on share price indices are taken from the Monthly Monetary and Financial Statistics (MEI) database by the OECD. For house price indices we employ data from the International House Price database provided by the Federal Reserve Bank of Dallas.

In most countries, house prices have increased sharply until the global financial crisis. The value of housing typically accounts for the bulk of household assets. A closer look at the balance sheet accounts of the household sector also reveals that the growth in household debt in the run-up to the global financial crisis can be largely attributed to borrowing for the purchase of housing. In France, Spain, Sweden, the United Kingdom and the United States and to a lesser extent in Italy, house prices and debt-to-income ratios of the household sector exhibit a similar pattern until the late 1990s. During the 2000s, the surge in house prices has been even more pronounced than the rise in household borrowing in some countries. In Ireland, household borrowing and house prices have grown broadly at the same rate until the global financial crisis. Figure 3 shows that the large build-up of household debt accumulation prior to the global financial crisis is closely linked to the house price boom. A notable exception is Germany which has experienced only a moderate increase in house prices over the last three decades.

It is apparent from Figure 3 that share prices exhibit a clear upward trend and the dynamics are similar across countries. Until the mid-1990s, share prices have slightly increased in all countries. During the dot-com boom of the late 1990s, share prices have grown at a significantly higher rate. After a steep drop starting in 2000, share prices have continued to rise until the global financial crisis. In France, Ireland, Spain and the United States, share prices and household borrowing show a similar pattern, although the boom-bust cycles in share prices during the 2000s are not completely reflected in fluctuations of debt-to-income ratios. Since 2007/08, Italy, Ireland and Spain have recorded the most pronounced declines in asset prices.

3.4 Financial deregulation

In order to assess the role of financial deregulation policies for credit to income expansions and financial instability, we use the financial reforms index provided by Abiad et al. (2010). Figure 4 shows credit aggregates and the financial reform index. Higher values of the reform index indicate a higher degree of financial liberalization.

As is apparent from Figure 4, there has been a trend towards less regulated financial sectors, even though heterogeneity across countries is considerable. Countries such as Germany, the United Kingdom and the United States have traditionally been characterized by highly deregulated financial markets. France, Italy, Ireland, Spain and Sweden have experienced a steady process towards higher levels of financial deregulation since the early 1980s. Obviously, policies implemented to liberalize the financial sector are expected to enhance access to credit markets, especially for low and middle income households, which in turn should be reflected in higher household borrowing. Some countries with highly liberalized financial sectors such as the United Kingdom and the United States show a substantial expansion in credit to income until the outbreak of the global financial crisis. Higher leverage of the household sector has also been observed in countries that experienced a steady progress towards less regulated financial markets over the last decades. However, there are also countries where financial reforms towards more liberalized financial sectors have been implemented such as France and Italy, showing only a moderate increase in household borrowing and Germany, where household debt has been relatively stable despite a high level of financial deregulation.

3.5 Income inequality

Since the 1980s, there has been a strong increase in overall income inequality as measured by the Gini coefficient of household disposable income in most industrialized countries (OECD, 2008, 2011). However, the patterns of top income shares vary considerably across countries. This discrepancy might be explained by the fact that the Gini coefficient attributes only a small weight to top incomes due to its mathematical construction. Moreover, Gini coefficients are usually based on income information from voluntary household surveys in which top incomes are underestimated (Behringer et al., 2014). Figure 5 plots the share of total pre-tax household income accruing to the top 1% and 10% of tax units for selected countries over the period 1980-2013. Data are taken from the World Wealth and Income Database (WID). Top income shares have increased substantially in the United Kingdom and the United States since the early 1980s. Germany, Italy, Ireland and Sweden reveal moderate or late increases in top income shares. In

France and Spain, on the contrary, the concentration of income at the top of the distribution has remained relatively constant. As is apparent from Figure 5, top income shares and household leverage exhibit a similar pattern in many countries. In Ireland, Spain or Sweden, however, the increase in household borrowing has accelerated since the late 1990s until the global financial crisis while top income shares have remained relatively stable.

4 Empirical methodology

In order to identify possible determinants of financial instability, we rely on causality tests as originally suggested by Granger (1969). In a bivariate framework, Granger causality of a variable X for a variable Y can inferred when lags of X are found to be statistically significant in a regression of Y on its own lags and lags of X.[4] More specifically, we examine how much of the current value of our credit variable can be explained by past values of the credit variable and whether including lagged values of different proxy variables for economic activity, monetary policy, asset prices, financial liberalization or income inequality can improve the explanation. Since macroeconomic variables are highly interrelated we perform two-way Granger causality tests to analyze whether there exists a feedback relationship between one of the proxy variables and the credit variable.

One of the main issues in the context of panel Granger causality tests refers to the specification of heterogeneity between cross-sectional units. In their seminal paper, Holtz-Eakin et al. (1988) propose to test the homogenous non causality hypothesis, which occurs when no individual causality relationship exists, against the homogenous causality hypothesis. The alternative hypothesis implies the existence of a causal relationship for each individual and that the specification of the model is valid for all individuals in the sample. To be more precise, the dynamics of the variables is identical for all individuals which is a rather strong assumption. To overcome this deficiency, Dumitrescu and Hurlin (2012) propose a Granger non causality test for heterogeneous panel data models by taking into account both the heterogeneity of the causal relationship and the heterogeneity of the regression model. Thus, we consider the following linear panel data model

[4]The concept of Granger causality is based on the two principles that the cause precedes the effect and that the causal series contains unique information about the future values of the effect.

$$\Delta Credit_{it} = \alpha_i + \sum_{p=1}^{P} \gamma_{ip} \Delta Credit_{i,t-p} + \sum_{p=1}^{P} \beta_{ip} \Delta X_{i,t-p} + \varepsilon_{it} \tag{2}$$

where $i = 1, \ldots, N$ and $t = 1, \ldots, T$ denote the cross-sectional and time dimensions, respectively. $Credit_{it}$ refers to either total credit to the household sector in percent of household disposable income or bank credit to the private non-financial sector in percent of private sector disposable income. X_{it} refers to a set of different proxy variables for economic activity, monetary policy, asset prices, financial liberalization or income inequality. The individual effects α_i are supposed to be fixed. The lag order P is assumed to be identical for all countries in the panel. The parameters of the autoregressive terms γ_{ip} and the coefficients of the explanatory variables β_{ip} are allowed to differ across countries. The errors ε_{it} are independently distributed across groups with zero means and finite heterogeneous variances σ_i^2.

The null hypothesis of homogenous non causality (HNC) is defined as

$$H_0 : \beta_i = 0 \quad \text{for all} \quad i = 1, \ldots, N \tag{3}$$

with $\beta_i = (\beta_{i1}, \ldots, \beta_{ip})'$. Under the alternative hypothesis, there is a causality relationship from the proxy variable X to $Credit$ for at least one country. The test allows for some, but not all, of the individual vectors to be equal to 0, i.e. there are $N_1 < N$ individual processes where X does not Granger cause $Credit$

$$\begin{aligned} H_1 : &\beta_i = 0 \quad \text{for all} \quad i = 1, \ldots, N_1 \\ &\beta_i \neq 0 \quad \text{for all} \quad i = N_1 + 1, \ldots, N \end{aligned} \tag{4}$$

where N_1 is unknown but satisfies the condition $0 \leq N_1/N < 1$. If the null hypothesis of Equation 3 is not rejected, the proxy variable X does not Granger cause $Credit$ for all countries in the panel. By contrast, if the homogenous non causality (HNC) hypothesis is rejected two cases have to be distinguished. If $N_1 = 0$, X Granger causes $Credit$ for all countries in the panel. That is, the causality relationship is homogenous even if the model is heterogeneous. If $N_1 > 0$, the causality relationship is heterogeneous.

Thus, instead of pooling the data, Dumitrescu and Hurlin (2012) propose to perform separate tests of the non causality hypothesis for each country. The test statistic is then defined as the average of the individual Wald statistics

$$W_{NT}^{Hnc} = \frac{1}{N} \sum_{i=1}^{N} W_{iT} \tag{5}$$

where W_{iT} is the Wald statistic of country i corresponding to the individual test $H_0 : \beta_i = 0$. In order to derive the distribution of the average statistic W_{NT}^{Hnc} under the null hypothesis of homogenous non causality, Dumitrescu and Hurlin (2012) consider the case of sequential convergence which can be deduced from the standard convergence result of the individual Wald statistic W_{iT} in a sample with large T. Under the assumption of cross-sectional independence, the individual Wald statistics W_{iT} are identically and independently distributed with finite second order moments as $T \to \infty$. The distribution of the average statistic W_{NT}^{Hnc} can then be deduced from a standard Lindberg-Levy central limit theorem. Let Z_{NT}^{Hnc} denote the standardized statistic

$$Z_{NT}^{Hnc} = \sqrt{\frac{N}{2K}}(W_{NT}^{Hnc} - P) \tag{6}$$

where Z_{NT}^{Hnc} has a standard normal limiting distribution as $T \to \infty$ followed by $N \to \infty$. For a sample with large N and T, the homogenous non causality (HNC) hypothesis is rejected if the realization of the standardized statistic Z_{NT}^{Hnc} is larger than the corresponding normal critical value for a given level of significance. However, individual Wald statistics W_{iT} do not converge towards an identical chi-squared distribution if the time dimension is small. Therefore, Dumitrescu and Hurlin (2012) propose an approximated standardized statistic $\tilde{Z}_{NT}^{Hnc}$ for the average Wald statistic W_{NT}^{Hnc} of the homogenous non causality (HNC) hypothesis for finite T samples (for a detailed description see Dumitrescu and Hurlin, 2012).

Since this approach follows the standard Granger causality methodology where the variables entered into the system need to be covariance-stationary we perform several panel unit root tests. We distinguish first generation panel unit root tests that are based on the assumption of cross-sectional independence such as the Levin-Lin-Chu test, Im-Pesaran-Shin test or Fisher-type tests and second generation tests that allow for different forms of cross-sectional dependence such as the cross-sectionally augmented Dickey-Fuller test. For a detailed description of the different panel unit root tests see Appendix B. The panel unit root tests provide somewhat mixed evidence. Since the results at least indicate the possibility of the presence for a unit root we decide to use first differences of all variables.

We also perform time series Granger causality tests to better understand the causal direction at the individual country level. To examine whether the variables follow a unit root process we use different tests such as the Augmented Dickey-Fuller (ADF) test, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, the Dickey-Fuller GLS test and the Phillips-Perron (PP) test.[5] It turned out that the results of the ADF test coincide with most of the results given by alternative unit root tests. Thus, the specification of the time series Granger causality tests relies on the ADF test results. Since the variables exhibit either a unit root or are generated by a trend stationary process, we distinguish the following specifications for the time series Granger causality tests

$$\Delta Credit_t = \alpha + \sum_{p=1}^{P} \gamma_p \Delta Credit_{t-p} + \sum_{p=1}^{P} \beta_p \Delta X_{t-p} + \varepsilon_t \tag{7}$$

$$\Delta Credit_t = \alpha + \delta t + \sum_{p=1}^{P} \gamma_p \Delta Credit_{t-p} + \sum_{p=1}^{P} \beta_p X_{t-p} + \varepsilon_t \tag{8}$$

$$Credit_t = \alpha + \delta t + \sum_{p=1}^{P} \gamma_p Credit_{t-p} + \sum_{p=1}^{P} \beta_p \Delta X_{t-p} + \varepsilon_t \tag{9}$$

$$Credit_t = \alpha + \delta t + \sum_{p=1}^{P} \gamma_p Credit_{t-p} + \sum_{p=1}^{P} \beta_p X_{t-p} + \varepsilon_t \tag{10}$$

where $Credit_t$ is used to denote either total credit to the household sector in percent of household disposable income or bank credit to the private non-financial sector in percent of private sector disposable income and X_t is used as a proxy for the different explanatory variables. The Granger causality tests are specified according to the time series properties of the variables. In Equation 7, both $Credit_t$ and X_t are assumed to follow a unit root process while in Equation 10, both variables are trend stationary. In Equation 8 (9), $Credit_t$ (X_t) is assumed to exhibit a unit root whereas X_t ($Credit_t$) is trend stationary. The number of lags is chosen using the AIC criterion and the maximum number of lags is restricted to five.

5 Empirical results

The following section presents the results of the empirical analysis. Tables 2-9 report the results of the causality tests for heterogeneous panel data models as proposed by Dumitrescu and Hurlin

[5]For a detailed description of the different univariate unit root tests see Appendix B.

(2012). More specifically, we test whether different proxy variables standing for economic activity, monetary policy, asset prices, financial liberalization and income inequality Granger cause total credit to the household sector and bank credit to the private sector, respectively. We also test for reverse causality relationships. In each case, we compute the standardized statistic $\tilde{Z}_{NT}^{Hnc}$ based on the approximation of finite sample moments and report the corresponding p-values. In order to assess the sensitivity of the results to the lag order, test statistics are computed for different lag lengths. Tables 10-17 report results of time series Granger causality tests to complement the evidence from the panel data analysis.[6]

5.1 Traditional determinants of credit to income expansions

One of our clearest results relates to the importance of economic activity as a driver of credit aggregates. The results of Table 2 reveal strong evidence for bidirectional causality regardless of the number of lags included in the model. Thus, past values of real GDP growth might be useful to forecast credit to income expansions of the household sector and the private non-financial sector, and vice versa. These findings are consistent with the observation that credit cycles often coincide with business cycles (see e.g. IMF, 2000; BIS, 2001). Episodes of strong credit expansion are typically accompanied by an economic upswing while a slowdown in credit expansion coincides with a downturn in the economy. The positive correlation between economic activity and credit may result from the effect of economic activity on credit demand and credit supply but also from the effect of credit availability on economic activity. Evidence from the panel data analysis is largely confirmed by time series Granger causality tests. The test statistics suggest that the link between economic activity and private sector credit by banks is substantially stronger than the relationship between real GDP growth and household credit (see Table 10). Economic activity is found to significantly affect private sector credit in most of the countries, and vice versa. This is reasonable since favourable economic conditions affect the demand for credit not only through the stimulation of consumption demand but also encourage business investment. Moreover, changes in economic activity may also affect the borrowing capacity of firms since their cash flow positions are highly procyclical (Hofmann, 2004).

A remarkable result is that the monetary policy stance does not appear to be a strong driver of the expansion in credit to income, at least in the context of our empirical framework. Potential links between monetary policy decisions and credit aggregates may arise through the interest

[6]As a further robustness check, Tables 21-28 in Appendix C report results of causality tests for homogeneous panel data models.

rate channel on credit demand or through balance sheet and bank lending channel on credit supply. Table 3 shows that the homogenous non causality hypothesis between the deviation from the standard Taylor rule, which is frequently used to model the monetary policy stance, and household leverage can be rejected at the 5% significance level only in the case of a model with three lags. Moreover, there is evidence for a reverse causality relationship if the corresponding model specification is used. We interpret this as first indication that policy changes of monetary authorities play a subordinated role in explaining excessive build-ups of household debt since the results are not robust to the choice of the lag order. Even more interesting for our purposes, we find no robust evidence that the monetary policy stance significantly affects bank credit to the private non-financial sector. These findings are backed by the results of time series Granger causality tests (see Table 11). However, it should be noted that the results of panel unit root tests suggest that the proxy variable for the monetary policy stance is generated by a trend stationary process (see Table 19). Unfortunately, the technical implementation of the Dumitrescu and Hurlin (2012) test currently does not allow including a trend term. Therefore, we use first differences of the variable to eliminate the deterministic trend although this transformation possibly leads to a substantial loss of information.

Table 4 displays the results of panel causality tests between house prices and credit aggregates. We find strong evidence for bidirectional causality which is in line with previous studies. This result is robust to different lag lengths and credit measures. As noted by Hofmann (2004) and Goodhart and Hofmann (2008), the causal link between house prices and household credit may arise through wealth and collateral effects of house prices on consumption which implies adjustments in credit demand and credit supply. Furthermore, house prices may affect credit demand through Tobin's q effects on residential investment. The causal relationship from house prices to private sector credit in turn may result from the fact that a higher value of collateralisable assets enhances the borrowing capacity of firms to finance investment activity. Conversely, the reverse causal link from credit aggregates to house prices may reflect repercussions of credit supply fluctuations on house prices. ECB (2003) and Tsatsaronis and Zhu (2004) argue that the link between house prices and bank credit to the private sector is affected by structural characteristics of national mortgage markets or the lending practice of mortgage lenders. The possibility of mortgage equity withdrawal is widely considered to be a substantial source of extra liquidity for the household sector. This process has been relevant in boosting consumption prior to the global financial crisis mainly for Anglo Saxon countries. Our results reveal no robust link between house prices and bank credit to the private sector for countries such as France, Germany, Italy or Switzerland where the extraction of housing equity has not been used during the

2000s. Those countries are also characterized by the fact that the level of (bank-internal) prudential ceilings on the loan-to-value ratio, which determines the ability of banks to lend against real estate collateral, is lower compared to other countries included in the analysis. Table 5 reports the results of panel causality tests between stock prices and credit aggregates. Interestingly, causality tests reveal no robust link between stock prices and household credit to income whereas stock prices are found to have a highly significant effect on future bank credit to the private non-financial sector. The correlation between stock prices and bank credit to the private non-financial sector may arise from the fact that stock prices affect the creditworthiness of firms and thus the ability to borrow and finance business investment. These findings are broadly consistent with evidence from time series Granger causality tests. Our results further suggest that the link between stock prices and household credit to income is substantially weaker than the relationship between house prices and household borrowing. There are several explanations for this finding. Firstly, the collateral value of housing is typically notably larger than that of equity. Secondly, housing assets account for a substantial share of total household assets, especially in European countries. Thus, the wealth effect of housing on consumption is expected to be larger than that of stocks, which is supported by recent evidence (Case et al., 2005). Thirdly, private ownership of residential or commercial property is largely financed by mortgage loans whereas the purchase of stocks is typically to a lesser extent based on debt financing.

An extensive literature has emphasized that credit to income expansions may arise due to financial innovation or deregulation. Surprisingly, we find no evidence for an interaction between the financial reform index, which provides a measure of financial deregulation, and credit aggregates. This result is robust to the choice of the lag order or the measure of credit (see Table 6). The financial reform index provides a multifaceted measure of financial liberalization that covers various financial reform dimensions. However, the overall index may neglect information which is not reflected in the individual components such as changes in the structuring of investment and money market funds, for instance the accreditation of credit funds. Moreover, the financial liberalization index is relatively sluggish so that first differencing is likely to eliminate considerable variation which affects the results of the causality tests. At the individual country level, however, our results offer some evidence for the relevance of financial liberalization as a driver of credit to income expansions. This is demonstrated most clearly for the interaction between the financial reform index and household credit to income. As shown in Table 14, the financial reform index is found to have a highly significant effect on future household leverage for the United States but also for some European countries such as Spain. A notable exception is the United Kingdom, where we find evidence for a feedback effect from household leverage to the financial reform index. As an alternative measure for the deregulation of domestic financial markets, we use the GDP share of the finance industry, i.e. the nominal income of the finance industry divided by nominal GDP. Table 7 shows that the results from panel causality tests reveal no robust link from the share of income generated by the financial sector to household leverage. However, the GDP share of the finance industry is found to significantly affect future bank credit to the private non-financial sector in the case of a model with two lags. There is also evidence for a feedback effect from credit aggregates to the finance income share. This result, coupled with the observation that credit to income expansions and economic activity are positively correlated, would suggest that financial intermediaries disproportionally benefit in episodes of cyclical upswings.

5.2 Is there a link between income inequality and credit to income expansions?

Finally, we turn to the hypothesis that growing income inequality might help in explaining the recent surge in household borrowing. The results of Table 8 provide strong evidence for bidirectional causality between the top 1% income share and household leverage.[7] That is, top income shares are found to have a significant effect on future credit to income of the household sector. This result can be interpreted as evidence for the relevance of income inequality among the drivers of household borrowing. As argued by Rajan (2010), higher top-end personal inequality may contribute to an increase in the demand for credit by low and middle income households in order to maintain their relative standards of consumption. This ultimately leads to highly indebted households and amplifies the risk of financial instability. The explanation is also broadly consistent with the notion that higher income inequality, especially at the very top of the income distribution, may lead to expenditure cascades if households are influenced by the spending patterns of others above them in the income distribution (Frank et al., 2010). At the individual country level, top income shares are found to have a causal impact on household borrowing for some European countries. It should be noted, however, that the link from top income shares to household leverage turns out to be substantially weaker for Anglo-Saxon countries despite the strong rise in top income shares prior to the global financial crisis (see Table 16). The results further suggest that the link between the top 1% income share and private sector leverage is somewhat less robust which likely is due to the fact that this specification also accounts for bank credit to the non-financial corporate sector. As noted above, there is also evidence for a feedback relationship from credit aggregates to top income shares. A potential explanation relates to the cyclical effects on the decomposition of household income. As is widely documented

[7] This result is also robust to the use of top 5% income shares or top 10% income shares.

in the literature, episodes of boom and bust in credit markets typically coincide with cycles in economic activity and asset price movements. If high-income households stand to benefit from an economic upswing due to sticky wages in the short-term, higher credit availability may increase income inequality since capital income is usually highly concentrated at the top of the income distribution. Conversely, the results of Table 9 reveal no robust causal link between the Gini coefficient of household disposable income and credit aggregates. However, in terms of the expenditure cascade model it is obvious that an increase of the Gini coefficient will have less strongly positive effects on household indebtedness since the Gini coefficient is relatively insensitive to changes in the tails of the distribution.

5.3 Policy implications

In the wake of the global financial crisis, a number of steps have been taken to regulate the banking sector including higher capital requirements by the Basel III regulatory framework (Basel Committee on Banking Supervision, 2010) and the creation of an institutionalized process for bank resolution by the European authorities (The Council of the European Union, 2013). These actions attempt to countervail the relaxation in financial markets restrictions prior to the crisis. Former developments such as the imprudent permission of high amounts of nominal capital linked to innovative financial market instruments or rather liberal risk management requirements are suspected to have raised the probability of systemic turmoil. Another strand of policies relates to the assessment of asset price dynamics. The awareness of harmful consequences of asset price bubbles for the real economy has increased (IMF, 2014). As a result, authorities have stepped up efforts for a more effective monitoring of house and stock price developments. Countermeasures such as a dynamic provisioning for mortgages have been put into operation. These measures are nowadays part of central banks' macro-prudential control which aims at providing a remedy beside traditional monetary policy (ESCB, 2014). Regarding the latter, a lively debate has developed as to whether interest rate policy helps in preventing financial turmoil. The effectiveness of such a policy, widely known as 'leaning against the wind', crucially depends on a positive correlation between price and financial stability. As there is no consensus in the literature about a stable correlation over time, most central banks consider this as an ultimate tool. Although it can be doubted whether policy actions regarding financial market regulation, the prevention of asset price bubbles and central bank policies are sufficient, sensible changes in those areas have taken place since the crisis in order to reduce global financial fragility. Our results indicate that rising income inequality may influence household leverage. Thus, the implementation of redistributive policies including more progressive income and wealth taxation might be appropriate to prevent excessive credit booms and financial instability.

6 Conclusions

The dramatic rise in income inequality in most industrialized countries over the last decades has provoked a lively debate among economists as to what extent the evolution of inequality can be considered as a root cause of the recent global financial crisis.

In this paper, we investigate the link between income inequality, leverage and financial crises over the last decades using bivariate Granger causality test. We argue that the causal relationship between inequality and leverage is sensitive to the specific measure of credit. Our findings suggest that top income shares significantly affect future credit to income of the private household sector. The test statistics reveal that the causal impact of changes in top income shares is stronger for total credit to the household sector than for bank credit to the private non-financial sector which is commonly used in empirical studies. This result is consistent with the notion, that households have increased their debt as a reaction to rising permanent income inequality. We interpret this finding as an indication for the relevance of income inequality as a driver of credit expansion. Surprisingly, however, top income shares are found to significantly impact household leverage in some European countries whereas the effect is considerably weaker for Anglo Saxon countries. Moreover, we do not find a robust causal relationship from the Gini coefficient of household disposable income to credit aggregates which may be due to the fact that changes in the tails of the income distribution are not completely reflected in changes in the Gini coefficient. Interestingly, our results suggest feedback effects which seem to be particular strong for top income shares. This might be explained by cyclical effects on the decomposition of household income, in particular on capital income which is typically concentrated at the top of the income distribution. From a theoretical perspective, the bidirectional causal relationship is not surprising. In this regard, the present paper underlines that endogeneity might be a serious problem for the validity of other empirical studies on the link between inequality and private sector borrowing.

Our results also point to the relevance of other determinants of credit to income expansions. We find two-way interactions between economic activity and credit aggregates on the one hand and asset prices and credit aggregates on the other indicating that mutually reinforcing boom-bust cycles may occur which augments the probability of future financial instability. By contrast, our results provide mixed evidence regarding the role of excessively loose monetary policy and financial liberalization.

Our methodological framework can be elaborated in different ways. Firstly, panel cointegration approaches used to detect long-run steady state relationships could be complemented by a pure time series perspective to assess the validity of the results at the individual country level. Secondly, our approach treats the potential determinants of credit to income expansions completely separately from one another. However, income inequality, asset price fluctuations and financial liberalization are likely interrelated. Thus, the channels through which income inequality contributes to financial and macroeconomic instability need further investigation.

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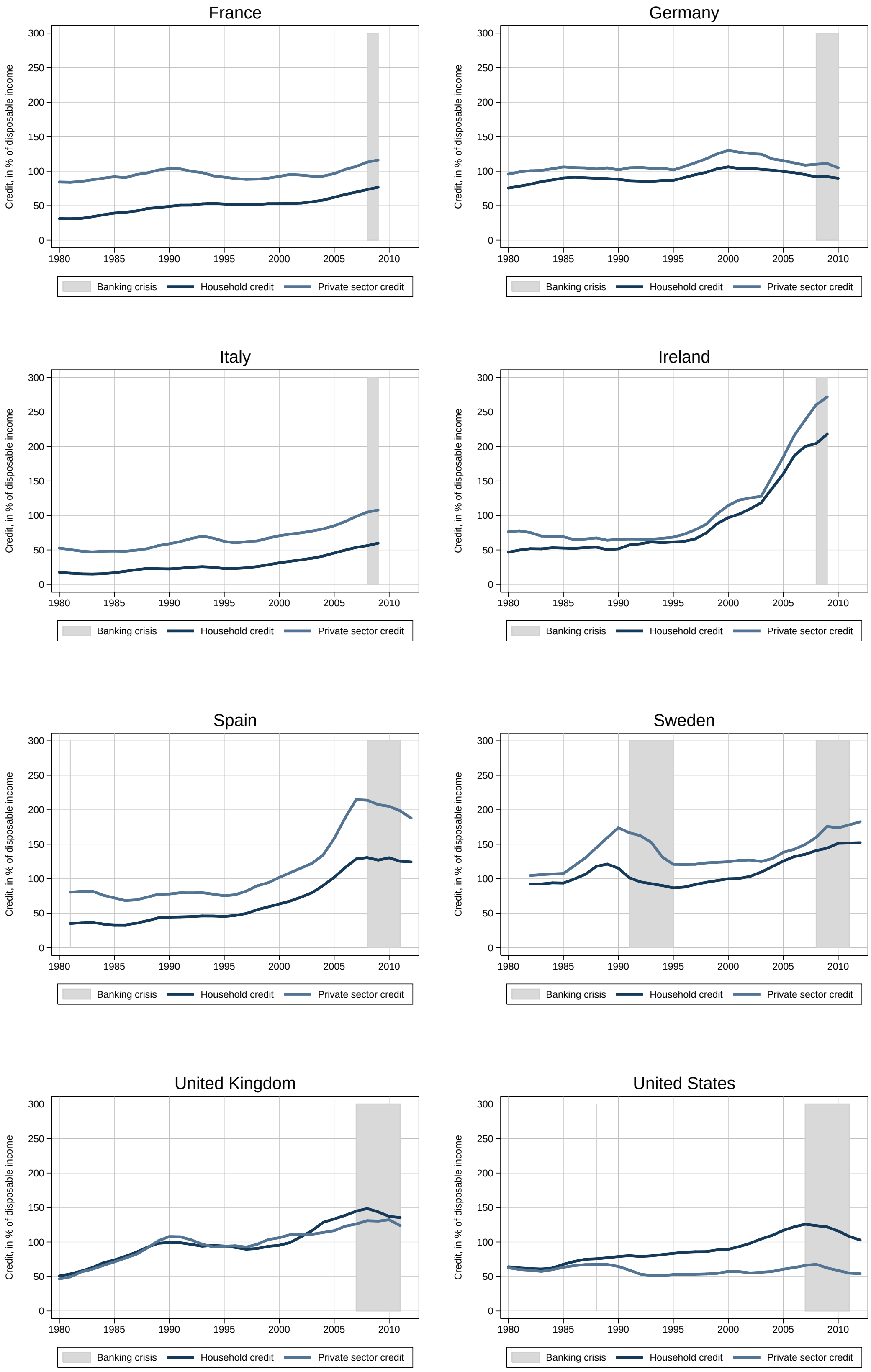

Figure 1: Credit and financial crises, 1980-2013

Figure 2: Credit and monetary policy, 1980-2013

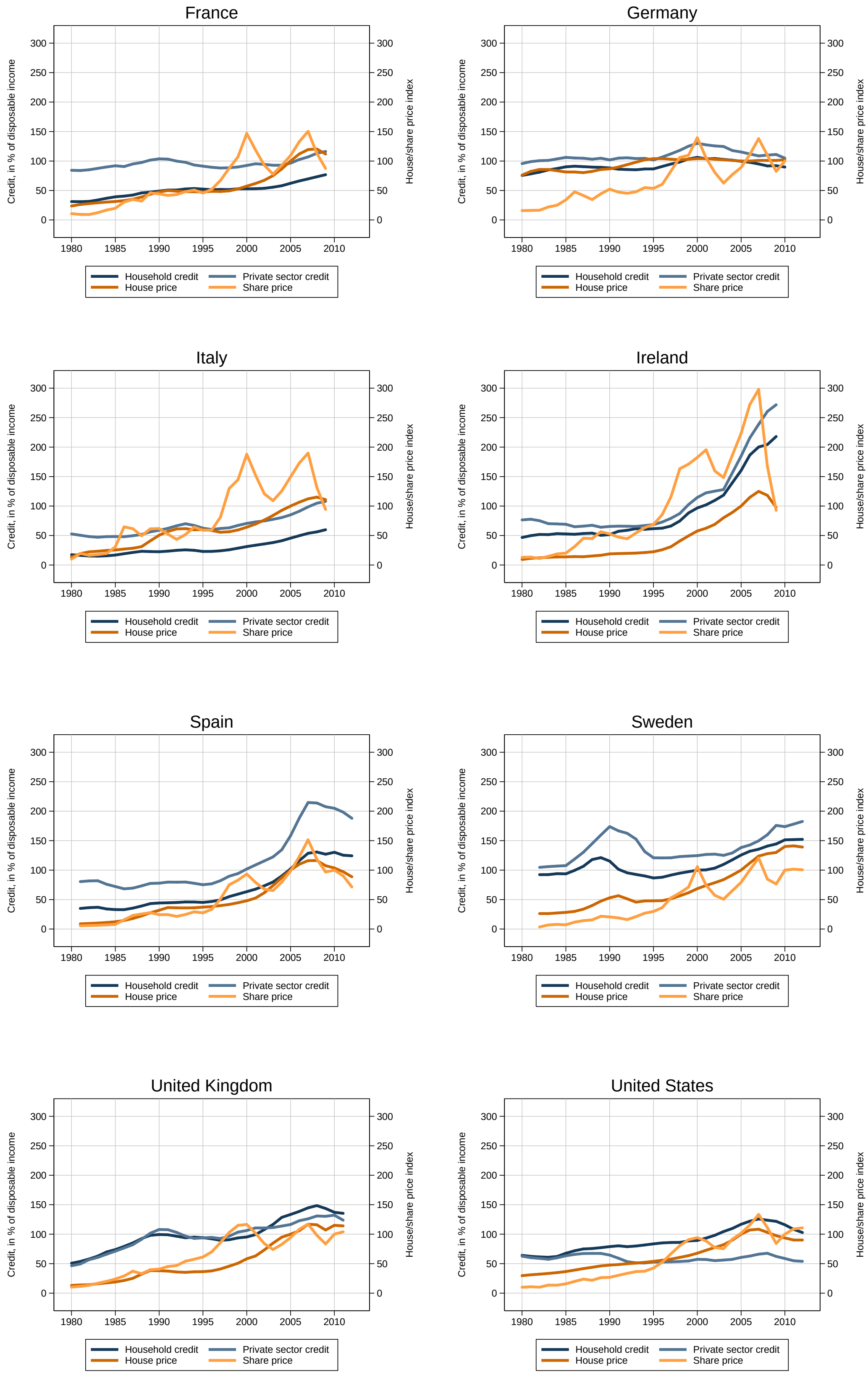

Figure 3: Credit and asset prices, 1980-2013

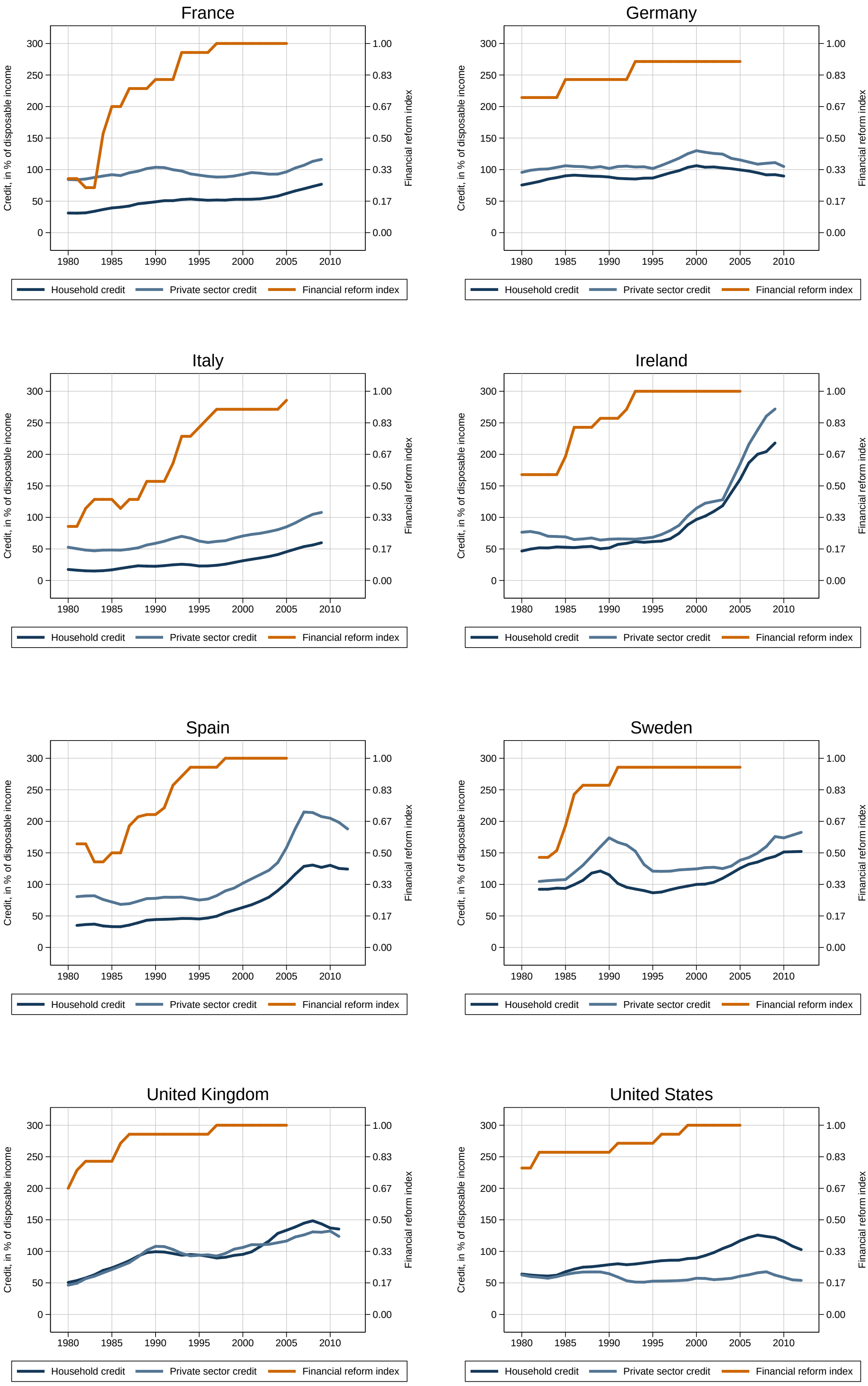

Figure 4: Credit and financial deregulation, 1980-2013

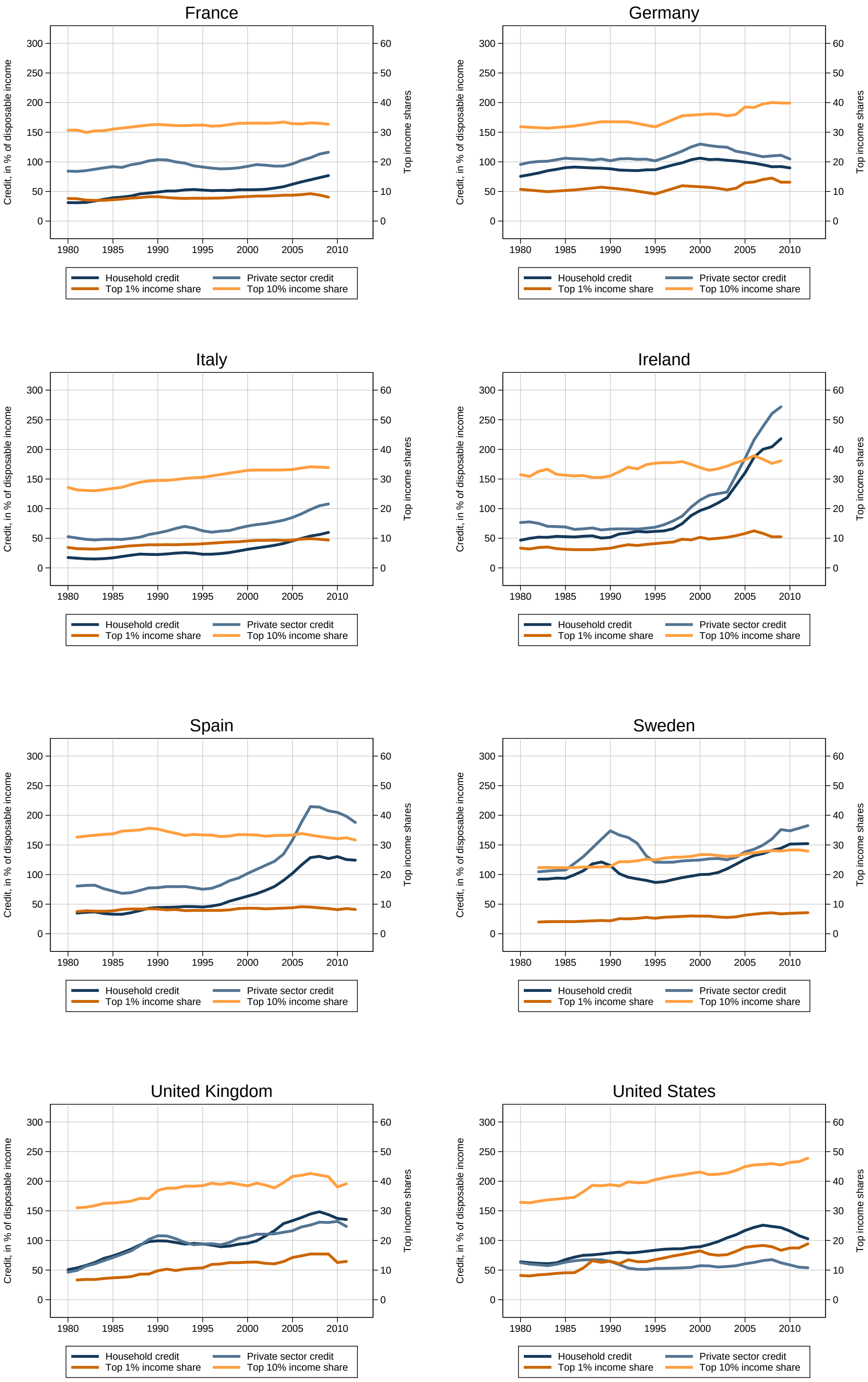

Figure 5: Credit and income inequality, 1980-2013

Table 1: Household credit and financial crises - OLS and Logit estimates, 1970-2013

Estimation method	OLS			Logit	
Regressor	(1)	(2)	(3)	(4)	(5)
(Household credit/disposable income)$_{t-1}$	-1.9583***	-1.7143***	-0.6494*	-16.4851***	-23.8082**
	(0.5070)	(0.3945)	(0.3521)	(4.4805)	(10.1686)
(Household credit/disposable income)$_{t-2}$	2.7577***	1.4806**	-0.2087	22.6320***	11.8301
	(1.0007)	(0.7191)	(0.7287)	(7.8844)	(18.0490)
(Household credit/disposable income)$_{t-3}$	-0.5142	0.9601**	1.2084**	-3.8116	28.2280**
	(0.6006)	(0.4533)	(0.5026)	(4.3547)	(12.5448)
Sum of lagged coefficients	0.2852***	0.7264***	0.3503***	2.3353***	16.2500***
	(0.0436)	(0.0612)	(0.0806)	(0.3391)	(3.1609)
Joint significance test: Household credit	17.52	49.81	7.51	61.38	32.75
p-value	0.0000	0.0000	0.0001	0.0000	0.0000
Joint significance test: Country fixed effects	-	7.62	2.09	-	34.50
p-value		0.0000	0.0142		0.0006
Joint significance test: Time fixed effects	-	-	8.77	-	-
p-value			0.0000		
Country fixed effects	No	Yes	Yes	No	Yes
Time fixed effects	No	No	Yes	No	No
Observations	395	395	395	395	380
Number of countries	14	14	14	14	14
Adjusted R^2/Pseudo R^2	0.175	0.353	0.606	0.211	0.603

*Note: The dependent variable is coded as a binary indicator variable equal to one when a banking crisis occured and zero otherwise. Robust standard errors are reported in parantheses. The Models 2, 3 and 5 include country fixed effects and Model 3 also includes time fixed effects. The estimates for the country fixed effects and time fixed effects are not shown. All estimations include a constant term. The adjusted R^2 (Pseudo R^2) is reported for OLS (Logit) estimations. *, **, and *** denotes significance at 10%, 5%, and 1% levels, respectively.*

Table 2: Panel causality test: Economic activity

	Real GDP (X) → Credit (Y)				Credit (X) → Real GDP (Y)			
	Total credit to household sector		Bank credit to private sector		Total credit to household sector		Bank credit to private sector	
Lag	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value
1	2.9668	0.0030	15.4222	0.0000	0.5337	0.5936	3.3998	0.0007
2	3.7915	0.0001	10.2637	0.0000	7.2672	0.0000	8.7731	0.0000
3	1.5753	0.1152	5.1261	0.0000	5.4884	0.0000	5.7328	0.0000

Table 3: Panel causality test: Monetary policy

	Taylor rule (X) → Credit (Y)				Credit (X) → Taylor rule (Y)			
	Total credit to household sector		Bank credit to private sector		Total credit to household sector		Bank credit to private sector	
Lag	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value
1	0.1473	0.8829	1.0456	0.2957	0.3491	0.7270	-0.6872	0.4920
2	1.1508	0.2498	0.8545	0.3928	1.5202	0.1284	0.6297	0.5289
3	2.0815	0.0374	1.0625	0.2880	2.0794	0.0376	0.4657	0.6415

Table 4: Panel causality test: House price index

	House prices (X) → Credit (Y)				Credit (X) → House prices (Y)			
	Total credit to household sector		Bank credit to private sector		Total credit to household sector		Bank credit to private sector	
Lag	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value
1	7.5179	0.0000	12.3435	0.0000	4.3258	0.0000	4.7352	0.0000
2	5.7155	0.0000	10.1270	0.0000	4.4825	0.0000	2.9217	0.0035
3	4.4183	0.0000	6.2626	0.0000	3.9642	0.0000	3.9326	0.0000

Table 5: Panel causality test: Stock price index

	Stock prices (X) → Credit (Y)				Credit (X) → Stock prices (Y)			
	Total credit to household sector		Bank credit to private sector		Total credit to household sector		Bank credit to private sector	
Lag	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value
1	1.4451	0.1484	7.2527	0.0000	-0.9594	0.3373	0.7940	0.4272
2	1.3939	0.1634	5.4247	0.0000	2.3682	0.0179	0.4406	0.6595
3	1.2167	0.2237	2.6296	0.0085	5.9003	0.0056	2.4764	0.0133

Note: The tables report the standardized statistic $\tilde{Z}_{NT}^{HNC}$ based on semi-asymptotic moments and the corresponding p-values. $X \rightarrow Y$ is used to denote the null hypothesis of homogenous non causality (HNC) from X to Y.

Table 6: Panel causality test: Financial reform index

	Financial reform (X) → Credit (Y)				Credit (X) → Financial reform (Y)			
	Total credit to household sector		Bank credit to private sector		Total credit to household sector		Bank credit to private sector	
Lag	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value
1	0.7801	0.4353	0.2393	0.8109	-0.4722	0.6368	-0.7536	0.4511
2	-0.0571	0.9545	0.3531	0.7240	-0.9339	0.3504	-0.5703	0.5685
3	0.8297	0.4067	-0.3897	0.6968	0.0973	0.9225	-0.6690	0.5035

Table 7: Panel causality test: Financial sector value added

	Financial sector VA (X) → Credit (Y)				Credit (X) → Financial Sector VA (Y)			
	Total credit to household sector		Bank credit to private sector		Total credit to household sector		Bank credit to private sector	
Lag	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value
1	-0.8746	0.3818	0.2871	0.7741	0.3670	0.7136	0.5597	0.5757
2	-0.7190	0.4722	3.3197	0.0009	3.9485	0.0000	3.0048	0.0027
3	-0.9253	0.3548	1.5068	0.1319	4.1421	0.0000	2.2282	0.0259

Table 8: Panel causality test: Top 1% income share

	Top 1% income share (X) → Credit (Y)				Credit (X) → Top 1% income share (Y)			
	Total credit to household sector		Bank credit to private sector		Total credit to household sector		Bank credit to private sector	
Lag	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value
1	6.2927	0.0000	3.8780	0.0001	1.0907	0.2754	1.1090	0.2674
2	3.9609	0.0000	2.0682	0.0386	3.9252	0.0000	1.8670	0.0619
3	1.7505	0.0800	0.4039	0.6863	3.7604	0.0002	1.9533	0.0508

Table 9: Panel causality test: Gini coefficient

	Gini coefficient (X) → Credit (Y)				Credit (X) → Gini coefficient (Y)			
	Total credit to household sector		Bank credit to private sector		Total credit to household sector		Bank credit to private sector	
Lag	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value	$\tilde{Z}_{NT}^{HNC}$	p-value
1	-0.67088	0.5023	-1.1910	0.2337	1.7263	0.0843	-0.0916	0.9270
2	-0.13872	0.8897	-0.3767	0.7064	0.5009	0.6164	-0.7995	0.4240
3	-0.65676	0.5113	-0.1226	0.9024	2.1272	0.0334	-0.5379	0.5906

Note: The tables report the standardized statistic $\tilde{Z}_{NT}^{HNC}$ based on semi-asymptotic moments and the corresponding p-values. $X \rightarrow Y$ is used to denote the null hypothesis of homogenous non causality (HNC) from X to Y.

Table 10: Individual country causality test: Economic activity

	Real GDP (X) → Credit (Y)		Credit (X) → Real GDP (Y)			
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Country	p-value	p-value	p-value	p-value	Lag	Lag
DNK	0.0012	0.1044	0.2421	0.1055	1	5
FIN	0.4467	0.0004	0.0065	0.1088	2	1
FRA	0.6532	0.0155	0.1018	0.1349	5	1
DEU	0.4451	0.1321	0.6555	0.7605	5	4
IRL	0.0012	0.0133	0.0310	0.0000	5	4
ITA	0.5193	0.1085	0.4832	0.0783	1	1
NLD	0.0271	0.0729	0.0001	0.0383	5	1
NOR	0.5288	0.6305	0.1956	0.0009	1	2
PRT	0.2173	0.1615	0.1099	0.1232	4	4
ESP	0.8156	0.7872	0.5832	0.0004	1	2
SWE	0.3124	0.0016	0.0807	0.7751	1	1
CHE	0.3670	0.1238	0.4704	0.4819	5	5
GBR	0.0477	0.3127	0.3986	0.1414	5	1
USA	0.2194	0.1024	0.0033	0.0103	2	2

Table 11: Individual country causality test: Monetary policy

	Taylor rule (X) → Credit (Y)		Credit (X) → Taylor rule (Y)			
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Country	p-value	p-value	p-value	p-value	Lag	Lag
DNK	0.0718	0.2800	0.6675	0.3106	2	5
FIN	0.2039	0.0168	0.1622	0.6891	5	2
FRA	0.1085	0.1251	0.0727	0.2273	5	5
DEU	0.6636	0.7292	0.1816	0.4671	2	3
IRL	0.6683	0.8520	0.1558	0.9630	5	1
ITA	0.8074	0.2097	0.7286	0.8260	1	2
NLD	0.0002	0.1055	0.3120	0.7999	5	5
NOR	0.1592	0.1055	0.9128	0.3864	1	2
PRT	0.2419	0.4995	0.2360	0.4216	4	5
ESP	0.4256	0.9113	0.6148	0.0964	1	2
SWE	0.2857	0.1561	0.0002	0.0056	5	1
CHE	0.3975	0.0201	0.6099	0.8318	5	4
GBR	0.5052	0.3704	0.9891	0.9935	5	3
USA	0.3952	0.9298	0.4744	0.6007	2	2

Table 12: Individual country causality test: House price index

	House prices (X) → Credit (Y)		Credit (X) → House prices (Y)			
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Country	p-value	p-value	p-value	p-value	Lag	Lag
DNK	0.0001	0.0166	0.4095	0.1211	1	5
FIN	0.1999	0.0495	0.0002	0.0707	2	2
FRA	0.5005	0.2304	0.9119	0.6028	5	1
DEU	0.4944	0.0722	0.6980	0.7306	4	4
IRL	0.0004	0.0001	0.0552	0.0074	4	5
ITA	0.3542	0.1130	0.2502	0.8250	2	5
NLD	0.1653	0.0350	0.0014	0.0925	4	4
NOR	0.1691	0.1609	0.6342	0.2241	1	2
PRT	0.5847	0.1146	0.2897	0.6007	5	4
ESP	0.0001	0.0012	0.0908	0.0072	3	4
SWE	0.1523	0.0260	0.0003	0.0427	1	1
CHE	0.7851	0.5094	0.1956	0.6261	5	5
GBR	0.2245	0.2426	0.2000	0.8674	5	3
USA	0.0362	0.0902	0.0444	0.0780	2	5

Table 13: Individual country causality test: Stock price index

	Stock prices (X) → Credit (Y)		Credit (X) → Stock prices (Y)			
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Country	p-value	p-value	p-value	p-value	Lag	Lag
DNK	0.0254	0.0644	0.7992	0.5477	1	1
FIN	0.7459	0.1597	0.0184	0.0573	5	5
FRA	0.5513	0.0172	0.0703	0.1398	5	1
DEU	0.0015	0.7984	0.0011	0.0011	3	4
IRL	0.1501	0.0133	0.0019	0.0017	5	5
ITA	0.5078	0.5234	0.2518	0.0355	4	5
NLD	0.2829	0.0051	0.0588	0.3257	4	1
NOR	0.4745	0.0274	0.6708	0.4763	1	2
PRT	0.2101	NA	0.3636	NA	5	NA
ESP	0.0430	0.0651	0.5537	0.3267	3	5
SWE	0.6933	0.5606	0.5574	0.3599	5	4
CHE	0.0285	0.9114	0.2416	0.7565	5	5
GBR	0.9387	0.3949	0.0377	0.5141	5	1
USA	0.1050	0.2558	0.4341	0.0811	5	4

Table 14: Individual country causality test: Financial reform index

	Financial reform (X) → Credit (Y)		Credit (X) → Financial reform (Y)			
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Country	p-value	p-value	p-value	p-value	Lag	Lag
DNK	0.5414	0.6708	0.2080	0.1289	1	5
FIN	0.2764	0.8299	0.5762	0.5868	5	1
FRA	0.1573	0.1260	0.4384	0.8536	5	1
DEU	0.5351	0.2580	0.7752	0.9735	4	4
IRL	0.1121	0.7962	0.3649	0.2338	5	5
ITA	0.0614	0.0239	0.7369	0.7147	5	5
NLD	0.5031	0.3796	0.0022	0.0823	5	1
NOR	0.0567	0.0789	0.6728	0.4387	5	5
PRT	0.5354	0.1050	0.1865	0.2827	4	4
ESP	0.0315	0.6134	0.3108	0.3662	3	5
SWE	0.0068	0.0049	0.0052	0.0381	5	5
CHE	NA	NA	NA	NA	NA	NA
GBR	0.7979	0.1689	0.0190	0.8294	5	1
USA	0.0227	0.2086	0.9638	0.6468	4	5

Table 15: Individual country causality test: Financial sector value added

	Financial sector VA (X) → Credit (Y)		Credit (X) → Financial sector VA (Y)			
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Country	p-value	p-value	p-value	p-value	Lag	Lag
DNK	0.3426	0.0535	0.3582	0.4060	1	1
FIN	0.8154	0.0068	0.0127	0.0614	5	4
FRA	0.7247	0.5970	0.0629	0.8076	4	1
DEU	0.1472	0.2735	0.5738	0.8575	5	5
IRL	0.6769	0.1116	0.1236	0.4912	5	1
ITA	0.6243	0.1742	0.1285	0.0005	1	2
NLD	0.4672	0.7167	0.2387	0.0856	5	4
NOR	0.0265	0.0983	0.0552	0.1085	4	5
PRT	0.3233	NA	0.7443	NA	5	NA
ESP	0.2912	0.1356	0.0214	0.1784	2	4
SWE	0.0002	0.1132	0.3495	0.0611	5	5
CHE	0.0839	0.2922	0.1842	0.7696	5	1
GBR	0.3602	0.0159	0.4243	0.9989	5	2
USA	0.0171	0.1262	0.0782	0.7707	4	2

Table 16: Individual country causality test: Top 1% income share

	Top 1% income share (X) → Credit (Y)		Credit (X) → Top 1% income share (Y)			
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Country	p-value	p-value	p-value	p-value	Lag	Lag
DNK	0.0358	0.0250	0.4298	0.3586	1	1
FIN	0.3383	0.0145	0.3431	0.6575	5	1
FRA	0.3513	0.4669	0.2362	0.9532	5	1
DEU	0.4262	0.7237	0.8939	0.4410	4	4
IRL	0.9720	0.2853	0.0696	0.0995	5	5
ITA	0.7190	0.3841	0.4500	0.0245	1	1
NLD	0.0633	0.0120	0.0485	0.4674	5	5
NOR	0.0000	0.0213	0.3440	0.1273	2	2
PRT	NA	0.8506	NA	0.2106	5	1
ESP	0.0213	0.4316	0.3882	0.3948	1	2
SWE	0.6568	0.2920	0.8757	0.3243	1	1
CHE	0.0032	0.9878	0.6808	0.5708	5	5
GBR	0.1270	0.0207	0.0844	0.2170	5	2
USA	0.3315	0.1461	0.3784	0.7196	4	4

Table 17: Individual country causality test: Gini coefficient

	Gini coefficient (X) → Credit (Y)		Credit (X) → Gini coefficient (Y)			
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Country	p-value	p-value	p-value	p-value	Lag	Lag
DNK	0.1259	0.1165	0.9420	0.5692	5	5
FIN	0.9654	0.6324	0.1832	0.9274	5	1
FRA	0.1676	0.0967	0.3854	0.6313	4	3
DEU	0.8413	0.5351	0.6400	0.7633	4	3
IRL	0.1338	0.1295	0.0305	0.0911	5	5
ITA	0.0339	0.3900	0.4342	0.7955	2	1
NLD	0.2203	0.3396	0.7229	0.7720	4	4
NOR	0.0299	0.2156	0.9344	0.8895	5	2
PRT	0.0562	0.1195	0.3531	0.4937	3	5
ESP	0.1001	0.4847	0.3366	0.6927	1	2
SWE	0.2362	0.6613	0.2523	0.3263	5	4
CHE	0.0957	0.1543	0.3424	0.2574	5	3
GBR	0.8753	0.0779	0.1037	0.8673	5	5
USA	0.2372	0.4744	0.5106	0.2464	3	2

A Description of data

This section provides a brief description of the variable definitions and data sources. We employ an unbalanced panel data set which consists of 13 European countries and the United States. More specifically, the following countries are included in the sample: Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom and the United States.

A.1 Variable definitions and data sources

Credit: As proxy for financial instability we use household credit as percent of household disposable income. Alternatively, we use series on bank credit to the private non-financial sector as percent of private disposable income. We employ either break-adjusted series on total credit to households and non-profit institutions serving households or bank credit to non-financial corporations, households and non-profit institutions serving households in national currency from the Bank for International Settlements (BIS). In terms of financial instruments, credit covers loans and debt securities where the latter includes bonds and short-term papers. The series are published at quarterly frequency and capture the outstanding amount of credit at the end of the period. For the empirical analysis, we construct annual averages of the series. Data on disposable income of the household sector and the private non-financial sector are taken from the AMECO database of the European Commission.

Business cycle: The impact of business cycle fluctuations on the expansion of household credit is captured by real GDP. We use chained series at 2010 market prices provided by the AMECO database of the European Commission.

Monetary policy: We use the deviation from a standard Taylor rule as proxy for monetary policy. The Taylor rule indicates how much the national central bank should respond to divergences of actual inflation rates from target inflation rates and of actual domestic GDP from potential GDP (Taylor, 1993). The Taylor rule can be written as follows:

$$i = r^* + \pi^* + \alpha_\pi(\pi - \pi^*) + \alpha_y y \tag{11}$$

where i is the nominal policy rate, r^* is the assumed equilibrium real rate of interest, π^* is the central bank's target inflation rate, π is the current period inflation rate as measured by the GDP deflator and y is the current period output gap. The parameters α_π and α_y are set to 0.5 as proposed by Taylor (1993) and the equilibrium interest rate r^* is set to 2 percent. The output gap is measured by the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997). The smoothing parameter lambda is set to 6.25, as recommended for annual data in the literature (e.g. Ravn and Uhlig (2002)). Data are in constant 2005 U.S. dollar and taken from the World Development (WDI) database provided by the World Bank.

Asset prices: The evolution of asset prices is captured both by share price and house price indices. Share price indices are calculated from the prices of common shares of companies traded on national or foreign stock exchanges provided by the Monthly Monetary and Financial Statistics (MEI) database from the OECD. Data on international share prices are available monthly using simple averages of the closing daily values and are expressed as an index where the year 2010 is the base year. Data on house price indices are taken from the International House Price Database provided by the Globalization and Monetary Policy Institute of the Federal Reserve Bank of Dallas. The database contains house price indices for 22 countries at a quarterly frequency, starting in the first quarter of 1975. For each country, a house price index is selected which is most consistent with the quarterly US house price index for existing single-family houses produced by the Federal Housing Finance Agency. The house price indices are seasonally adjusted over the entire sample period using an unobserved components time series model and then rebased to 2005.

Financial liberalization: In order to assess how the evolution of household credit is affected by financial liberalization and the deregulation of financial sector we use data on financial reforms from Abiad et al. (2010), covering 91 countries over the period 1973-2005. The database provides internationally comparable indices related to specific financial reforms which are then combined in an aggregate index normalized between zero and one. More specifically, Abiad et al. (2010) distinguish between the following seven different dimensions of financial sector policy: credit controls, interest rate controls, entry barriers/pro-competition measures, banking supervision, privatization, international capital flows and security markets. As an alternative measure we use the financial sector's share in total value added. According to our definition, the financial sector comprises financial intermediation, insurance and pension funds and activities related to financial intermediation. Data are taken from the OECD database for Structural analysis (STAN). The STAN dataset is based on the International Standard Industrial Classification Revision 3 (ISIC Rev. 3) which allows analyzing industrial performance at a relatively detailed level of activity across countries.

Income inequality: As proxy for income inequality we use different top income shares taken from the World Wealth and Income Database (WID). These data are collected from personal income tax returns following the methodology outlined in Piketty (2003). Income reported is typically gross total income and includes labour, business and capital income (and in a few cases also realized capital gains) before taxes and transfers. Top income shares are then calculated as the ratio of top incomes divided by the total amount of personal income. As an alternative measure of income inequality we use the Gini coefficient from version 5.0 of the Standardized Income Inequality Database (SWIID). The SWIID dataset provides internationally comparable estimates of Gini coefficients of market (i.e. before taxes and transfers) income inequality and net (i.e. after taxes and transfers) income inequality for 174 countries over the period 1960-2013. Solt (2014) provides a detailed description of the SWIID dataset.

A.2 Summary statistics

Table 18: Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Total credit to household sector, % of disposable income	442	92.735	51.806	15.027	290.333
Bank credit to private sector, % of disposable income	442	102.785	45.363	43.612	283.245
Real GDP at constant prices (2010 = 100)	442	74.096	20.120	22.285	109.969
Deviation from standard Taylor rule	442	-0.599	3.535	-13.148	14.007
House price index	442	60.373	33.813	3.770	150.600
Share price index	442	60.395	48.118	2.400	297.809
Financial reform index	370	0.794	0.196	0.238	1.000
GDP share of the financial sector	393	5.545	1.872	2.164	13.641
Top 1% income share	442	8.214	2.960	3.490	18.880
Gini coefficient	441	28.453	4.806	17.964	37.816

B Unit root tests

In this section, we discuss different unit root tests that are employed in the empirical analysis. Firstly, we consider various univariate unit root tests. Detailed test results are available from the authors upon request. Secondly, we extend our analysis to panel unit root tests. The primary reason behind the application of panel unit root tests compared to univariate test procedures is to gain statistical power by increasing the number of observations. Unit root tests are known to have limited power against alternative hypotheses with highly persistent deviations from equilibrium. Levin et al. (2002) argue that this problem is particularly severe in small samples and therefore most relevant for the univariate unit root tests. Conversely, panel unit root tests may not be able to account for all individual specific heterogeneity. Since the observations of each cross-sectional unit are considered to be equally important, we have to bear in mind that the major role of the US in contributing to global financial instability is not necessarily sufficiently reflected.

B.1 Time series unit root tests

The Augmented Dickey-Fuller test

The Augmented Dickey-Fuller (ADF) test allows to consider higher order autocorrelation by including lagged differences. With ϕ as the coefficient of the first lag of y_t and μ as its mean, one first defines $\alpha := (1-\phi)\mu$ and $\rho := (\phi - 1)$. If also including a deterministic trend, then the basic test equations will be

$$\Delta y_t = \alpha + \beta t + \rho y_{t-1} + \sum_{j=1}^{p} \delta_j \Delta y_{t-j} + \epsilon_t \tag{12}$$

for $t = p+1, p+2, \ldots, T$. The null is that y_t has an unit root, formally

$$H_0 : \rho = 0. \tag{13}$$

Under the null, the test statistic for $t_\rho = \hat{\rho}/\hat{\sigma}_\rho$ converges to the so-called Dickey-Fuller distribution. Its simulated values tend to be higher than those of a normal distribution.

The Kwiatkowski-Phillips-Schmidt-Shin test

Including a deterministic trend, the test by Kwiatkowski et al. (1992) states the hypotheses as follows

$$H_0 : y_t = \alpha + \beta t + \epsilon_t \sim I(0) \tag{14}$$

$$H_1 : y_t \sim I(1). \tag{15}$$

The sum of partial residual sums,

$$S_t = \sum_{i=1}^{t} \hat{\epsilon}_i, \tag{16}$$

can be compared with asymptotic results presented in Kwiatkowski et al. (1992), i.e. formally

$$T^{-2} \sum_{t=1}^{T} S_t^2 \to \omega_\epsilon^2 KPSS_c(1). \tag{17}$$

This requires to estimate

$$\hat{\omega}_\epsilon^2 = \hat{\sigma}_\epsilon^2 + 2 \sum_{h=1}^{B} w_h \hat{cov}(\hat{\epsilon}_t, \hat{\epsilon}_{t+h}) \tag{18}$$

with an appropriate specification of the bandwidth B and the kernel w_h.

The Dickey-Fuller GLS test

For cases, in which a linear time trend and/or a constant should be included, Elliott et al. (1996) propose a modification of the ADF test. For simplicity reason, the presented equation refer only to a trend inclusion. The authors define quasi-differences depending on a function of the sample size, $f(T)$, by

$$d(y_t|f) := \begin{cases} y_t & : t = 1 \\ y_t - f * y_{t-1} & : t > 0 \end{cases}, \qquad d(t|f) := \begin{cases} t & : t = 1 \\ t - f * (t-1) & : t > 0 \end{cases} \tag{19}$$

and regress those quasi-differenced data on the quasi-differenced trend:

$$d(y|f) = \beta d(t|f) + \nu_t. \tag{20}$$

After obtaining the estimator for $\beta(f)$, the data can be 'GLS detrended' by

$$y_t^d := y_t - \hat{\beta}t \tag{21}$$

and the standard ADF test equation translates into

$$\Delta y_t^d = \rho y_{t-1}^d + \sum_{j=1}^{M} \delta_j \Delta y_{t-j}^d + \epsilon_t. \tag{22}$$

If a trend is included, critical values needed will also change relative to the standard ADF.

The Phillips-Perron test

Instead of augmenting the standard Dickey-Fuller test equation by additional lags, Phillips and Perron (1988) propose to adjust the test statistic t_ϕ in order to capture higher order autocorrelation. More precisely, they use the long-run variance of ϵ_t, like in the KPSS test, and show

$$Z\left(t_\phi, \hat{\sigma}_\epsilon^2, \hat{\omega_\epsilon^2}\right) \rightarrow DF_c(1). \tag{23}$$

B.2 Panel unit root tests assuming cross-sectional independence

The various panel unit root test procedures that belong to the first generation differ in several key aspects. First, the unit root tests proposed by Levin et al. (2002), Harris and Tzavalis (1999) and Breitung (2000) assume that all cross-sectional units share a common autoregressive parameter while the tests developed by Im et al. (2003), Maddala and Wu (1999) and Choi (2001) allow the autoregressive parameter to be individual specific. Second, the tests make differing assumptions about the way in which the number of cross-sectional units N and the number of time periods T tend to infinity, which is crucial for determining the asymptotic properties of estimators and test statistics (Phillips and Moon, 1999).

The Levin, Lin and Chu test

Levin et al. (2002), hereafter referred to as LLC, proposed a panel unit root test assuming that the autoregressive parameter is identical for all cross-sectional units whereas the other parameters are allowed to vary across the panel units. A general form of the model can be written as

$$\Delta y_{it} = \alpha_i + \beta_i t + \rho y_{i,t-1} + \sum_{j=1}^{p_i} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \tag{24}$$

where $i = 1, \ldots, N$ and $t = 1, \ldots, T$ denote the cross-sectional and time series dimensions, respectively. α_i represents a vector of coefficients of panel-specific means (fixed-effects) and β_i represents a vector of coefficients of linear time trends. Short-run dynamics of the errors are accounted for by including lagged differences of the dependent variable. The errors ε_{it} are independently distributed across i and t with zero means and finite (possibly) heterogeneous variances, σ_i^2.

The null hypothesis is that each individual time series contains a unit root, i.e. $H_0 : \rho = 0$, against the alternative that each time series is stationary, i.e. $H_1 : \rho = \rho_i < 0$ for all $i = 1, \ldots, N$. Since the lag order p_i is unknown, LLC suggest a three-step procedure. First, the test performs individual-specific augmented Dickey-Fuller (ADF) regressions and generates orthogonalized residuals. Subsequently, the test procedure requires estimating the ratio of long-run to short-run standard deviations for each individual. The null hypothesis of a unit root can then be tested using the standard t-statistic

$$t_\rho = \frac{\hat{\rho}}{\hat{\sigma}_{\hat{\rho}}} \tag{25}$$

where

$$\hat{\sigma}_{\hat{\rho}} = \hat{\sigma}_{\tilde{\varepsilon}}[\sum_{i=1}^{N} \sum_{t=2+p_i}^{T_i} \tilde{\upsilon}_{i,t-1}^2]^{-1/2} \tag{26}$$

$$\hat{\sigma}_{\tilde{\varepsilon}^2} = \frac{1}{N\tilde{T}} \sum_{i=1}^{N} \sum_{t=2+p_i}^{T} (\tilde{e}_{it} - \hat{\rho}\tilde{\upsilon}_{i,t-1})^2 \tag{27}$$

and $\hat{\rho}$ is the OLS coefficient from a pooled regression of the orthogonalized residuals $\tilde{e}_{it}$ on $\tilde{\upsilon}_{i,t-1}$ based on $N\tilde{T}$ observations with $\tilde{T} = T - \bar{p} - 1$ (see Baltagi, 2013). $\tilde{T}$ is the average number of observations per cross-sectional unit and $\bar{p} = \frac{1}{N} \sum_{i=1}^{N} p_i$ is the average lag order of individual ADF regressions.

The asymptotic results by LLC show, that under the null hypothesis of a unit root, the regression t-statistic diverges to negative infinity if individual-specific means and time trends are included. Therefore, LLC propose a bias-adjusted test statistic which is given by

$$t_\rho^* = \frac{t_\rho - N\tilde{T}\hat{S}_N \hat{\sigma}_{\tilde{\varepsilon}}^{-2} \sigma_{\hat{\rho}} \mu_{\tilde{T}^*}}{\sigma_{\tilde{T}^*}} \tag{28}$$

where the mean adjustment $\mu_{\tilde{T}^*}$ and the standard deviation adjustment $\sigma_{\tilde{T}^*}$ are simulated by LLC. Equation 28 shows that the average standard deviation ratio $\hat{S}_N = \frac{1}{N}\sum_{i=1}^{N}\hat{s}_i$ is used to adjust the t-statistic. The ratio of long-run to short-run standard deviations is estimated by $\hat{s}_i = \frac{\hat{\sigma}_{yi}}{\hat{\sigma}_{\varepsilon i}}$ where $\hat{\sigma}_{yi}$ denotes a kernel estimator of the long-run variance. LLC show that t^*_ρ is asymptotically distributed $N(0, 1)$ as $N/T \to 0$.

The Im, Pesaran and Shin test

Im et al. (2003), hereafter referred to as IPS, developed a test that allows for heterogeneity in the autoregressive parameter. The model with panel-specific means and a linear time trend can be written as

$$\Delta y_{it} = \alpha_i + \beta_i t + \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \delta_{ij}\Delta y_{i,t-j} + \varepsilon_{it} \tag{29}$$

where $i = 1, \ldots, N$ and $t = 1, \ldots, T$ denote the cross-sectional and time series dimensions, respectively. The errors ε_{it} are independently distributed across i and t with zero means and finite (possibly) heterogeneous variances, σ_i^2.

The null hypothesis is that all panels contain a unit root, i.e. $H_0 : \rho_i = 0$ for all $i = 1, \ldots, N$. The alternative hypothesis is that N_0 of the N $(0 < N_0 \leq N)$ panel units are stationary with individual specific autoregressive parameters, i.e. $H_1 : \rho_i < 0$ for $i = 1, \ldots, N_0$ with $0 < N_0 \leq N$. Thus, instead of pooling the data, the IPS test performs separate unit root tests for each cross-sectional unit. The test statistic is then defined as the average of the individual t-statistics

$$t - bar_{NT} = \frac{1}{N}\sum_{i=1}^{N} t_{iT}(p_i, \delta_i) \tag{30}$$

where $t_{iT}(p_i, \delta_i)$ is the ADF statistic of cross-sectional unit i. When T is fixed, the individual ADF statistics depend on the nuisance parameter δ_i even under the null hypothesis $\rho_i = 0$. In this case, the standardization using the mean and the variance of $t_{iT}(p_i, \delta_i)$ is not practical. IPS therefore propose a standardization of the *t-bar* statistic using the means and variances of $t_{iT}(p_i, 0)$ evaluated under the null hypothesis $\rho_i = 0$. The standardized *t-bar* statistic is then given by

$$W_{t-bar}(p) = \frac{\sqrt{N}[t - bar_{NT} - \frac{1}{N}\sum_{i=1}^{N} E[t_{iT}(p_i)|\rho_i = 0]]}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} Var[t_{iT}(p_i)|\rho_i = 0]}} \tag{31}$$

where $W_{t-bar}(p)$ has a standard normal limiting distribution as $T \to \infty$ followed by $N \to \infty$.

Breitung (2000) shows that the LLC and the IPS test suffer from a dramatic loss of power if individual specific trends are included. Instead of computing orthogonalized residuals, Breitung (2000) proposes to construct standardized proxies by removing only the autoregressive component. Hadri (2000) suggests a test that computes individual specific KPSS statistics which are averaged across the panel units under the assumption of cross-sectional independence. Under certain conditions, the normalized result converges to a standard normal distributed random variable.

Fisher-type tests

Maddala and Wu (1999) and Choi (2001) proposed a test against the alternative that at least one panel is stationary which is originally suggested by Fisher (1938). This test procedure is based on combining the p-values of the individual test statistics. Let π_i denote the p-value of the individual unit root test applied to each cross-sectional unit. If these test statistics are continuous, the corresponding p-values are independently uniformly distributed random variables in the unit interval [0, 1]. The P test statistic proposed by Maddala and Wu (1999) is then defined as

$$P = -2\sum_{i=1}^{N} ln(\pi_i) \quad \text{and} \quad P \sim \chi^2(2N) \tag{32}$$

and has a chi-square distribution with $2N$ degrees of freedom when $T \to \infty$ and N is fixed. Under the null hypothesis, as $T \to \infty$ followed by $N \to \infty$, P tends to infinity implying that P has a degenerate limiting distribution. Choi (2001) therefore suggested using the inverse normal test statistic Z which is given by

$$Z = \frac{1}{\sqrt{N}}\sum_{i=1}^{N} \Phi^{-1}(\pi_i) \quad \text{and} \quad Z \sim N(0, 1) \tag{33}$$

where Φ_i is the inverse of the standard normal cumulative distribution function.

B.3 Panel unit root tests allowing for cross-sectional dependence

The previously discussed panel unit root tests are all based on the assumption of independent cross-sectional units. However, in many macroeconomic applications, it might be inappropriate to assume that the individual time series in the panel are independently distributed. Pesaran et al. (1995) suggested subtracting cross-sectional means from the series as an early attempt to mitigate the impact of cross-sectional dependence. However, this approach relies on the assumption that cross-sectional correlation is caused by a single aggregate effect which is common to all individuals and is not useful in cases where the pair-wise cross-sectional covariances of the error terms differ across the panel units. To overcome this deficiency, various tests, so-called second generation panel unit root tests, have been proposed which allow for different forms of cross-sectional dependence.

In our analysis, we use the cross-sectionally augmented Dickey Fuller (CADF) test as proposed by Pesaran (2007). This approach is based on augmenting the standard ADF regressions with the cross-sectional average of lagged levels and first-differences of the individual series to account for cross-sectional dependence through a single factor structure. If there is serial correlation in the error term or the factor, the CADF regression can be written as

$$\Delta y_{it} = \alpha_i + \beta_i t + \rho_i y_{i,t-1} + \theta \bar{y}_{i,t-1} + \sum_{j=0}^{p} \vartheta_{ij} \Delta \bar{y}_{i,t-j} + \sum_{j=1}^{p} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \tag{34}$$

where $\bar{y}_{t-1} = \frac{1}{N} \sum_{i=1}^{N} y_{i,t-1}$ and $\Delta \bar{y}_t = \frac{1}{N} \sum_{i=1}^{N} \Delta y_{it}$. The order of augmentation is estimated using the AIC information criterion. Pesaran (2007) showed that the distribution of the individual CADF t-statistics are asymptotically independent of the nuisance parameter. The null hypothesis of a unit root can then be tested using a cross-sectionally augmented version of the IPS test

$$CIPS(N,T) = \frac{1}{N} \sum_{i=1}^{N} t_i(N,T) \tag{35}$$

where $t_i(N,T)$ denotes the individual CADF statistic given by the t-ratio of the coefficient of $y_{i,t-1}$ in the CADF regression. Pesaran (2007) also considers a truncated version of the CADF statistics which allows to avoid undue influences of extreme outcomes that could arise when T is small.

B.4 Results of unit root tests

Table 19: First generation panel unit root tests

	Variables in levels							
	LLC (2002)		IPS (2003)		MW (1999)		Choi (2001)	
Variables	p-value	Result	p-value	Result	p-value	Result	p-value	Result
Total credit to household sector, in % of disposable income	0.2342	I(1)	0.0011	I(0)	0.0002	I(0)	0.9975	I(1)
Bank credit to private sector, in % of disposable income	0.8566	I(1)	0.3275	I(1)	0.1274	I(1)	0.9999	I(1)
Real GDP at constant prices (2010 = 100)	0.6199	I(1)	0.0874	I(0)	0.0754	I(0)	0.9975	I(1)
Deviation from standard Taylor rule	0.0145	I(0)	0.0000	I(0)	0.0001	I(0)	0.0000	I(0)
House price index	0.1670	I(1)	0.0001	I(0)	0.0000	I(0)	0.9999	I(1)
Share price index	0.9326	I(1)	0.0301	I(0)	0.0145	I(0)	0.9486	I(1)
Financial reform index	0.4829	I(1)	0.6285	I(1)	0.3118	I(1)	1.0000	I(1)
GDP share of the financial sector	0.0146	I(0)	0.0611	I(0)	0.0269	I(0)	0.8325	I(1)
Top 1% income share	0.3007	I(1)	0.0859	I(0)	0.0204	I(0)	0.1432	I(1)
Gini coefficient	0.7954	I(1)	0.0026	I(0)	0.0168	I(0)	0.4626	I(1)
	Variables in first differences							
	LLC (2002)		IPS (2003)		MW (1999)		Choi (2001)	
Variables	p-value	Result	p-value	Result	p-value	Result	p-value	Result
Total credit to household sector, in % of disposable income	0.0249	I(0)	0.0014	I(0)	0.0003	I(0)	0.0022	I(0)
Bank credit to private sector, in % of disposable income	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)
Real GDP at constant prices (2010 = 100)	0.0005	I(0)	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)
Deviation from standard Taylor rule	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)
House price index	0.0007	I(0)	0.0000	I(0)	0.0000	I(0)	0.0108	I(0)
Share price index	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)
Financial reform index	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)
GDP share of the financial sector	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)
Top 1% income share	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)
Gini coefficient	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)	0.0000	I(0)

Note: LLC refers to the Levin, Lin and Chu (2002) test, IPS refers to the Im, Pesaran and Shin (2003) test and MW refers to the Maddala and Wu (1999) test.The null hypothesis of the Levin, Lin and Chu (2002) test is that all series contain a common unit root. The null hypothesis of the tests proposed by Im, Pesaran and Shin (2003), Maddala and Wu (1999) and Choi (2001) is that all series contain individual unit roots. The Dickey Fuller regressions for variables in levels and in first differences are augmented with a constant and a trend term.

Table 20: Second generation panel unit root test: Pesaran (2003)

Variable	Z-tbar	p-value	Lag	Result
	Variables in levels			
Total credit to household sector, in % of disposable income	2.567	0.995	3	I(1)
Bank credit to private sector, in % of disposable income	0.975	0.835	2	I(1)
Real GDP at constant prices (2010 = 100)	-0.153	0.439	3	I(1)
Deviation from standard Taylor rule	0.150	0.560	3	I(1)
House price index	1.147	0.874	3	I(1)
Share price index	4.918	1.000	3	I(1)
Financial reform index	-0.443	0.329	3	I(1)
GDP share of the financial sector	-0.220	0.413	1	I(1)
Top 1% income share	1.643	0.950	3	I(1)
Gini coefficient	-0.847	0.199	1	I(1)
	Variables in first differences			
Variable	Z-tbar	p-value	Lag	Result
Total credit to household sector, in % of disposable income	-1.605	0.054	3	I(0)
Bank credit to private sector, in % of disposable income	-1.250	0.106	2	I(1)
Real GDP at constant prices (2010 = 100)	-0.686	0.246	2	I(1)
Deviation from standard Taylor rule	-9.768	0.000	1	I(0)
House price index	-0.068	0.473	2	I(1)
Share price index	0.356	0.639	3	I(1)
Financial reform index	-2.357	0.009	3	I(0)
GDP share of the financial sector	-6.970	0.000	1	I(0)
Top 1% income share	0.390	0.652	3	I(1)
Gini coefficient	-2.038	0.021	3	I(0)

C Granger causality tests assuming cross-country homogeneity

This section shows panel causality tests assuming cross-country homogeneity for the purpose of comparison with Tables 2-9. However, as argued throughout the paper, cross-country homogeneity is a strong assumption which can hardly be reconciled with the research question at hand.

Table 21: Panel causality test: Economic activity

	Real GDP (X) → Credit (Y)		Credit (X) → Real GDP (Y)	
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Lag	p-value	p-value	p-value	p-value
1	0.0094	0.0000	0.3979	0.0071
2	0.0002	0.0000	0.0000	0.0051
3	0.0011	0.0000	0.0000	0.0000
4	0.0005	0.0000	0.0000	0.0000
5	0.0003	0.0000	0.0000	0.0000

Table 22: Panel causality test: Monetary policy

	Taylor rule (X) → Credit (Y)		Credit (X) → Taylor rule (Y)	
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Lag	p-value	p-value	p-value	p-value
1	0.5618	0.0031	0.7892	0.1951
2	0.7755	0.0019	0.7759	0.0173
3	0.7035	0.0045	0.0013	0.0105
4	0.6665	0.0067	0.0015	0.0074
5	0.7252	0.0108	0.0020	0.0125

Table 23: Panel causality test: House price index

	House prices (X) → Credit (Y)		Credit (X) → House prices (Y)	
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Lag	p-value	p-value	p-value	p-value
1	0.0000	0.0000	0.6414	0.0094
2	0.0000	0.0000	0.0000	0.0015
3	0.0000	0.0000	0.0000	0.0009
4	0.0004	0.0000	0.0000	0.0103
5	0.0006	0.0000	0.0001	0.0122

Table 24: Panel causality test: Stock price index

	Stock prices (X) → Credit (Y)		Credit (X) → Stock prices (Y)	
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Lag	p-value	p-value	p-value	p-value
1	0.1443	0.0000	0.6125	0.0191
2	0.3375	0.0000	0.0000	0.0013
3	0.2389	0.0000	0.0000	0.0000
4	0.1921	0.0004	0.0000	0.0003
5	0.1216	0.0006	0.0000	0.0012

Table 25: Panel causality test: Financial reform index

	Financial reform (X) → Credit (Y)		Credit (X) → Financial reform (Y)	
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Lag	p-value	p-value	p-value	p-value
1	0.5231	0.6147	0.4951	0.7141
2	0.9288	0.8258	0.5741	0.7605
3	0.8076	0.8206	0.6743	0.5266
4	0.4248	0.7047	0.5918	0.5543
5	0.2606	0.5915	0.5092	0.6406

Table 26: Panel causality test: Financial sector value added

	Financial sector VA (X) → Credit (Y)		Credit (X) → Financial sector VA (Y)	
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Lag	p-value	p-value	p-value	p-value
1	0.9540	0.3527	0.0248	0.0740
2	0.7896	0.1614	0.0354	0.1077
3	0.2383	0.0777	0.0301	0.1087
4	0.1615	0.1523	0.0048	0.0041
5	0.2111	0.1324	0.0041	0.0018

Table 27: Panel causality test: Top 1% income share

	Top 1% income share (X) → Credit (Y)		Credit (X) → Top 1% income share (Y)	
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Lag	p-value	p-value	p-value	p-value
1	0.0000	0.0012	0.9105	0.1828
2	0.0000	0.0002	0.0253	0.0406
3	0.0000	0.0026	0.0363	0.0573
4	0.0000	0.0075	0.1168	0.1109
5	0.0001	0.0007	0.1099	0.0452

Table 28: Panel causality test: Gini coefficient

	Gini coefficient (X) → Credit (Y)		Credit (X) → Gini coefficient (Y)	
	Total credit to household sector	Bank credit to private sector	Total credit to household sector	Bank credit to private sector
Lag	p-value	p-value	p-value	p-value
1	0.9559	0.6560	0.9251	0.7320
2	0.9303	0.4510	0.2745	0.9062
3	0.6055	0.6074	0.5420	0.8896
4	0.6786	0.4293	0.2810	0.6631
5	0.6248	0.5799	0.0340	0.1656

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