# The risk of financial crises: Is there a role for income inequality?

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**Abstract**

Could macroeconomic factors such as income inequality be the real root cause of financial crises? We explore a broad variety of financial and macroeconomic variables and employ a general-to-specific model selection process to find the most reliable predictors of financial crises in developed countries over a period of more than 100 years. Our in-sample results indicate that income inequality has predictive power beyond loan growth and several other financial variables. Out-of-sample forecasts for individual predictors show that their predictive power tends to vary considerably over time, but income inequality has predictive power in each forecasting period.

**Keywords:** Early warning indicators, bank loans, income inequality, fixed effects logit

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# 1 Introduction

Financial crises are recurring phenomena in modern economies. The crisis of 2007-2009 was a stark reminder of the treacherous nature of financial crashes because it took almost the whole world by surprise. The search for its underlying causes has consequently revived academic interest in financial crises and their history (see Rajan (2010); Bordo and Meissner (2012); Gorton (2012); Schularick and Taylor (2012), among others). Income inequality has received increasing attention because it was highly elevated before the crisis of 2007-2009 (as it was before the Great Depression), and it has remained high in many developed economies after the crisis (Alvaredo *et al.* 2013). However, there is no consensus on the role that income inequality plays as a driver of financial crises and the channels it works through. There is not even a consensus whether real (macroeconomic) or financial factors play a more important role in predicting financial crises.

In this paper, we contribute to the discussion around the drivers of financial crises in two ways. First, we consider a long time-series and a relatively large set of real and financial variables that have been identified as potential drivers of crises in the previous literature to gain a more comprehensive understanding of their respective roles. On the real side, our major factor of interest is income inequality. While its role on the onset of financial crises has recently been studied in a number of theoretical contributions, the empirical evidence is scant and mixed. Some papers find that income inequality increases the probability of financial crises (Roy and Kemme 2012) or drives credit booms (Perugini *et al.* 2015; Klein 2015; Malinen 2016), whereas others do not find income inequality to be a consistent ingredient in the growth of bank loans (Bordo and Meissner 2012) or the development of financial crises (Atkinson and Morelli 2011). On the financial side, Schularick and Taylor (2012) point to credit booms as the primary contributor to financial crises in developed countries over the past 140 years (see also Lang and Schmidt (2016)). In a recent paper, Jorda *et al.* (2015) show that mortgage lending to households in particular has increased considerably over the past century and Jorda *et al.* (2013) link credit booms to the severity of economic downturns. However, Gorton (2012) links abnormal credit growth to only one out of three financial crises that occurred during the period between 1970 and 2007. Rivas and Perez-

Quiros (2015) also show that the role of credit in the identification of the business cycle was very limited before the financial crisis of 2007-2008. Therefore, by themselves, credit booms appear to be insufficient prerequisites of financial crises.[1]

Second, in our analysis we explicitly consider the various channels through which income inequality may impact financial crises and study whether income inequality is a direct driver of crises or whether it is the real root-cause behind the financial drivers such as credit booms. Iacoviello (2008) provides compelling evidence that income inequality was the primary driver of the increase in household debt in the United States during the 1980s and 1990s. Kumhof *et al.* (2015) show that inequality can raise leverage in middle-income and poor households as a result of consumption smoothing by borrowing against future incomes. Linking these findings to the credit boom literature implies that income inequality might be the actual real-side root cause of the risk of financial instability that has thus far been fully and directly attributed to credit bubbles. In a similar vein, Rajan (2010) argues that rising inequality caused redistribution in the form of subsidized housing finance, which led to the housing boom and the subsequent crash.

Our empirical evidence comes from a dataset of 14 developed countries over the 1870-2008 period. Our modeling strategy allows the predictive power to be distributed among a large set of variables and examines these potential predictors and their lags in joint models. Importantly, we employ a methodology that allows for a flexible general-to-specific model selection between different predictors without imposing restrictive assumptions on the channels through which, e.g., income inequality impacts the risk of financial crises. More specifically, we begin with (the year-to-year change) in the top 1% income share as our measure of income inequality, real bank loans, gross real investments, the real current account balance, broad money (M2), gross real government debt, the real price of stocks, short-term real interest rates and six lags of each factor. We also add a dummy variable indicating when a deposit insurance scheme was introduced.[2] In each step of our empir-

[1] In addition to income inequality and credit booms, other factors that have been proposed to explain the occurrence of financial crises include collapses of asset bubbles, deregulation, financial innovations, movements of real interest rates, deposit insurance schemes, the growth of the monetary base, and current account imbalances (see Gorton (1988); Calvo *et al.* (1994); Stoker (1994); Demirgüc-Kunt and Detragiache (1998); Brunnermeier (2008); Tett (2009); In't Veld *et al.* (2011); Davis *et al.* (2016)).

[2] We experimented also with a dummy variable indicating the existence of a central bank, but it failed to

ical analysis, we then apply a general-to-specific model selection procedure to obtain the most parsimonious choice of variables that provides the most predictive information on the probability of a financial crisis. In addition, we consider various out-of-sample forecasting checks to assess the robustness of our in-sample results.

Our results hint at a distinct role for income inequality as a driver of financial crises, while we confirm that credit booms do play a role in creating financial instability. Altogether, our results suggest that the drivers of financial crises tend to vary in time and between crises.

Specifically, our empirical analysis yields four main findings. First, income inequality is an influential factor in our in-sample results: the top 1% income share (our measure of income inequality) has the highest individual predictive power and yields additional predictive power over and above the previously used factors, such as real bank loans, when included in a joint model. Second, the role of bank loans as an in-sample predictor of financial crises diminishes considerably when jointly controlling for several other factors. Third, multivariable recursive out-of-sample results underpin the importance of using various predictive variables in the model. Fourth, studying our predictors individually in out-of-sample forecasts for different time periods shows that income inequality and current account contain predictive power in each forecasting period but that the predictive power of most factors tends to vary considerably over time. This finding implies that focusing on shorter time periods may lead to incomplete conclusions regarding the drivers of financial crises.

The focus of this paper is on the long time series, which we exploit to achieve a maximally comprehensive picture of the roles of various real and financial factors in predicting crises in general and to determine whether and how these roles vary among different crises. The long time series is also essential for performing out-of-sample forecasting. This long-term focus comes at a cost: some factors that have potentially gained importance since the 1980s, when financial liberalization began, must be neglected because the data for the indicators of financial innovation and deregulation are available only for comparatively short time periods. However, we examine an in-sample robustness check for the 1962-2008 pe-

have any statistically significant effect on the probability of a financial crisis.

riod, for which we have available data on the size of the US mutual fund industry as an indicator of investments in innovative and potentially riskier investment classes. The results confirm the full-sample findings. In addition, the results show that a larger US mutual fund industry increases the risk of a financial crisis, but only immediately before a crisis erupts.

The remainder of the paper is organized as follows. Section 2 discusses the related literature and how it motivates our choice of predictor variables and our data. Section 3 outlines the methodology, and Section 4 presents the results. Section 5 concludes the paper.

# 2 Financial Crises and Their Predictors

## 2.1 Predictors of Financial Crises

In his seminal paper, Gorton (1988) links the systemic nature of banking panics to the business cycle. One of the strongest signals of an upcoming recession is a decline in investment expenditures (Zarnowitz and Moore 1982; De Long and Summers 1991; Crowder and de Jong 2011). Investment expenditures also reflect the level of aggregate demand for capital goods in the economy. In addition, the nature of investments might influence the probability of a crisis (see Schularick and Taylor 2012). If the money available in an economy is invested productively rather than driving consumption or speculation, then it should lower the risk that a crisis will occur. Therefore, we account for the change in real gross investments in our empirical analysis.

The idea that financial crises are driven by credit boom and bust cycles has long been stipulated in the literature (Minsky 1977; Kindleberger 1978). Additionally, recent studies have found that large credit booms are associated with financial crises (Bordo *et al.* 2001; Mendoza and Terrones 2008; Reinhart and Rogoff 2009; Schularick and Taylor 2012). The increased leverage and the potential concurrent decrease in lending standards introduce fragilities into the banking system and make it vulnerable. We measure the evolution of credit in each country by the change in real bank loans.

As Claessens *et al.* (2010) document, one of the similarities between previous financial crises and the recent crisis is that they are preceded by asset price booms. Increased asset prices may lead to an increase in lending against higher collateral values, which in turn further increases asset prices. Once this spiral of activity stops, households and firms struggle to pay back their accumulated debt. This type of asset price boom, which eventually threatens the stability of the financial system, could be observed in the US and in many European countries in the run-up to the recent crisis. In contrast, the tech bubble at the end of the 1990s and the beginning of the 2000s did not result in a massive systemic financial crisis. In our empirical analysis, we account for asset price booms by the change in the real value of stock market indexes.[3]

Current account imbalances and short-term interest rates may also contribute to the development of financial crises. A current account deficit implies that the economy consumes more than it produces such that other countries lend their savings to this economy. Such capital inflows may lead to stock market bubbles and the excessive expansion of domestic credit and may cause inflationary pressures (Calvo *et al.* 1994; Caballero 2014). Davis *et al.* (2016) find that an increase in debt matters for the outbreak of a crisis especially if the current account deficit of a country is large. We use the change in the real value of the current account as a measure of international capital flows. Jorda *et al.* (2015) show that environments with low interest rates lead to an increase in mortgage lending and housing price booms and ultimately lead to financial instability. In contrast, increasing interest rates can hurt banks' balance sheets if banks cannot quickly increase their lending rates. Alternatively, if an interest rate increase can be passed on to borrowers, such an action can increase the number of non-performing loans and the risk of moral hazard on the borrowers' side (Demirgüc-Kunt and Detragiache 1998). In our empirical analysis, we account for the real short-term interest rate.

Recently, a growing body of literature has developed theories and arguments as to how income inequality can contribute to financial instability and thereby increase the likelihood of a crisis through various channels, such as credit and asset price booms or current account imbalances. These channels emphasize that asset and credit bubbles might actually develop as a result of real causes.

[3] In one of our robustness checks, we use a shorter sample period and account for housing price changes, for which data coverage is much less comprehensive.

Rajan (2010) argues that rising inequality forced US politicians to enact measures to better the situation of low- and middle-income households to avoid losing them as voters. Because redistribution in the form of social security payments or increased taxes for the rich are impossible solutions in the US political environment, redistribution in the form of subsidized housing finance was expedited. This provision of inexpensive mortgage lending together with the concurrent deregulation of the financial sector in turn led to the observed housing boom and the subsequent crash.

Kumhof *et al.* (2015) model a more direct link between income inequality and increasing debt levels that does not rely on a specific political system. In their closed-economy model, crises emerge endogenously as a result of rising income inequality because low-income and middle-income households seeking to maintain their levels of consumption must borrow more as their real wages decrease, whereas the top 5% of income earners provide the funding for these loans. Extending the model to an international environment with open economies, Kumhof *et al.* (2012) show that rising inequality increases the risk of financial crises because it endogenously leads to credit expansion, increased leverage and increased current account deficits.[4]

Fitoussi and Saraceno (2010) argue that income inequality leads to depressed aggregate demand, which induces central banks to maintain low interest rates, thereby contributing to the accumulation of private debt. Simultaneously, those who benefit from increasing inequality search for high-yield investments and drive asset bubbles. The increase in non-performing loans after the burst of the asset bubble then exposes the banking sector to the risk of a run. Similarly, Stockhammer (2015) suggests that increased income inequality leads to more speculation or risk-taking because the consumption opportunities of those benefiting from increasing incomes become exhausted, and speculative investments become more likely. Atkinson and Morelli (2011) argue that banks also take higher risks when income inequality is elevated and that this risk-taking occurs through securitization. In our empirical analysis, we measure income inequality using the top 1% income share of the population.

[4] See also Seppecher and Salle (2015).

To complete our pool of potential crisis predictors, we use three additional variables that have been shown to help predict financial crises in previous studies. First, we control for the potential impact of monetary aggregates on the probability of a financial crisis using the change in broad money (M2). Second, government debt was found to be relevant to the financial sector (Demirgüc-Kunt and Detragiache 1998). A government that is short of funds may postpone measures aimed at strengthening banks' balance sheets. However, even if a government is prepared to support the country's banking sector despite budgetary problems, the public might not trust such an endeavor, which could in turn trigger a bank run. Third, deposit insurance is typically designed and introduced to prevent depositors from running and thereby threatening the stability of the financial system. Meanwhile, the existence of deposit insurance introduces a moral hazard on the bank managers' side because they have an incentive to increase their risk-taking, knowing that the deposit insurance scheme will pay depositors if the risky investments go bad. Deposit insurance may therefore actually increase the likelihood of financial crises despite its intended stabilizing effect (Demirgüc-Kunt and Detragiache 1998). In our analysis, deposit insurance is a binary variable that equals one in all years in which a country has an active deposit insurance scheme.

## 2.2 Data

Our primary source of data is the dataset compiled by Schularick and Taylor (2012). These data cover 14 developed countries over the period from 1870 to 2008. The countries included are Australia, Canada, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the United Kingdom and the United States. For the dependent variable, we use the financial crisis episodes collected by Schularick and Taylor (2012), who combine the datasets of Bordo *et al.* (2001), Laeven and Valencia (2008), Cecchetti *et al.* (2009) and Reinhart and Rogoff (2009). In total, our dataset includes 79 country-year financial crisis observations. The observed binary dependent variable $y_{it}$ takes the value one ($y_{it} = 1$) if there is a financial crisis in country $i$ ($i = 1, \ldots, N$) at time $t$ ($t = 1, \ldots, T$). In other words,

$$y_{it} = \begin{cases} 1, \text{if there is a financial crisis in country } i \text{ at time } t, \\ 0, \text{otherwise} . \end{cases} \tag{1}$$

Financial crises are defined as periods in which a country's banking sector experiences runs, sharp increases in default rates accompanied by large losses of capital leading to government interventions, bankruptcy, or forced mergers of financial institutions (see Schularick and Taylor (2012) for details on the crisis data compilation). We assume that a crisis begins (i.e., $y_{it} = 1$) in the year when a country falls into the crisis.

We also obtain data on real bank loans, broad money (M2), government debt, and stock market indexes from Schularick and Taylor (2012). In addition, we obtain data on investments and current account deficits from Taylor (2002) and from the World Bank World Development Indicators, data on real GDP per capita from the Maddison Database of the Groningen Growth and Development Center (Bolt and van Zanden 2014), and data on the introduction of deposit insurance from the World Bank Deposit Insurance Database (Demirgüc-Kunt *et al.* 2005).

Our data on the top 1% income share come from the Top Income Database by Alvaredo *et al.* (2013). We use the top 1% income share for three reasons. First, several of the theoretical channels presented in Section 2.1 concentrate on the relationship between the accumulation of debt and the incomes of rich households making the top 1% income share the proper measure of income inequality for this study. Second, calculating synthetic indexes such as the Gini or Theil index requires accurate country-specific information, such as the mean household (or person) income of a country. Such indexes may be unreliable because their calculation often ignores the fact that the underlying data contain inconsistencies and anomalies that are likely to be country-dependent (Piketty 2014). In contrast, the top income share measure is constructed using the same raw data and methodology for every country (Piketty 2007).[5] Third, the top 1% income share data are available for a time span of approximately 100 years (albeit with gaps) for most of our sample countries, while the

[5]Nevertheless, Leigh (2007) demonstrates that the top 1% income share series has a high correlation with other measures of income inequality, such as the Gini index.

synthetic indexes generally cover only the past 40 years and often contain missing observations for several years. Because financial crises are an infrequent phenomenon in developed economies, using synthetic indexes would restrict our analysis considerably and might lead to incomplete conclusions. The focus of our study is instead on the long term to gain an as comprehensive as possible picture of the (potentially varying) roles of different financial and real factors in the run-up to different crises.

That said, Table 1 shows the number of observations available for each of our predictor variables, emphasizing that our panel is unbalanced because the income inequality time series starts in 1886 only and contains missing values in the early years of observation in particular. We address this issue in the empirical analysis by studying various subsample periods that yield more balanced panels. Table 1 also provides summary statistics for all predictive variables.

# 3 Statistical Model

In this section, we describe the fixed-effects panel logit model and the model selection process used throughout this study. Given that our dependent variable is binary, it is meaningful to rely on binary response models rather than on the panel models designed for continuous dependent variables. The latter models have various problems in the binary-dependent framework. For example, the financial crisis probabilities do not necessarily fall within the unit interval. In the model, we allow country-fixed effects to control for all time-invariant heterogeneity at the country level. Such a model specification has the additional advantage that our results are derived from within-country variation in the crisis predictors, eliminating any potential bias that stems from different data-reporting standards in different countries.

Our basic model is essentially the same as that used by Schularick and Taylor (2012) (see a more complete description of the model in Hsiao (2003, Chapter 7)), but our model selection approach and our multivariable analysis differ considerably from theirs. We employ a methodology that allows for a more flexible general-to-specific model selection between different predictors without imposing restrictive assumptions on the channels through which, e.g., income inequality impacts the risk of financial crises. We also allow the predictive power to be distributed among a considerably larger set of variables and examine these potential predictors and their lags in joint models.

## 3.1 Logit Model

In the fixed-effects panel logit model (hereafter, logit model), conditional on the information set at time $t-1$ (denoted by $\mathcal{F}_{t-1}$) including, e.g., the relevant predictive variables, $y_{it}$ has a Bernoulli distribution:

$$y_{it}|\mathcal{F}_{t-1} \sim B(p_{it}), \quad i = 1,\dots,N, \qquad t = 1,\dots,T. \tag{2}$$

Let $E_{t-1}(\cdot)$ and $P_{t-1}(\cdot)$ denote the conditional expectation and conditional probability, respectively, given the information set $\mathcal{F}_{t-1}$. Thus, the conditional probability that $y_{it}$ takes the value 1 (i.e., that there is a financial crisis at time $t$ in country $i$) can be written as

$$p_{it} = P_{t-1}(y_{it} = 1) = E_{t-1}(y_{it}) = \Lambda(\pi_{it}), \tag{3}$$

where $\pi_{it}$ is a linear function of variables included in the information set $\mathcal{F}_{t-1}$, and $\Lambda(\cdot)$ is a logistic cumulative distribution function:

$$\Lambda(\pi_{it}) = \frac{\exp(\pi_{it})}{1+\exp(\pi_{it})}. \tag{4}$$

Following Schularick and Taylor (2012), we assume that the linear function $\pi_{it}$ has the form

$$\pi_{it} = \omega_i + b_1(L)x_{1it} + \ldots + b_K(L)x_{Kit}, \tag{5}$$

where $b_j(L)x_{jit} = b_{j1}x_{ji,t-1} + \ldots + b_{jp}x_{ji,t-p}$, $j = 1,\dots,K$, and the country-specific vector $\omega_i$ includes all the deterministic terms (such as country-specific dummy variables), reflecting the possible heterogeneity between countries. In model (5), the lag-polynomials for different predictors have the form

$$b_j(L) = b_{j1}L + \ldots + b_{jp}L^p, \quad j = 1,\dots,K, \tag{6}$$

where $L$ is the usual lag operator (i.e., $L^k z_t = z_{t-k}$). In other words, we explicitly allow the possibility that the predictive power of different predictors is distributed among several lags. Note that using the same lag length $p$ in (6) for all predictors is only for notational convenience and can easily be relaxed in practice (see Section 3.2). Notably, the polynomial (6) begins with lag one (i.e., only the lags of the predictors are included in (5)).

The logit model can be conveniently estimated by using the maximum likelihood (ML) method. Using the conditional probabilities constructed in (3), one can write the likelihood function and obtain the ML estimates using numerical methods (see details, e.g., from Hsiao (2003), pp. 194–199). In our setup, the number of cross-sectional units (countries) $N$ is small, whereas the length of the time series $T$ is relatively long. Because the model is not necessarily specified correctly, the ML estimator can be interpreted as a quasi-maximum-likelihood estimator in the usual way. Therefore, to account for this possible misspecification, we use robust standard errors for the estimated coefficients throughout this study.

## 3.2 Model Selection and Goodness-of-Fit Evaluation

Because our panel data are highly unbalanced, we need to pay special attention to the model selection throughout the analysis. In particular, depending on the predictive variables included in the model, the number of observations differs across different model specifications. Therefore, the usual information criterion-based model selection procedures are not straightforwardly applicable. Nevertheless, using an unbalanced panel is common in the previous crisis prediction literature because such a panel includes as much information as possible given that different variables are available over different time spans (see, e.g., Demirgüc-Kunt and Detragiache 1998; Barrell *et al.* 2010; Schularick and Taylor 2012).

The model selection employed in this study can be divided into two parts. First, we are interested in examining which predictive variables should be included in the model. Second, we need to determine for each variable how many lags $p$ (see (5) and (6)) have useful predictive power. In practice, the (optimal) lag lengths $p$ for different predictors are unknown. However, assuming that the upper bound, e.g., $p_{max}$, is known, we can use the following sequential general-to-specific model selection method, which is essentially the same as the procedure proposed by researchers such as Lütkepohl (2007, pp. 143–144) for vector autoregressive models. We begin with a large model containing all the explanatory variables and their lags. To maintain a lag structure and thus predictive model that are as parsimonious as possible, we consider lags up to six (i.e., $p_{max} = 6$) for each variable.[6] After the parameters have been estimated, we examine the $t$-ratios of all variables at lag six. We reduce the lag length of any variable by one if the $t$-ratio associated with the longest lag coefficient is less than 1.65. We continue this procedure until all the $t$-ratios for the remaining longest lags are larger than this threshold.

The predictive performance of the model is evaluated using two well-known goodness-of-fit measures. For the binary dependent variables, various alternative measures are roughly analogous to the coefficient of determination $R^2$ used in linear models. As in Schularick and Taylor (2012), one such alternative is McFadden's pseudo-$R^2$ measure, given as

$$\text{pseudo} - R^2 = 1 - L_u/L_c. \tag{7}$$

In this expression, $L_u$ is the maximum value of the estimated unconstrained log-likelihood function, and $L_c$ is its constrained counterpart in a model that contains only a constant term. The form of (7) ensures that the values 0 and 1 correspond to "no fit" and "perfect fit," respectively, and that the intermediate values have roughly the same interpretation that $R^2$ has in linear models.

Another evaluation criterion used in this study is the area under the receiver operating characteristic (ROC) curve. The ROC curve methodology is a common evaluation criterion for binary predictions and outcomes in other sciences. In addition to Schularick and Taylor (2012), recent examples of economic and financial applications include Berge and Jorda (2011) and Jorda and Taylor (2011).

Specifically in our application, the area under the ROC curve (AUROC) is used to evaluate each model's ability to distinguish between signals for financial crises $y_{it} = 1$ and normal periods $y_{it} = 0$. Let us denote $\hat{y}_{it} = 1$ as a signal forecast for a crisis if the probability fore-

[6] We consider lags up to six years to keep the lag structure reasonable for our estimations. However, we acknowledge that some of the factors such as income inequality take a longer time to manifest.

casts (3) obtained with the logit model are $p_{it} > c$ for some threshold value $c$, and vice versa for $\hat{y}_{it} = 0$. The ROC curve describes all possible combinations of the true positive rate $TPR(c) = P(\hat{y}_{it} = 1|y_{it} = 1)$ and the false positive rate $FPR(c) = P(\hat{y}_{it} = 1|y_{it} = 0)$ that arise as one varies the probability threshold $c$. The threshold $c$ is allowed to vary from 0 to 1; the ROC curve is traced out in $TPR(c)\&FPR(c)$ space describing the classification ability of the model. In our application, in which financial crisis periods are rare, the determination of a single threshold $c$ is complicated. Hence, we believe that the ROC methodology is more sensible than a method concentrating on the results based on one particular cutoff $c$.

To summarize the classification ability of a given model, the AUROC is a well-known summary statistic. The value of AUROC=0.5 corresponds to a coin toss (i.e., the model has no predictive power at all). In contrast, the value 1 signifies a perfect fit. Overall, a higher value indicates superior classification ability.

# 4 Results

We begin our empirical analysis with in-sample estimations, the objective of which is to distinguish between different predictors and their predictive power for financial crisis periods. The full sample results based on the entire (unbalanced) panel of countries during the full time span of our data from 1870 (1886) to 2008 serve as our benchmark case because they contain the maximal amount of information (Section 4.1). The subsequent analysis of shorter sample periods can be regarded as a robustness check based on more balanced panels (Section 4.2). We then proceed to an out-of-sample forecasting experiment for various time periods to further assess the robustness of our results (Section 4.3) and to gain deeper insights into how the predictive power of various factors might vary over time (Section 4.4).

In all estimations, we employ our variables in first differences to eliminate the stochastic and deterministic trends they may include (see, e.g., Klein (2015); Malinen (2016)). All our estimated models contain country-fixed effects to control for time-invariant heterogeneity at the country level and to focus the analysis on within-country variation. We do not include time-fixed effects in our panel logit model because the resulting model could be estimated only using the years in which the dependent variable actually changes values. Given that financial crises are rather rare events in developed economies, we would lose most observations with such a procedure. As a robustness check we estimate OLS linear probability models for each predictive variable separately and include time fixed effects (results are available from the authors upon request). We find that the year effects are significant indicating that there is a common global component that drives financial crises, while our main findings on income inequality and credit growth still hold. But as Schularick and Taylor (2012) argue such global trends are not known *ex-ante* and therefore are not of practical use in out-of-sample forecasts.

## 4.1 Full Sample Predictions

We first estimate the fixed-effects logit model using one predictive variable at a time. We select the optimal lag length $p$ for each variable using the sequential testing approach outlined in Section 3.2. Table 2 reports the full sample results. For each predictor, the table displays the optimal lag length and the values of the pseudo-$R^2$ and the AUROC. The number of observations differs for various predictors based on data availability.

Table 2 shows that the optimal lag length varies between two and five lags (with six lags being the maximum that we studied). Two exceptions are the short-term real interest rate and the indicator of whether a deposit insurance scheme is in place; as single predictors, these do not have statistically significant predictive power at any lag length. Table 2 also shows that our measure of income inequality (the top 1% income share) clearly yields the best performance: income inequality appears to have substantial predictive power for financial crises. Real bank loans constitute the second-best single predictor, with the second-highest pseudo-$R^2$ and AUROC. Overall, the pseudo-$R^2$ level is not very high in any model, partly reflecting the limited number of financial crises. However, the AUROC statistics obtained are well above 0.5 for all predictors, indicating that the models can distinguish between non-crisis and crisis periods.

Consistent with previous studies (e.g., Bordo *et al.* 2001; Mendoza and Terrones 2008; Reinhart and Rogoff 2009; Schularick and Taylor 2012), our univariate results confirm that an increase in credit (real bank loans) is an important predictor - or a warning signal -

of financial crises. However, although some of these studies emphasize the singular role of credit bubbles, our results suggest that other factors play at least an equally important role. The fact that credit bubbles are not the only drivers of financial crises also appears to be reasonable in light of Gorton's (2012) finding that only approximately one-third of the crises between 1970 and 2007 saw credit booms during their run-ups.

In the next step, we use a multi-predictor analysis to examine which of the effects survives the joint inclusion of various predictors in one model. For example, some of the financial variables may actually present the channels through which the real factors predict financial crises. Based on the previous literature and the results in Table 2, we continue our analysis by focusing on models that contain real bank loans and income inequality. Table 3 reports the results for the full sample period.[7] To compare our results to those of Schularick and Taylor (2012) we first of all replicate their baseline specification, a model that contains five lags of loan growth and country fixed effects, in column 1 of Table 3 and find exactly the same results as they do. In column 2 we then add five lags of income inequality to the Schularick and Taylor (2012) specification. We find that income inequality is a significant predictor of financial crises beyond loan growth.

Having established the importance of studying further predictors of financial crises in addition to loan growth, income inequality in particular, we continue by examining loan growth and income inequality in a more flexible estimation set-up and let our model selection procedure decide on the lag structure. Columns 3 and 4 include the models containing real bank loans (two lags) and the top 1% income (five lags) as predictors separately. These two models replicate the Table 2 results of these two predictors, but we now present the actual estimated coefficients of all included lags, facilitating a comparison with the model containing both predictors (column 5). Column 5 of Table 3 again shows that both variables are significant predictors of financial crises in a joint model. The separate tests for the predictive power of the lags of the variables are statistically significant at the 1% level and are similar to the univariate results reported in columns 3 and 4. The values of the pseudo-$R^2$ and the AUROC in this joint specification are larger than in the single variable models.

[7] Canada and the Netherlands are omitted from some estimation samples because there were no financial crises in Canada during the years 1924-2008 or in the Netherlands in 1925-1938 and 1993-1999.

Thus, income inequality indeed appears to have additional predictive power over and above bank loans (i.e., it does not merely affect the probability of a financial crisis via its possible impact on credit growth).

In column 6 of Table 3, we interact real bank loans and the top 1% income share to test whether income inequality and loan growth are indeed reinforcing drivers of crises, as suggested by Rajan (2010) and Kumhof *et al.* (2015). We report only the first lag of the interaction term because it appears that the other lags do not significantly predict a crisis. The interaction term is significantly positive, and both main effects are also significantly positive, implying that loan growth is more likely to lead to a crisis when income inequality is high and vice versa.

How large, in economic terms, is the effect of income inequality on the probability of a financial crisis? In Table 4 we shed light on this question from various perspectives. In column 1 we present marginal effects for the full sample from our preferred baseline model from Table 3, column 5. The sum of the marginal effects in this estimation is 0.06. Given that the average change in the top 1% income share has a standard deviation of 0.72, this result implies that a one standard deviation increase in the change in the top 1% income share increases the probability of a crisis by 0.06*0.72 = 0.04, or 4 percentage points. This effect is economically very large since the sample frequency of a crisis is just 4.5 percent.

Next, we compare the effect of different levels of income inequality on the likelihood of a crisis. Column 2 of Table 4 restricts the estimation sample to all observations that fall below the 25% percentile of the top 1% income share, which is 7.2. The sum of the marginal effects in this specification is 0.04, while the standard deviation of the change in income inequality in this sample is 0.31. Therefore, a one standard deviation increase in the change in income inequality increases the likelihood of a crisis by about 0.01. Similarly, column 3 reports these results for the estimation sample restricted to all observations that fall above the 75% percentile of the top 1% income share, which is 11.7. In this specification, a one standard deviation increase in the change in income inequality (1.07) increases the likelihood of a crisis by about 0.09. Columns 4 and 5 then use Sweden and the US in the early 2000s as examples for a country with low income inequality (Sweden with a top 1%

income share of 6.2 on average between 2000 and 2008) vs. a country with high income inequality (the US with a top 1% income share of 16.7 on average between 2000 and 2008). The results are similar to those presented in columns 2 and 3 given that Sweden's level of income inequality is close to the 25% percentile and the US's is quite close to, albeit higher than, the 75% percentile. Accordingly, for Sweden, a one standard deviation increase in the change in income inequality (0.26) increases the likelihood of a crisis by about 0.01. For the US, a one standard deviation increase in the change in income inequality (0.57) increases the likelihood of a crisis by about 0.08. Looking at a longer time period for the US, the average change in the top 1% income share was 0.34 between 1980 and 2008 (increasing from 8.18 to 17.89). Evaluating the marginal effects at this number, we find that a one standard deviation increase in the change in income inequality (0.75) increases the likelihood of a crisis by about 0.04 (results are available from the authors upon request). In sum, these computations show that income inequality is an economically relevant predictor of financial crises especially in countries and time periods of relatively high income inequality.

In the next step, we augment the two-variable model presented in Table 3 with the additional predictors introduced in Section 2, which have been identified by the previous literature as playing an important role. Again following the general-to-specific model selection method introduced in Section 3.2, we first add all our remaining predictive variables and their lags from one to six to the model presented in column 5 of Table 3. Then, we sequentially exclude the longest lag in each step until its $t$-ratio is larger in absolute value than 1.65. The resulting model is presented in Table 5.

Table 5 reveals several interesting findings. The top 1% share (income inequality) is still a strong and statistically significant predictor, whereas the role of real bank loans is now limited. In fact, its lagged values are not statistically significant, and the estimation results presented in Table 5 remain qualitatively unchanged if bank loans are excluded from the model (results are available upon request). This result is in contrast to the evidence presented by Schularick and Taylor (2012), who find a strong role of loan growth when employing the same dataset that we use. However, in contrast to our study, those researchers do not employ as great a variety of predictors and lags in a joint model that is derived from a general-to-specific model selection process.

Table 5 also shows that factors beyond the change in income inequality have predictive power over and above loan growth. As expected, the probability of financial crises increases for countries that run current account deficits. The negative first lag of real stocks (as also found by Schularick and Taylor (2012)) indicates that once an asset price boom begins to revert, the probability of a financial crisis increases. However, monitoring the long-term evolution of stock prices does not appear to be a useful tool for policy makers to predict financial crises well in advance. Furthermore, we do not find a significant effect of real short-term interest rates, perhaps because they affect credit growth and, through this channel, increase the likelihood of a financial crisis rather than having direct predictive power.

In conclusion, the full sample results show that an increase in income inequality increases the probability of financial crises. This finding is consistent with the anecdotal evidence that both of the two fiercest crises in the US, the Great Depression and the recent Great Recession, were preceded by high income inequality. This result also confirms the reasoning in the academic literature that income inequality is one of the causes of financial crises and rejects the suggestion that income inequality works solely through credit booms. However, the full sample results also emphasize that the predictive power in the models is clearly distributed among various predictors and their lags.

## 4.2 Subsample Predictions

In this section, we present the results of two robustness tests. First, we replicate our previous analysis for the post-WW2 sample to examine whether the predictive power of the real and financial variables depends on the sample period. The post-WW2 period provides an important robustness check because Schularick and Taylor (2012) find "two eras of financial capitalism" when they study money and credit before and after WW2. Additionally, some of our predictor variables, particularly the top 1% income share, are available only for a shorter time span. The panel is therefore much more balanced in the post-WW2 analysis, which eases the comparison of effects between different variables. Second, we study two further channels through which income inequality may have an impact on financial crises:

housing price booms (Rajan 2010) and increased risk-taking by higher-income households (Stockhammer 2015). Because indicators for both channels are available for much shorter time periods than those employed in our primary analysis, we perform this robustness test using our shortest sample period, which covers the years from 1962 to 2008.

One concern with our previous results might be that the top 1% income share has superior predictive performance because the sample period of this variable is so different from the sample period of the other variables. In Table 6, we present the models, including one predictor at a time, for the post-WW2 subsample, beginning in 1950. The numbers of observations are now much closer to one another for all variables. The results reveal that income inequality is again the best single predictor in terms of the pseudo-$R^2$ and the AUROC. With regard to the other variables, real bank loans are still a useful predictor, although several other variables have higher predictive power.

Table 7 presents the estimation results for the 1950-2008 subsample when we include various predictors in the model. We use the same stepwise model selection procedure as in Section 4.1. Overall, this robustness test yields results that are similar to the findings for the full sample analysis (see Table 5). The primary differences are that the existence of deposit insurance has predictive power in the post-WW2 sample, whereas the short-term interest rates do not. The introduction of deposit insurance increases the likelihood of the outbreak of a financial crisis, indicating that the inherent moral hazard problems may interfere with the intended stabilizing effects of deposit insurance. The potentially destabilizing effect of deposit insurance has long been discussed in the literature: Keely (1990), Demirgüc-Kunt and Detragiache (1998), Demirgüc-Kunt and Huizinga (2004) and Anginer *et al.* (2014), among others, find evidence of such an effect. In addition, consistent with the finding by Schularick and Taylor (2012) that the share of credit in the economy has increased after WWII, Table 7 suggests that credit booms play a more important role in the second half of our observation period, with the lags of real bank loans being jointly statistically significant at the 1% level. Meanwhile, income inequality is an equally strong predictor as it is in the full sample analysis.[8]

[8] To broaden our view, we re-examine the post-WWII analysis using the income share received by the top decile (10%) as an alternative measure of income inequality (e.g., Piketty and Saez 2003; Piketty 2014). The

Our results thus far are indicative that income inequality is a contributing factor to financial crises over and above credit growth, current account deficits, real interest rates and stock price booms. However, as we outlined in Section 2, income inequality can also have an effect on the development of a crisis through housing price booms (Rajan 2010) and increased investment in risky assets by high-income households (Stockhammer 2015). To test for the effects of housing price booms, we use housing price data from the Bank for International Settlement for the time span from 1970 to 2006. To account for investments in riskier asset classes, we use data on the size of the US mutual fund industry (total assets held in mutual funds as a share of total CRSP market capitalization) collected from the CRSP Mutual Funds Data, which is available from 1962 onward. We estimate a restricted-form model beginning with only those variables through which income inequality is expected to affect the likelihood of crises. That is, the model includes real bank loans, housing prices, the size of US mutual funds, real stocks, and current accounts, in addition to the top 1% income share. We follow the same general-to-specific model selection approach used above.[9]

The results in Table 8 show that when we control for these different channels through which income inequality may affect the likelihood of financial crises, it still has unilateral predictive power, although its effect is somewhat diminished. In addition, the results show that a larger US mutual fund industry increases the risk of a financial crisis, but only immediately before a crisis erupts.

In summary, our in-sample results suggest that credit growth plays a role in predicting financial crises, as highlighted by previous studies. It is a good univariate predictor and has statistically significant predictive power in a multi-predictor setting for the post-WW2 period. However, we do not find an effect of credit growth in the multivariable full sample estimations. Meanwhile, in contrast to some of the previous literature, our results highlight

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results are similar to those for the top 1% income share and are available upon request. Because the top 10% income share series are basically unavailable for the pre-WWII period, we do not use them in our primary analysis.

[9]None of the lags of housing prices has statistically significant explanatory power, and thus, this variable is excluded from the final estimation results presented in Table 8. In contrast, Jorda *et al.* (2015) find some predictive power for housing prices but in a model with fewer other control variables. In our model, the individual predictive power of real housing prices is rather high (AUROC=0.81), but its coefficient becomes statistically non-significant after the top 1% income share is added to the regression. The individual predictive power of US mutual funds is also high (AUROC=0.65).

an explicit role of income inequality as a crisis predictor in all subperiods and specifications. One possible reason that our results partially differ from those of previous studies is that we employ general-to-specific model selection that begins with a variety of real and financial factors and their lags. This process makes our procedure less restrictive. In general, we conclude that the power to predict financial crises is distributed among several variables and their lags.

## 4.3 Out-of-Sample Forecasting Performance: 1980-2008

The estimation results in Sections 4.1 and 4.2 suggest that it is possible to obtain statistically significant in-sample predictive power for financial crisis periods in different developed countries. Next, we turn to exploring out-of-sample forecasts for the recent crisis periods.

Similar to Schularick and Taylor (2012), we consider rolling regressions using the lagged data to forecast financial crisis periods during the period from 1980 to 2008. A given model is estimated using data from the beginning of the sample to time $T$ using the information set $\mathcal{F}_T$ to construct one-year-ahead probability forecasts (see (3)) for the observations $y_{i,T+1}$, $i = 1,\ldots,N$. This procedure is repeated for each year through the end of the sample. This type of analysis leads to a more realistic comparison of the predictive ability of different variables and models because no future data are included in the information set when estimating the parameters of the models.[10] This exercise can therefore also be regarded as a robustness check against the potential overfitting of the logit models considered in Sections 4.1 and 4.2.

Table 9 reports the forecasting results. We use the out-of-sample AUROC as the criterion to assess forecasting performance because of the lack of a widely used out-of-sample version of the pseudo-$R^2$ measure. However, we note that the AUROC criterion and related tests are originally designed for in-sample analyses, and their out-of-sample results should therefore be interpreted as indicating tendencies in the predictive power of variables. Column 1 of Table 9 shows the AUROC for the full sample of 14 countries over the entire observation period, while column 2 focuses on the "common sample" that consists of the

[10] However, we note that real-time data are often unavailable, i.e., data for different variables may be released with a time lag and revised later on.

same observations used for all models.[11]

The first seven rows of the table report the results for each individual predictor variable. The results show that loan growth performs best out-of-sample, independent of the estimation sample that we consider. The top 1% income share also does perform rather well, but in contrast to the in-sample findings it is not the best sole predictor. This picture changes, however, when we employ the joint model from Table 4 in the out-of-sample analysis, as presented in the bottom four rows of Table 9.[12] First, it is important to note that these models yield superior forecasting accuracy compared with any single predictor. This finding confirms the importance of using various predictive variables in forecasting financial crises. Meanwhile, loan growth loses its predominant role when we control for other obviously important financial and real factors. The model without real bank loans leads to a smaller loss in terms of the out-of-sample AUROC compared with the model excluding the top 1% income share. This diminishing role of loan growth when we control for various other predictive factors is consistent with the in-sample results reported in Table 5. When the common sample is used, the difference between real bank loans and the top 1% income share becomes negligible.

## 4.4 Out-of-Sample Performance: Varying Forecasting Periods

The selection of the forecasting period (1980–2008) may affect our out-of-sample results obtained in Section 4.3. In particular, the era beginning in the early 1980s is commonly referred to as the period of financial liberation, marked by a phenomenal rise in the share of bank assets to GDP (Singh 1997; Schularick and Taylor 2012). This trend may have increased the predictive power of real bank loans during this period.[13]

In Section 4.3, the model specifications and the lag lengths of the predictors are based on

[11] The sample is limited by the variable that has the fewest observations, which is the top 1% income share, such that every estimation uses the same time dimension. However, the sample is not balanced because some variables have missing observations in some years. Again, Canada and the Netherlands are excluded from this analysis.

[12] Because of numerical convergence issues in the estimation of the model, we had to omit the two longest lags of the top 1% income share variable. In all other aspects, the model is the same as in Table 5.

[13] Rivas and Perez-Quiros (2015) also find that the predictive role of credit in the identification of the business cycle was limited before the financial crash of 2007-2008.

the model selection results obtained for the full sample period. In this section, by contrast and as a robustness check, we consider different forecasting periods, with the lag lengths specifically selected for each period using the data up to the starting point of the forecasting sample. For instance, for the 1950–2008 period, the model selection and parameter estimation are conducted using the sample period through 1949. Again, these results should be interpreted with caution because some forecasting periods contain few crises. For this reason, we consider models with only one predictor in this analysis.

The Table 10 results offer several interesting insights. First, none of the lags of real bank loans is statistically significant in the in-sample model selection when data through 1979 are used. Therefore, real bank loans are omitted from the out-of-sample forecasts for the period from 1980 to 2008. Second, only the top 1% income share, current account and real stock prices yield satisfactory predictive power in all time periods (AUROC > 0.5), although they usually do not exhibit the best individual predictive power. This finding implies that there are few universally strong predictors of crises and that economists and policy makers should pay attention to a range of factors. Third, the predictive power of our variables increases when we focus on the more recent decades between 1990 and 2008. Most variables actually have little or no predictive power when we use the entire post-WW2 period in column 2 as the forecasting period, but they yield better predictive power in the period from 1990 to 2008 (column 3). Fourth, further dividing the recent decades into two shorter periods comprising the years from 1990 to 2000 (column 4) and from 2000 to 2008 (column 5) emphasizes that focusing on shorter sample periods might lead to incomplete conclusions.

In conclusion, our out-of-sample forecasting results underpin the importance of focusing on various real and financial variables and assessing various forecasting periods to understand the drivers of financial crises.

# 5 Discussion

Our results imply that income inequality has a distinct role as a driver of financial crises. More precisely, the results presented in Section 4.2 suggest that even when trying to include all the channels proposed in the literature through which income inequality may lead to financial instability our measure of inequality still has predictive power. However, in our attempt we might not fully capture, e.g., the extent of the risk-taking of wealthier households. We miss data on hedge fund activities or subprime derivatives. We also do not have indicators for the increased risk-taking of banks in the form of subprime securitization. In addition, while financial deregulation leads to the observed increased risk-taking of wealthier households and banks and to current account imbalances, our variables might not capture all facets of the effects of financial deregulation (e.g. financial innovation, speculation, market integration as well as financial fragility and contagion) and how income inequality interacts with them.

A long-term cross-country study on the macro-level as ours is likely to not fully identify the above mentioned effects. This aspect raises two interesting questions for future research. First, financial deregulation is a phenomenon of the past 20-30 years, whereas our focus lies on the last 50-100 years. An interesting question then would be how to establish a long-term measure that captures the risky investments of the rich households and banks in different time periods in a comparable manner. Second, a micro-level study that exploits specific deregulatory measures or institutional changes in one country might add to our understanding of the effects of deregulation and income inequality on the probability of a crisis. However, the latter approach then comes at the cost of studying a very narrow sample. Future research may also broaden the analysis by linking the predictive performance of various factors to the underlying characteristics of financial systems at different times. For instance, the effect of income inequality on financial stability might depend on the quality of credit growth, that is, the types of loans that are extended and the types of borrowers that take up these loans.

It is known that income inequality can have a broad effect on the economy. If income inequality leads to shorter growth spells (Berg and Ostry 2011) and, more broadly, to higher macroeconomic fluctuations (see, e.g., Motta and Tirelli (2014); Kalliovirta and Malinen (2015)), it is likely to increase the likelihood of crises by increasing business cycle fluctuations affecting a wide variety of macroeconomic variables, such as business bankruptcies and the volume of nonperforming loans, which, in turn, are likely to contribute to financial instability. Inequality can also lead to high aggregate savings because individuals in higher income groups tend to save more (Dynan *et al.* 2004; Eggertson and Mehrotra 2014). Excessive saving hinders consumption, while the imbalance between savings and investment pulls down the natural interest rates leading to a state of *secular stagnation* (Hansen 1939; Summers 2013; Eggertson *et al.* 2016). This gives rise to a paradox of a high level of speculative investments (because of the low return of traditional investments) and a low level of real investments (because of low aggregate demand), which both can increase the likelihood of financial crises. Also these broader channels need to be further addressed in future studies.

# 6 Conclusions

In this paper we study the performance of various financial and macroeconomic variables when predicting financial crisis periods in 14 developed countries over long time periods of up to more than 100 years. We focus on income inequality in particular because it was elevated before the recent crisis as well as before the Great Depression in the 1930s but the empirical evidence on its role as a crisis predictor is scant and mixed. One reason for the mixed results in the existing literature might be that income inequality can work through various channels such as asset and credit bubbles indicating that it could be the actual real root cause for these phenomena. Financial crises also tend to be caused by different factors at different times, ranging from the run on private banknotes during the Panic of 1819 to the runs on repo, commercial paper, and primer broker balances during the crisis of 2007-2008. This is why we use a general-to-specific model selection procedure that begins with a large array of financial and macroeconomic predictors and their lags, thereby combining the insights of previous works in the macroeconomic and banking literature. The results show that the predictive power of our model is clearly distributed among various variables and their lags.

In particular, we can conclude that in the run-up to a crisis, several variables have substantial additional predictive power over and above credit booms, which were recently emphasized by, e.g., Schularick and Taylor (2012) and Taylor (2015) as the main culprits. Our results indicate that income inequality is a useful predictor; it is the best predictor in in-sample estimations, and it is a universal predictor in out-of-sample forecasts, although some variables perform better during some out-of-sample forecasting periods. The out-of-sample forecasts also emphasize that focusing on short subperiods yields considerably varying results for several factors, such as government debt, which might lead to incomplete conclusions regarding the usefulness of a certain predictor.

Alarmingly, if income inequality has the destabilizing effect that our results suggest, then the current trend of increasing inequality could set the stage for further financial turmoil. However, to formulate policy interventions clearly more research is warranted to better understand the potential interconnectedness of different predictive factors, including bank credit, external imbalances, financial innovation (securitization), asset price booms, business cycle fluctuations and income inequality to pin down the exact channels through which factors like income inequality generate financial instability.

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# Tables and Figures

Table 1: Summary statistics of the predictive variables

| Variable | Transformation | Countries | Obs. | Mean | Std. deviation |
|---|---|---|---|---|---|
| real bank loans | log & 1st diff. | 14 | 1481 | 0.055 | 0.08 |
| top 1% income | 1st diff. | 14 | 853 | 0.039 | 0.72 |
| gross r. investments | log & 1st diff. | 14 | 1560 | 0.022 | 0.17 |
| current account | 1st diff. | 14 | 1548 | 9.240 | 206.17 |
| money (M2) | log & 1st diff. | 14 | 1574 | 0.079 | 0.06 |
| government debt | log & 1st diff. | 14 | 1501 | 0.036 | 0.10 |
| r. stocks | log & 1st diff. | 14 | 1454 | 0.213 | 0.23 |
| s.t. real interest | 1st diff. | 14 | 1300 | -0.041 | 0.05 |
| deposit insurance | - | 14 | 1736 | - | - |

Table 2: In-sample results, full sample period 1870-2008

| Variable | Obs. | Lag length | Pseudo-$R^2$ | AUROC |
|---|---|---|---|---|
| $\Delta$real bank loans | 1398 | 2 | 0.046 | 0.684 |
| $\Delta$top 1% income | 652 | 5 | 0.126 | 0.766 |
| $\Delta$gross r. investments | 1373 | 4 | 0.028 | 0.629 |
| $\Delta$current account | 1431 | 3 | 0.033 | 0.648 |
| $\Delta$money (M2) | 1491 | 2 | 0.025 | 0.635 |
| $\Delta$government debt | 1351 | 4 | 0.037 | 0.670 |
| $\Delta$r. stocks | 1257 | 4 | 0.037 | 0.684 |
| $\Delta$s.t. real interest | 1061 | (none) | - | - |
| deposit insurance | 1689 | (none) | - | - |

Notes: This table reports the values of the pseudo-$R^2$ and the area under the ROC curve (AUROC) for logit models including one single predictive variable at a time using the full sample (Obs. denotes the number of observations). The predictive variables are introduced in more detail in Table 1 and Section 2. The underlying forecast horizon is one year. The lag length is selected using the model selection procedure introduced in Section 3.2. (None) implies that none of the lags were selected in the employed model selection procedure.

Table 3: In-sample results, loan growth and income inequality, full sample period 1870-2008

| Variable (lags) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| L1. Δr. bank loans | -0.398 | 4.523* | 0.0301 | - | 4.28* | 5.071** |
| | ( 2.110 | (2.654) | (1.893) | | (2.574) | (1.694) |
| L2. Δr. bank loans | 7.138*** | 9.035** | 5.781*** | - | 9.481** | 10.845*** |
| | (2.613) | (3.642) | (1.694) | | (3.672) | (3.228) |
| L3. Δr. bank loans | 0.888 | 1.8565 | - | - | - | |
| | (2.948) | (2.879) | | | | |
| L4. Δr. bank loans | 0.203 | 0.791 | - | - | - | |
| | (1.378) | (3.130) | | | | |
| L5. Δr. bank loans | 1.867 | 0.742 | - | - | - | |
| | (1.640) | (2.985) | | | | |
| L1. Δtop 1% income | - | 0.661*** | - | 0.641** | 0.643*** | 0.451** |
| | | (0.230) | | (0.249) | (0.223) | (0.230) |
| L2. Δtop 1% income | - | 0.818 | - | 1.040** | 0.786 | 0.564 |
| | | (0.513) | | (0.480) | (0.511) | (0.494) |
| L3. Δtop 1% income | - | 0.308 | - | 0.381 | 0.385 | 0.197 |
| | | (0.329) | | (0.310) | (0.331) | (0.298) |
| L4. Δtop 1% income | - | 0.483 | - | 0.315 | 0.546*** | 0.336 |
| | | (0.329) | | (0.269) | (0.099) | (0.321) |
| L5. Δtop 1% income | - | 1.043** | - | 0.743** | 1.019*** | 0.904** |
| | | (0.418) | | (0.309) | (0.360) | (0.354) |
| L1. Δtop 1%* Δr. bank loans | - | - | - | - | - | 0.031*** |
| | | | | | | (0.012) |
| Observations | 1272 | 630 | 1398 | 652 | 645 | 645 |
| Countries | 14 | 12 | 14 | 12 | 12 | 12 |
| Pseudo-$R^2$ | 0.0659 | 0.193 | 0.046 | 0.126 | 0.192 | 0.232 |
| AUROC | 0.717 | 0.848 | 0.684 | 0.766 | 0.845 | 0.864 |
| Δ r. bank loans lags = 0 | 17.23*** | 15.41*** | 14.20*** | - | 14.80*** | 19.27*** |
| Δtop 1% lags = 0 | - | 14.67** | - | 15.68*** | 15.60*** | 8.10 |
| Δtop 1%* Δr.b. loans lags = 0 | | - | - | - | - | 7.28*** |

Notes: This table contains the full sample estimation results of logit models when real bank loans and income inequality are examined as predictors. Robust standard errors are presented in parentheses. L$k$ denotes the $k$th lag of the variable (i.e., L1. $x_t = x_{t-1}$). L1. top 1%*r. bank loans is the interaction between the first lags of our indicators for income inequality and credit growth. The results for the goodness-of-fit measures (Pseudo-$R^2$ and AUROC) and the test statistics for the joint significance of the lags of the included explanatory variables are also reported. Furthermore, *, ** and *** denote the statistical significance of the estimated parameter coefficients and the test statistics at the 10%, 5% and 1% significance levels, respectively.

Table 4: Marginal effects of income inequality

| Variable (lags) | full sample | <25% (7.2) | >75% (11.68) | <Sweden (6.2) | >US (16.7) |
|---|---|---|---|---|---|
| L1. Δtop 1% income | 0.114 | 0.008 | 0.016 | 0.007 | 0.026 |
| L2. Δtop 1% income | 0.014 | 0.009 | 0.019 | 0.008 | 0.031 |
| L3. Δtop 1% income | 0.007 | 0.005 | 0.010 | 0.004 | 0.015 |
| L4. Δtop 1% income | 0.010 | 0.006 | 0.013 | 0.006 | 0.022 |
| L5. Δtop 1% income | 0.018 | 0.012 | 0.025 | 0.011 | 0.041 |
| | | | | | |
| Sum | 0.060 | 0.040 | 0.083 | 0.035 | 0.135 |
| Observations | 645 | 196 | 133 | 117 | 60 |
| Countries | 12 | 12 | 12 | 12 | 12 |

Notes: This table presents the marginal effects of income inequality based on the model presented in Table 3, column 5. It reports the marginal effects for the full sample and subsamples selected according to the income inequality thresholds given in the first row. The thresholds 25% and 75% refer to the respective percentiles of the income inequality distribution, while "Sweden" and the "US" (average inequality levels between 2000–2008) are the example cases of low- and high-inequality countries.

Table 5: In-sample results with several predictors, full sample period 1886 -2008

| | Lags | | | | | |
|---|---|---|---|---|---|---|
| Variable | L1. | L2. | L3. | L4. | L5. | L6. |
| Δr. bank loans | 6.071 | 4.728 | - | - | - | - |
| | (5.075) | (4.803) | | | | |
| Δtop 1% | 1.063** | 1.693*** | 1.475*** | 1.190** | 0.076 | - |
| | (0.499) | (0.550) | (0.427) | (0.495) | (0.485) | |
| Δg.r. investments | 4.071 | -4.450* | 1.516 | -4.177** | - | - |
| | (3.635) | (2.391) | (3.419) | (1.948) | | |
| Δcurrent account | -0.0008 | -0.0042*** | -0.0031* - | - | - | - |
| | (0.0015) | (0.0009) | (0.0017) | | | |
| Δgov. debt | -6.916* | 8.384** | -10.492** | - | - | - |
| | (4.025) | (3.910) | (4.698) | | | |
| Δr. stocks | -3.129** | - | - | - | - | - |
| | (1.251) | | | | | |
| Δs.t. real interest | 8.948 | -13.999 | 17.992 | -12.357* | - | - |
| | (9.513) | (18.456) | (13.121) | (6.787) | | |
| Observations | | 466 | | | | |
| Countries | | 12 | | | | |
| Pseudo-$R^2$ | | 0.329 | | | | |
| AUROC | | 0.925 | | | | |
| | | | | | | |
| Test of Δr. bank loans lags = 0 | | 4.19 | | | | |
| Test of Δtop 1% lags = 0 | | 26.03*** | | | | |
| Test of Δg.r. investments lags = 0 | | 13.47*** | | | | |
| Test of Δcurrent account lags = 0 | | 20.21*** | | | | |
| Test of Δgov.debt lags = 0 | | 7.90** | | | | |
| Test of Δr. stocks lags = 0 | | 6.26** | | | | |
| Test of Δs.t. real interest lags = 0 | | 5.75 | | | | |

Notes: This table contains the full sample estimation results of logit models when several predictors and their lags are examined jointly. Robust standard errors are presented in parentheses. L*k* denotes the *k*th lag of the variable (i.e., L1. $x_t = x_{t-1}$). L1. top 1%*r. bank loans is the interaction between the first lags of our indicators for income inequality and credit growth. The results for the goodness-of-fit measures (Pseudo-$R^2$ and AUROC) and the test statistics for the joint significance of the lags of the included explanatory variables are also reported. Furthermore, *, ** and *** denote the statistical significance of the estimated parameter coefficients and the test statistics at the 10%, 5% and 1% significance levels, respectively.

Table 6: In-sample results, post-WWII period 1950-2008

| Variable | Obs. | Lag length | Pseudo-$R^2$ | AUROC |
|---|---|---|---|---|
| $\Delta$real bank loans | 721 | 2 | 0.071 | 0.717 |
| $\Delta$top 1% income | 545 | 3 | 0.135 | 0.781 |
| $\Delta$gross r. investments | 636 | 5 | 0.051 | 0.686 |
| $\Delta$current account | 660 | 3 | 0.090 | 0.718 |
| $\Delta$money (M2) | 722 | 2 | 0.043 | 0.643 |
| $\Delta$government debt | 679 | 1 | 0.067 | 0.713 |
| $\Delta$r. stocks | 702 | 4 | 0.092 | 0.777 |
| $\Delta$s.t. real interest | 607 | (none) | - | - |
| deposit insurance | 754 | 1 | 0.085 | 0.737 |

Notes: This table reports the values of the pseudo-$R^2$ and the AUROC for logit models including one single predictive variable at a time when using the post-WWII subsample (Obs. denotes the number of observations). The predictive variables are introduced in more detail in Table 1 and Section 2. The underlying forecast horizon is one year. The lag length is selected using the model selection procedure introduced in Section 3.2. (None) implies that none of the lags were selected in the employed model selection procedure.

Table 7: In-sample results with several predictors, period 1950–2008

| | Lags | | | | | |
|---|---|---|---|---|---|---|
| Variable | L1. | L2. | L3. | L4. | L5. | L6. |
| Δr. bank loans | -3.405 | 17.729*** | - | - | - | - |
| | (6.160) | (4.453) | | | | |
| Δtop 1% | 1.251* | 3.638*** | 2.920*** | 1.240 | -1.373 | - |
| | (0.646) | (0.661) | (0.852) | (1.081) | (0.873) | |
| Δg.r. investments | 24.170*** | -24.233** | 6.228 | -15.757** | - | - |
| | (6.502) | (9.502) | (10.914) | (6.692) | | |
| Δcurrent account | 0.00089 | -0.0099*** | -0.0073** | - | - | - |
| | (0.0025) | (0.0017) | (0.0031) | | | |
| Δgov. debt | -15.941*** | 8.756 | -11.136* | - | - | - |
| | (5.117) | (5.706) | (5.823) | | | |
| Δr. stocks | -6.007** | -3.139* | - | - | - | - |
| | (2.051) | (1.804) | | | | |
| deposit insurance | 4.010*** | - | - | - | - | - |
| | (1.344) | | | | | |
| Observations | | 399 | | | | |
| Countries | | 12 | | | | |
| Pseudo-$R^2$ | | 0.44 | | | | |
| AUROC | | 0.961 | | | | |
| | | | | | | |
| Test of Δr. bank loans lags = 0 | | 13.25*** | | | | |
| Test of Δtop 1% lags = 0 | | 34.05*** | | | | |
| Test of Δg.r. investments lags = 0 | | 23.99*** | | | | |
| Test of Δcurrent account lags = 0 | | 39.38*** | | | | |
| Test of Δgov.debt lags = 0 | | 17.74** | | | | |
| Test of Δr. stocks lags = 0 | | 9.03** | | | | |
| deposit insurance lags = 0 | | 8.90*** | | | | |

Notes: This table contains the post-WWII subsample estimation results of logit models when several predictors and their lags are examined jointly. Robust standard errors are presented in parentheses. L*k* denotes the *k*th lag of the variable (i.e., L1. $x_t = x_{t-1}$). L1. top 1%*r. bank loans is the interaction between the first lags of our indicators for income inequality and credit growth. The results for the goodness-of-fit measures (Pseudo-$R^2$ and AUROC) and the test statistics for the joint significance of the lags of the included explanatory variables are also reported. Furthermore, *, ** and *** denote the statistical significance of the estimated parameter coefficients and the test statistics at the 10%, 5% and 1% significance levels, respectively.

Table 8: In-sample results with selected predictors, period 1962–2008

| | Lags | | | | | |
|---|---|---|---|---|---|---|
| Variable | L1. | L2. | L3. | L4. | L5. | L6. |
| Δr. bank loans | 4.074 | 19.142*** | - | - | - | - |
| | (5.192) | (6.695) | | | | |
| Δtop 1% | 1.337** | 2.655*** | 1.247 | 0.177 | -0.023 | - |
| | (0.667) | (0.741) | (1.112) | (1.382) | (0.797) | |
| ΔUS mf | 1.595** | -2.372 | -6.311* | 0.797 | -3.612** | -3.972* |
| | (0.785) | (2.787) | (5.280) | (0.623) | (1.445) | (2.349) |
| Δr. stocks | -3.858*** | 0.402 | -0.550 | 4.413** | - | - |
| | (1.244) | (0.774) | (1.788) | (1.774) | | |
| Δcurrent account | -0.0001 | -0.0038*** | - | - | - | - |
| | (0.0038) | (0.0013) | | | | |
| Observations | | 364 | | | | |
| Countries | | 10† | | | | |
| Pseudo-$R^2$ | | 0.440 | | | | |
| AUROC | | 0.942 | | | | |
| | | | | | | |
| Test of Δr.b.loans lags = 0 | | 13.40*** | | | | |
| Test of Δtop 1 lags = 0 | | 14.75** | | | | |
| Test of ΔUS mf lags = 0 | | 10.86* | | | | |
| Test of Δr. stocks lags = 0 | | 21.19*** | | | | |
| Test of Δcurrent acc. lags = 0 | | 7.76** | | | | |

Notes: This table contains the 1962-2008 subsample estimation results of logit models when several predictors and their lags are examined jointly. Four countries are excluded because of a lack of data. Robust standard errors are presented in parentheses. L$k$ denotes the $k$th lag of the variable (i.e., L1. $x_t = x_{t-1}$). L1. top 1%*r. bank loans is the interaction between the first lags of our indicators for income inequality and credit growth. The results for the goodness-of-fit measures (Pseudo-$R^2$ and AUROC) and the test statistics for the joint significance of the lags of the included explanatory variables are also reported. Furthermore, *, ** and *** denote the statistical significance of the estimated parameter coefficients and the test statistics at the 10%, 5% and 1% significance levels, respectively.

Table 9: Out-of-sample AUROCs for the sample period 1980–2008

| Model (included predictors) | Out of sample AUROC | Out of sample AUROC, common sample |
|---|---|---|
| Δr. bank loans | 0.631 | 0.680 |
| Δtop 1% | 0.564 | 0.564 |
| Δg.r. investments | 0.548 | 0.513 |
| Δcurrent account | 0.594 | 0.636 |
| Δmoney (M2) | 0.591 | 0.496 |
| Δgovernment debt | 0.578 | 0.552 |
| Δr. stocks | 0.614 | 0.605 |
| Δr. bank loans + Δtop 1% | 0.635 | 0.637 |
| Full model (see Table 5) | 0.748 | 0.760 |
| – excluding top 1% | 0.646 | 0.748 |
| – excluding r. bank loans | 0.728 | 0.743 |
| – excluding r. bank loans and top 1% | 0.628 | 0.724 |

Notes: This table reports the out-of-sample AUROCs for the sample period 1980–2008. The first seven rows report results from models that include only one single predictor at a time, whereas the full model refers to the model presented in Table 5 and its subsequent restricted versions. The common sample refers to a sample that is limited by the variable with the fewest observations, which is the top 1% income share. However, the sample is not balanced because some variables have missing observations for some years.

Table 10: Out-of-sample AUROCs for different sample periods

| Model (included predictors) | 1980-2008 | 1950-2008 | 1990-2008 | 1990-2000 | 2000-2008 |
|---|---|---|---|---|---|
| Δr. bank loans | - | 0.502 | 0.736 | 0.815 | 0.689 |
| Δtop 1% | 0.509 | 0.541 | 0.571 | 0.680 | 0.572 |
| Δg.r. investments | 0.513 | - | 0.574 | 0.775 | - |
| Δcurrent account | 0.595 | 0.564 | 0.613 | 0.825 | 0.532 |
| Δmoney (M2) | - | 0.432 | - | - | 0.474 |
| Δgovernment debt | 0.552 | 0.501 | 0.648 | 0.920 | 0.469 |
| Δr. stocks | 0.518 | 0.502 | 0.568 | 0.640 | 0.566 |

Notes: This table reports the out-of-sample AUROCs for individual variables in different forecasting periods. The analysis is conducted with a common sample (see above). "-" indicates that none of the lags of a variable were statistically significant in the model selection.