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The risk of financial crises: Is it in real or financial factors?*

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Abstract

Are macroeconomic factors such as income inequality the real root causes of financial crises? We explore a variety of financial and macroeconomic variables to find the most reliable predictors for financial crises in 14 developed countries over a period of more than 100 years. Our results, based on a general-to-specific model selection process, indicate that the power to predict financial crises is distributed among several predictors, including income inequality and growth of bank credit. This is in line with the argument that the best predictive factors tend to vary in time.

Keywords: bank loans, income inequality, fixed effects logit.

JEL Classification: C33, C53, E44, G01.

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1 Introduction

Financial crises are recurring phenomena in modern economies.[1] The crisis of 2007-2009 was a stark reminder of the treacherous nature of financial crashes as it took almost the whole world by surprise. Its massive global costs are estimated to be in the range of $5 trillion to $15 trillion (Adelson 2013), and the search for its underlying reasons has also revived academic interest in financial crises and their history (see Rajan 2010; Bordo and Meissner 2012; Gorton 2012; Schularick and Taylor 2012, among others). If a set of useful early warning indicators of financial crises could be identified, the work of economists and policy makers with respect to recognizing and preventing the build-up of crises would be tremendously facilitated. Yet, there is no consensus whether real (macroeconomic) or financial factors play a more important role in predicting financial crises.

This study takes a step towards better understanding the relative role of real and financial predictors as drivers of financial crises. Our aim is to evaluate the probability of a financial crisis when considering the predictive power of a broad set of potential financial and macroeconomic factors over a long time series of more than 100 years. Besides the more traditional factors based on the findings obtained in the previous literature, we specifically explore the role of income inequality which has received increasing attention in various areas of economic research including economic growth, political economy, saving behavior, and schooling (Perotti 1993; Bénabou 1996; Fishman and Simhon 2002; Dynan *et al.* 2004; Galor and Moav 2004). Its potential role as a driver of financial crises remains, however, ambiguous (see, e.g., Atkinson and Morelli 2011; Bordo and Meissner 2012; Kumhof and Rancière 2010).

In their influential paper, Schularik and Taylor (2012) point to credit booms as the main contributor to financial crises in developed countries during the past almost 140 years. However, Gorton (2012) links abnormal credit growth to just one out of three financial crises that occurred during the period between 1970 and 2007. Therefore, by themselves, credit booms seem insufficient prerequisites of financial crises. Other

[1]For example, Laeven and Valencia (2012) have identified 147 banking crises over the period of 1970-2011.

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). Interactions between these factors are evident. Large capital inflows, e.g., may lead to stock market bubbles, excessive expansion of domestic credit, inflationary pressures and, ultimately, lower real short-term interest rates (Calvo *et al.* 1994). Furthermore, financial innovation may lead to inflows of capital, but inflows of capital may also drive financial innovation (Tett 2009). Therefore, some variables may rather reflect the effects of other variables.

The potential interactions between real and financial factors become particularly evident in the case of income inequality. Income inequality was highly elevated before the crisis of 2007-2009 (as it was before the Great Depression) and has remained as such in many developed economies after the crisis (Alvaredo *et al.* 2013). Iacoviello (2008) provides compelling evidence that income inequality was the main driver of the increase in household debt in the United States during the 1980s and 1990s. Also Kumhof and Rancière (2010) 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 so far fully and directly been 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 subsequent crash.

The very scant empirical evidence on the impact of income inequality on financial crises is mixed. Roy and Kemme (2012) find that an increase in income inequality increases the probability of a financial crisis. Perugini *et al.* (2013) find a significant role for income inequality in driving credit booms in 18 OECD countries over the time period 1970 to 2007. In a second step they relate credit booms to financial crises and confirm the existing evidence that credit booms increase financial fragility. In contrast, Bordo and Meissner (2012) find that changes in income inequality do not have an effect on the growth of bank loans in their data set of 14 developed economies between 1920 and 2000. Also Atkinson and Morelli (2011) do not find rising income inequality to be a consistent ingredient to the build-up of financial crises.

Our study contributes to the scarce but growing literature on income inequality and financial crises by employing 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 on the risk of financial crises. In addition to the model selection, the fact that we allow the predictive power to be distributed among a large set of variables, including income inequality, distinguishes our study from Schularik and Taylor (2012), whose data and estimation techniques we use as a starting point for our exercise.

Our results suggest that the predictive power of financial crises is distributed among several – real and financial - variables and their lagged values. Our results support previous findings, as in Schularik and Taylor (2012), that credit booms play a non-negligible role in creating financial instability. However, our results also highlight that a pure focus on credit booms as crisis drivers falls alarmingly short of the complexity of the matter.

More specifically, our empirical analysis yields three main findings. First, income inequality is indeed an influential factor: according to our in-sample results, top 1% income share (our measure of income inequality) has the highest single predictive power. We also find that income inequality still has additional predictive power over and above previously used factors such as real bank loans, real investments, current account, government debt and real stock prices. Second, and interestingly, the role of bank loans as a predictor of financial crises diminishes considerably when controlling for these other factors. Third, recursive out-of-sample forecasts largely confirm the in-sample results and underpin the importance of using various predictive variables in the model.

The rest of the paper is organized as follows. Section 2 discusses our data set and the related literature to motivate our choice of predictor variables. Section 3 outlines the methodology, while section 4 presents the results. Section 5 concludes.

2 Financial Crises and Their Predictors

2.1 Predicting financial crises

The drivers of financial crises have been studied since the seminal paper by Gorton (1988) in which he links the systemic nature of banking panics to the business cycle.[2] One of the strongest signals for an ongoing recession is a fall 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. Apart from that, the argument is sometimes made that it is the nature of the investments that influences the probability of a crisis (see Schularik and Taylor (2012)). If the money available in an economy is invested productively rather than driving consumption or speculation, the risk that a crisis occurs should be lower. 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). The recent literature on the determinants of financial crises has also highlighted the role of credit booms: Bordo *et al.* (2001), Mendoza and Terrones (2008), Reinhart and Rogoff (2009) and Schularik and Taylor (2012) find that large credit booms are associated with financial crises. 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. We do not scale bank loans by GDP, because such a scaled measure may rather proxy for the nature of the financial system (bank-based vs. market-based) than for the risk of a financial crisis in our sample of developed economies (Barrell *et al.* 2010).

Claessens *et al.* (2010) document that one of the similarities between previous financial crises and the recent one is that they were preceded by asset price booms. Increased asset prices may lead to an increase in lending against the higher collateral values, which in turn increases asset prices even more. Once this spiral stops, households and firms

[2] According to Gorton (1988), banks hold claims against firms and, during recessions, firms fail, which causes losses to banks. Due to this 'downturn' depositors reassess the riskiness of their deposits against recession signals, and panic when the recessionary signal is strong enough.

start struggling to pay back their accumulated debt. This kind of asset price boom that 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 in 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 build-up of financial crises. A current account deficit implies that an economy is consuming more than it produces so that other countries lend their savings to this economy. Such capital inflows may lead to stock market bubbles and excessive expansion of domestic credit, and may cause inflationary pressures (Calvo *et al.* 1994). We use the change in the real value of the current account as a measure of international capital flows. Low short-term real interest rates might have similarly contributed to the asset price and credit booms observed prior to many financial crises. Then again, increasing interest rates can hurt banks' balance sheets if banks cannot quickly increase their lending rates. But even if the increase in the interest rate can be passed on to borrowers, such an action would 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.

Very recently, a growing body of literature has developed theories and arguments 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, current account imbalances and short-term interest rates. These channels show that the interaction of real and financial factors might be the driving force behind financial crises and that asset and credit bubbles might actually develop from some real root causes.

Rajan (2010) argues that rising inequality forced US politicians to enact measures to better the situation of low- and middle-income households to not loose them as voters. Since 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

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

form of subsidized housing finance was expedited. Such provision of cheap mortgage lending together with the concurrent deregulation of the financial sector, in turn, led to the observed housing boom and subsequent crash.

Kumhof and Rancière (2010) 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 due to rising income inequality because poor and middle-income households have to borrow the more the more their real wages drop in order to maintain their level of consumption. 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.

Fitoussi and Saraceno (2009) argue that income inequality leads to depressed aggregate demand, which induces central banks to keep interest rates low, which then contributes to the build-up of private debt. At the same time, those who benefit from the increasing inequality search for high-yield investments and drive asset bubbles. The increase of non-performing loans after the burst of the asset bubble then exposes the banking sector to the risk of a run. Similarly, Stockhammer (2012) suggests that increased income inequality leads to more speculation or risk-taking because the consumption opportunities of those benefiting from increasing incomes get exhausted and speculative investments become more likely.[4] Atkinson and Morelli (2011) argue that also banks take higher risks when income inequality is elevated, and that this risk-taking happens through securitization.

To measure income inequality we use the top 1% income share of the population provided by Alvaredo *et al.* (2013). Calculating synthetic indexes, like the Gini and Theil indexes, 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 contains inconsistencies and anomalies that are likely to be country-dependent (Piketty 2014). The top income share

[4]Lysandrou (2011) suggests that wealth inequality stemming from the widening gap between wages and profits drove the demand for securities and fueled banks' creation of asset-backed securities and structured products to absorb the abundance of global demand.

measure, in contrast, is constructed using the same raw data and methodology for every country (Piketty 2007).[5]

To round off our pool of potential crisis predictors, we use three additional variables that have been shown to help predict financial crises in the previous literature. First, central banks can steer aggregate credit through monetary aggregates.[6] We control for the potential impact of monetary aggregates on the probability of a financial crisis with the change in broad money (M2).[7] Second, government debt matters for the financial sector (Demirgüc-Kunt and Detragiache 1998). If a government is short of funds, it may postpone measures aimed at strengthening banks' balance sheets. But even if a government was ready to support the country's banking sector despite budgetary problems, the public might not trust such an endeavor, which, in turn, might trigger a bank run. Third, deposit insurance is usually designed and introduced to prevent depositors from running and thus threatening the stability of the financial system. At the same time, the existence of deposit insurance introduces 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 make the occurrence of financial crises actually more likely 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 running.

2.2 Data

Our main source of data is the data set compiled by Schularik and Taylor (2012). It comprises 14 developed countries over the time period 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. As our dependent variable we use the financial crises episodes collected by Schularik and

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

[6]However, Schularik and Taylor (2012) argue that this channel of monetary policy might have decreased in importance.

[7]M2 can also be used as an alternative proxy for credit. See Schularik and Taylor (2012).

Taylor (2012), who combine the datasets of Bordo *et al.* (2001), Laeven and Valencia (2008), Cecchetti *et al.* (2009) and Reinhart and Rogoff (2009). The observed binary dependent variable y_{it} takes the value one ($y_{it} = 1$) if there is a financial crisis in a 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 Schularik and Taylor (2012) for details on the crisis data compilation). We assume that the crisis starts (i.e. $y_{it} = 1$) in the year when a country falls into a crisis.

We also obtain data on real bank loans, broad money (M2), government debt, and stock market indexes from Schularik and Taylor (2012). In addition, we obtain data on the top 1% income share from the Top Income Database by Alvaredo *et al.* (2013), on investments and current account deficits from Taylor (2002), on real GDP per capita from the Maddison Database of the Groningen Growth and Development Center, and on the introduction of deposit insurance from the World Bank Deposit Insurance Database (Demirgüc-Kunt *et al.* 2005). Details and summary statistics of all predictive variables are provided in Table 1.

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 instead of the panel models designed for continuous dependent variables. The latter models have various problems in the binary-dependent framework. As an example, the financial crisis probabilities are not necessarily inside the unit interval.

Our model is essentially the same as the one used by Schularik and Taylor (2012) (see a more complete description of the model in Hsiao (2003, Chapter 7)) but our model selection approach differs considerably to theirs. 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 stemming from different data reporting standards in different countries.

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

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

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

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

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

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

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 to several lags. Note that using the same lag length p in (6) for all the predictors is only for notational convenience and can easily be relaxed in practice (see Section 3.2). It is also worth noting that polynomial (6) starts from lag one, i.e., only the lags of the predictors are included in (5).

The estimation of the logit model can be conveniently carried out by the maximum likelihood (ML) method. Using the conditional probabilities constructed in (3), one can write the likelihood function and obtain the ML estimates by using numerical methods (see details, e.g., at Hsiao 2003, p.194–199).[8] In our setup, the number of cross-sectional units (countries) N is small while the length of the time series T is relatively long. As the model is not necessarily correctly specified, the ML estimator can be interpreted as a quasi-maximum-likelihood estimator in the usual way. Therefore, to take this possible misspecification into account, we use robust standard errors for the estimated coefficients throughout this study.

3.2 Model Selection and Goodness-of-Fit Evaluation

As our panel data is 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. The usual information criterion-based model selection procedures are therefore not straightforwardly applicable. Nevertheless, using an unbalanced panel is common in the previous crisis literature to include 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; Schularik 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

[8] In our analysis, we use Stata 11.1 and its logit function. The estimation codes are based on the ones provided by Schularik and Taylor (2012) and made available at http:www.aeaweb.org/articles.php?doi=10.1257/aer.102.2.1029.

useful predictive power. In practice, the (optimal) lag lengths p for different predictors are unknown. However, assuming that the upper bound, say p_{max}, is known, then we can use the following sequential general-to-specific model selection method which is essentially the same as the procedure proposed by, e.g., Lütkepohl (2005, pp. 143–144) for vector autoregressive models. We start with a large model containing all the explanatory variables and their lags. Similarly as Schularik and Taylor (2012), to keep the lag structure and thus the predictive model overall as parsimonious as possible, we consider lags up to six (i.e. $p_{max} = 6$) for each variable. After the parameters have been estimated, we look at 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 (or, equivalently, a corresponding p-value is larger than 0.10). 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 with two well-known goodness-of-fit measures. For the binary dependent variables, there are various alternative measures roughly analogous to the coefficient of determination R^2 used in linear models. As in Schularik 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 which only contains 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 as 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 has been a common evaluation criterion for binary predictions and outcomes in other sciences. In addition to Schularick and Taylor (2012), recent economic and financial applications include, e.g., Berge and Jorda (2011) and Jorda and Taylor (2011).

Specifically in our application, the area under the ROC curve 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 $\hat{y}_{it} = 1$ a signal forecast for crisis if the probability forecasts (3) obtained with the logit model is $p_{it} > c$ for some threshold value c, and vice versa with $\hat{y}_{it} = 0$. The ROC curve describes all possible combinations of true positive rate $TPR(c) = P(\hat{y}_{it} = 1|y_{it} = 1)$ and 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 a $TPR(c)\&FPR(c)$ space describing the classification ability of the model. In our application where the financial crisis periods are rare the determination of one single threshold c is complicated. Hence, we believe that the ROC methodology makes more sense than concentrating on the results based on one particular cutoff c.

To summarize the classification ability of a given model, the area under the ROC curve (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 a superior classification ability. As shown by Berge and Jorda (2011), the AUROC has standard asymptotic properties and we can easily test the hypothesis that the AUROC is significantly higher than 0.5.

4 Results

We start our empirical analysis with the in-sample estimations where the objective is to distinguish between different predictors and their predictive power for financial crisis periods. We consider three different sample periods: The first one comprises the whole (unbalanced) panel of countries during the full time span of our data from 1870 to 2008. The second period starts after the Second World War (WW2) in 1950 and the third sample covers the years from 1962 to 2008. The full sample results serve as our benchmark case because they contain the maximal amount of information (Section 4.1). The shorter sample periods can be seen as robustness checks based on more balanced panels (see Section 4.2). In the final step of our analysis, we conduct an out-of-sample forecasting experiment to further assess the robustness of our results (Section 4.3).

All our estimated models contain country fixed effects to control for the time-invariant heterogeneity at the country-level and to focus the analysis on within-country variation. We do not include time fixed effects into our panel logit model because the resulting model could only be estimated 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 in such a procedure.

4.1 Full Sample Predictions

We first estimate the fixed effects logit model with 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, it displays the optimal lag length and the values of the pseudo-R^2 and the area under the ROC curve (AUROC). The number of observations differs for different 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 for whether a deposit insurance scheme is in place, which, as single predictors, do not have statistically significant predictive power at any lag length. Table 2 also shows that our measure for income inequality (the top 1% income share) clearly yields the best performance: income inequality seems to have substantial predictive power for financial crises. Real bank loans is the second-best single predictor with the second-highest pseudo-R^2 and AUROC. Overall, the level of the pseudo-R^2 is not very high in any model, partly reflecting the fact that the number of financial crises is limited. However, the obtained AUROC statistics are statistically significant at the 1% significance level for all the predictors indicating that the models can distinguish between non-crisis and crisis periods.

In line with previous studies (see, e.g., Bordo *et al.* (2001), Mendoza and Terrone (2008), Reinhart and Rogoff (2009) and Schularik and Taylor (2012)), our univariate results confirm that an increase in credit (real bank loans) is an important predictor - or warning signal - of financial crises. However, while some of these studies have emphasized 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 seems also reasonable in the light of Gorton's (2012) finding that only around one third of the crises between 1970 and 2007 saw credit booms in their run-ups.

In the next step, we examine in a multi-predictor analysis 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 with focusing on models that contain both real bank loans and income inequality. Table 3 reports the results for the full sample period. Columns 1 and 2 include the models containing real bank loans and top1% income as predictors separately. These two models replicate the Table 2 results of these two predictors, but now we present the actual estimated coefficients of all included lags facilitating a comparison to the model containing both predictors (column 3).

Column 3 of Table 3 shows that both variables are also significant predictors for financial crises in a joint model. The separate tests of the predictive power of the lags of the variables are statistically significant at the 1% level and very similar to the univariate results reported in columns 1 and 2. The values of the pseudo-R^2 and the AUROC in this joint specification are larger than in the single variable models. Thus, it appears that income inequality indeed has additional predictive power over and above bank loans and not just an effect on the probability of a financial crisis via its possible impact on credit growth.

Despite the evidence above, income inequality may still work through various other channels. 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 to play an important role.[9] Again following the general-to-specific model selection method, we first add all our remaining predictive variables and their

[9]Canada and the Netherlands drop out from the subsequent estimation sample because there are no financial crises in Canada during the years 1924-2008 and in the Netherlands between 1925-1938 and 1993-1999.

lags from one to six (maximum lag length) to the model presented in the last column of Table 3. Then we sequentially exclude the longest and least significant lag in each step until the longest lag of each predictor is statistically significant at the 10% level (based on their *t* ratios). The resulting model is presented in Table 4.

Table 4 yields several interesting findings. In particular, when comparing the values of the pseudo-R^2 and AUROC between Tables 2–4, we can conclude that the predictive power is clearly distributed among various predictors and their lags. Top 1% share (income inequality) is still a strongly 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 4 remain qualitatively unchanged if bank loans are excluded from the model (results are available upon request). This is in contrast to the evidence presented by Schularik and Taylor (2012) who find a strong role for loan growth when employing the same data set as we do arguing that their results largely support the idea that financial crises are "credit booms gone wrong". However, unlike us, they do not employ such a variety of predictors and their lags in a joint model that is derived from a general-to-specific model selection process.

In addition, the results in Table 4 show that an increase in income inequality increases the probability of financial crises. This finding is in line with the anecdotal evidence that the two fiercest crises in the US, the Great Depression and the recent crisis, were both preceded by high income inequality. It also confirms the reasoning in the academic literature that income inequality is one of the root causes of financial crises and rules out that income inequality works solely through credit booms as suggested in Kumhof and Rancière (2010) or Perugini *et al.* (2013).

Table 4 also shows that not only the change in income inequality has 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 (also found by Schularik and Taylor (2012)) indicates that once an asset price boom starts to revert, the probability of a financial crisis increases. However, watching the long-term evolution of stock prices does not seem 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, which might be because they first of all affect credit growth and through this channel make a financial crisis more likely rather than having direct predictive power.

4.2 Robustness Checks

In this section, we present the results from 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 shorter after-WW2 time series 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. Also, some of our predictor variables, the top 1% income share in particular, are only available for a shorter time span. The panel is therefore much more balanced in the after-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 (see Rajan (2010)) and increased risk-taking by the higher-income households (see Stockhammer (2012)). Since both variables are only available at much shorter time periods than employed in our main analysis, we perform this robustness test with our shortest sample period covering the years 1962 to 2008.

One concern with our previous results might be that the superior predictive performance of the top 1% income share is due to the fact that the sample period during which we observe it is so different from the sample period of the other variables. In Table 5, we present the models including one predictor at a time for the post-WW2 subsample starting in 1950. The numbers of observations are now much closer to each other for all the variables. It turns out that income inequality is again the best single predictor in terms of the pseudo-R^2 and the AUROC. As for the other variables, real bank loans is still a useful predictor, although there are several other variables with higher predictive power.

Table 6 presents the estimation results for the 1950-2008 subsample when including various predictors in the model. We use the same stepwise model selection procedure as in Section 4.1. Overall, this robustness test yields very similar results as the full sample analysis (see Table 4). The main difference is that the existence of deposit insurance has predictive power in the post-WW2 sample, while the short-term interest rates do not. The introduction of deposit insurance makes the outbreak of a financial crisis more likely indicating that the inherent moral hazard problems seem to 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, have found evidence for it.

In line with the finding by Schularik and Taylor (2012) that the share of credit in the economy has increased after the WWII, Table 6 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. At the same time, income inequality is an equally strong predictor as in the full sample analysis.

Our results so far are indicative of income inequality being a contributing factor to financial crises over and above credit growth, current account deficit, real interest rates and stock price booms. However, we outlined in Section 2 that income inequality can have an effect on the build-up of a crisis also through housing price booms (Rajan 2010), and increased investment in risky assets by high-income households (Stockhammer 2012). To test for the effects of housing price booms, we use house price data from the Bank for International Settlement for the time span 1970 to 2006. To account for investments in more risky 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 onwards. We estimate a restricted-form model starting from only those variables through which income inequality is expected to affect the likelihood of crises. That is, the model includes real bank loans, house prices, size of the US mutual funds, real stocks, and current account, in addition to the top 1% income share. We follow the same general-to-specific model selection approach as above. The results in Table 7 show that when controlling 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.[10]

In summary, our in-sample results suggest that credit growth does play 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 full sample estimations. At the same time, and in contrast to some of the previous literature, our results highlight an explicit role for income inequality as a crisis predictor in all sub-periods and specifications. One reason why our results partially differ from previous studies might be that we employ a general-to-specific model selection which starts from a variety of real and financial factors and their lags. This 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 Performance

The estimation results in Sections 4.1–4.2 suggest that it is possible to obtain statistically significant predictive power for financial crises periods in different developed countries in-sample. So far, our main interest has been to examine which financial and macroeconomic variables are useful crisis predictors in general. Next, we turn to exploring out-of-sample forecasts for the recent crisis periods.

Similarly to Schularik and Taylor (2012), we consider rolling regressions using the lagged data to forecast the financial crisis periods during the period from 1980 until 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 forecast (see (3)) for the observations $y_{i,T+1}$, $i = 1,\ldots,N$. This procedure is repeated for each year up to 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. This exercise can therefore also be seen as a robustness check against the potential overfitting of the logit

[10]None of the lags of housing prices had statistically significant explanatory power, and thus it dropped out of the final estimation result presented in Table 7.

models considered in Sections 4.1 and 4.2.

Table 8 reports the forecasting results. We use the out-of-sample AUROC as the criterion to assess the forecasting performance because there is no widely used out-of-sample version of the pseudo-R^2 measure (7). Column 1 of Table 8 shows the AUROC for the full sample of 14 countries over the whole observation period, while column 2 focuses on the "common sample" that consists of the same observations used for all the models. The first five rows of the table report the results for each predictor variable at a time.

The results show that loan growth performs best out of sample independent of the sample considered, which is in line with the findings of Schularick and Taylor (2012). In contrast to the in-sample findings, the top 1% income share does not perform as well when used as a sole predictor in the out-of-sample model.

This picture changes when we employ the joint model from Table 4 in the out-of-sample analysis as presented in the bottom four rows of Table 8. [11] First of all, it is important to note that these models yield superior forecasting accuracy compared to any single predictor. This finding confirms the importance of using various predictive variables in forecasting financial crises. At the same time, loan growth loses its predominant role when controlling for other obviously important financial and real factors. The model without real bank loans leads to a smaller loss in terms of out-of-sample AUROC compared with excluding top 1% income share. This diminishing role of loan growth when controlling for various other predictive factors is in line with the in-sample results reported in Table 4. However, when the common sample is used the difference between real bank loans and top 1% income share becomes negligible.

The selection of the forecasting period can affect the out-of-sample results. The era since the beginning of the 1980s is commonly referred to as the period of financial liberation which has been marked by a phenomenal rise in the share of bank assets to GDP (Singh 1997; Schularik and Taylor 2012). This may have increased the predictive power of real bank loans. Table 9 presents the AUROC results for individual predictive variables for the period from 1960 to 2008. The out-of-sample predictive power of top

[11] Due to numerical convergence issues in the estimation of the model, we had to drop the two longest lags of the top 1% income share variable. In all other aspects the model is the same as in Table 4.

1% income is higher in this sample, while the power of real bank loans (as well as all other predictors) is lower.[12]

Although the share of income received by the top 1% is highly correlated with broader measures of the income distribution, it only focuses on the share of income received by a very small group of people. To broaden our view we use the income share received by the top decile (10%) as an alternative measure of income inequality (see, e.g., Piketty and Saez (2003); Piketty (2014)).[13] Table 10 presents the results with top 10% income share. We find that the top 10% income share has in fact a somewhat higher predictive power than the top 1% share. For instance, excluding top 10% income share from the full model leads to a higher drop in the forecasting power of the model than when real bank loans is dropped. This enforces the view that income inequality is an important early warning indicator of financial crises.

To conclude, our out-of-sample forecasting results underpin the importance of using various predictive variables in a model to understand the drivers of financial crises.

5 Conclusions

This paper studies the performance of various financial and macroeconomic variables in predicting financial crisis periods using an extensive data set covering 14 developed countries from 1870 to 2008. We use a general-to-specific model selection procedure that starts from a large array of financial and macroeconomic predictors and their lags, thereby combining the insights of previous works in the macroeconomic and banking literatures. The results suggest that multiple predictors are likely to play an important role in financial crisis prediction as the predictive power 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

[12]This trend of diminishing forecasting power of real bank loans continues when we increase the forecasting horizon. Letting the out-of-sample forecasting period begin in the year 1950, the common sample AUROC for top 1% income share is 0.541 and for real bank loans 0.582.

[13]Other broader measures of income inequality, like the Gini or Theil indexes, are not available, because their time series are considerably shorter that top 1% or top 10% income shares. We are thus unable to use them in our estimations that include multiple predictive variables.

emphasized by Schularick and Taylor (2012). We introduce income inequality into the range of potential crisis predictors - a factor that has received considerable attention in various strands of the economic literature, but has only been scarcely studied in the empirical analyses of the drivers of financial crises. We find that income inequality is indeed a useful predictor. The results show that it is not necessarily the best possible single predictor, but combined with a set of other variables, it has statistically significant additional predictive power.

All in all, our results suggest that predicting future financial crises remains a challenging task. While several factors, such as credit booms, have attracted special attention in the aftermath of the recent crisis, they are not universal culprits. The reason for this is the fact that financial crises tend to be caused by different factors at different times. Future research should focus on understanding the interconnectedness of different predictive factors including bank credit, external imbalances, securitization, asset-price booms, and income inequality. Our results imply that especially the role of income inequality behind financial crises requires more attention. If it has the destabilizing effect our results suggest, the current trend of increasing inequality could set a stage for yet another financial turmoil.

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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	0.003
top 1% income	1st diff.	14	853	0.039	0.027
gross r. investments	log & 1st diff.	14	1560	0.022	0.006
current account	1st diff.	14	1548	9.240	11.245
money (M2)	log & 1st diff.	14	1574	0.079	0.002
government debt	log & 1st diff.	14	1501	0.036	0.004
r. stocks	log & 1st diff.	14	1454	0.213	0.011
s.t. real interest	1st diff.	14	1300	-0.041	0.011
deposit insurance	-	14	1736	-	-

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

Variable	Obs.	Lag length	Pseudo-R^2	AUROC
Δreal bank loans	1398	2	0.046	0.684
Δtop 1% income	652	5	0.126	0.766
Δgross r. investments	1373	4	0.028	0.629
Δcurrent account	1431	3	0.033	0.648
Δmoney (M2)	1491	2	0.025	0.635
Δgovernment debt	1351	4	0.037	0.670
Δr. stocks	1257	4	0.037	0.684
Δs.t. real interest	1061	(none)	-	-
deposit insurance	1689	(none)	-	-

Notes: This table reports the values of the pseudo-R^2 and the ROC area (AUROC) for logit models including one single predictive variable at a time (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 p (see (5) and (6)) is selected using the model selection procedure introduced in Section 3.2. (None) implies that none of the lags were statistically significant at the 10 % level.

Table 3: In-sample estimation results, full sample period 1870-2008

Variable (lags)			
L1. Δr. bank loans	0.0301	-	4.28*
	(1.893)		(2.574)
L2. Δr. bank loans	5.781***	-	9.481**
	(1.694)		(3.672)
L1. Δtop 1% income	-	0.641**	0.643***
		(0.249)	(0.223)
L2. Δtop 1% income	-	1.040**	0.786
		(0.480)	(0.511)
L3. Δtop 1% income	-	0.381	0.385
		(0.310)	(0.331)
L4. Δtop 1% income	-	0.315	0.546***
		(0.269)	(0.099)
L5. Δtop 1% income	-	0.743**	1.019***
		(0.309)	(0.360)
Observations	1398	652	645
Pseudo-R^2	0.046	0.126	0.192
Test of Δ r. bank loans lags = 0	14.20***	-	14.80***
p-value	<.001		<.001
Test of Δtop 1% lags = 0	-	15.68***	15.60***
p-value		0.008	0.008
AUROC	0.6837***	0.766***	0.845***
s.e. (AUROC)	0.0365	0.0494	0.0361

Notes: This table contains the 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. $x_t = x_{t-1}$). Furthermore, *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively, for the single parameter coefficients, joint tests for the lags of Δr. bank loans and Δtop 1%, as well as the AUROC area. The standard error of the AUROC area (s.e. (AUROC)) is given in the last row.

Table 4: Estimation results with several predictors, full sample period 1870-2008

	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***				
s.e. (AUROC)		0.0206				
Test of Δr. bank loans lags = 0		4.190				
p-value		0.123				
Test of Δtop 1% lags = 0		26.03***				
p-value		0.0001				
Test of Δg.r. investments lags = 0		13.47***				
p-value		0.009				
Test of Δcurrent account lags = 0		20.21***				
p-value		0.0002				
Test of Δgov.debt lags = 0		7.90**				
p-value		0.0482				
Test of Δr. stocks lags = 0		6.26**				
p-value		0.0124				
Test of Δs.t. real interest lags = 0		5.750				
p-value		0.219				

Notes: This table reports estimation results of logit model including several predictors and their lags. The presented model is obtained using the sequential model selection procedure described in Section 3.2. See also the notes to Table 3.

Table 5: In-sample results, post IIWW period 1950-2008

Variable	Obs.	Lag length	Pseudo-R^2	ROC area (AUROC)
Δreal bank loans	721	2	0.071	0.717
Δtop 1% income	545	3	0.135	0.781
Δgross r. investments	636	5	0.051	0.686
Δcurrent account	660	3	0.090	0.718
Δmoney (M2)	722	2	0.043	0.643
Δgovernment debt	679	1	0.067	0.713
Δr. stocks	702	4	0.092	0.777
Δs.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 ROC area (AUROC) for logit models including one single predictive variable at a time (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 p (see (5) and (6)) is selected using the model selection procedure introduced in Section 3.2. (None) implies that none of the lags were statistically significant at the 10 % level.

Table 6: Estimation results with several predictors for the sample 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***				
s.e. (AUROC)		0.0146				
Test of Δr. bank loans lags = 0		13.25***				
p-value		0.0013				
Test of Δtop 1% lags = 0		34.05***				
p-value		<.0001				
Test of Δg.r. investments lags = 0		23.99***				
p-value		0.0001				
Test of Δcurrent account lags = 0		39.38***				
p-value		<.0001				
Test of Δgov.debt lags = 0		17.74***				
p-value		0.0646				
Test of Δr. stocks lags = 0		9.03**				
p-value		0.011				
deposit insurance lags = 0		8.90***				
p-value		0.0029				

Notes: This table reports estimation results of logit model including several predictors and their lags. The presented model is obtained using the sequential model selection procedure described in Section 3.2. See also the notes to Table 3.

Table 7: Estimation results with selected predictors for the sample 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***					
s.e (AUROC)	0.022					
Test of Δr.b.loans lags = 0	13.40***					
p-value	0.001					
Test of Δtop 1 lags = 0	14.75**					
p-value	0.012					
Test of ΔUS mf lags = 0	10.86*					
p-value	0.093					
Test of Δr. stocks lags = 0	21.19***					
p-value	0.0003					
Test of Δc.a. lags = 0	7.76**					
p-value	0.021					

Notes: In this table ΔUS mf is a proxy for 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 onwards. See also the notes to Table 3.
*

Table 8: 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%	0.509	0.509
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 4)	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 AUROC areas 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 4 and its subsequent restricted versions. Common sample repeats the forecasting experiment using the common sample periods for 12 countries.

Table 9: Out-of-sample AUROCs for the sample period 1960–2008

Model (included predictors)	Out of sample AUROC	Out of sample AUROC, common sample
Δr. bank loans	0.551	0.630
Δtop 1%	0.552	0.556
Δg.r. investments	0.422	0.495
Δcurrent account	0.541	0.592
Δmoney (M2)	0.415	0.477
Δgovernment debt	0.461	0.523
Δr. stocks	0.561	0.618
Δr. bank loans + Δtop 1%	0.641	0.642
Full model (see Table 4)	0.728	0.750

Notes: This table reports results when replicating the Table 8 analysis for a longer time span (1960–2008).

Table 10: Out-of-sample AUROCs for the sample period 1980–2008 with top 10% income share

Model (included predictors)	Out of sample AUROC	Out of sample AUROC, common sample
Δr. bank loans	0.631	0.717
Δtop 10%	0.587	0.587
Δg.r. investments	0.548	0.606
Δcurrent account	0.594	0.674
Δmoney (M2)	0.591	0.636
Δgovernment debt	0.578	0.597
Δr. stocks	0.614	0.670
Δr. bank loans + Δtop 10%	0.746	0.756
Full model	0.894	0.894
– excluding top 10%	0.787	0.857
– excluding r. bank loans	0.876	0.876
– excluding r. bank loans and top 10%	0.765	0.839

Notes: This table reports the out-of-sample AUROC areas for the sample period 1980–2008 when the top 10% share is used as a measure of income inequality. The full model refers to the model obtained with the sequential model selection procedure employed throughout this paper. See also the notes to Tables 8 and 9.