Can We Predict Financial Crises?

Wen Dang[1(✉)], Jiayi Peng[2], Ruidan Fan[3], and Zifei Wang[4]

[1] Olive Tree International Academy, BFSU, Hangzhou 311100, China
13357130350@qq.com
[2] Shanghai World Foreign Language Academy, Shanghai 200233, China
[3] Shenzhen College of International Education, Shenzhen 518000, China
[4] The Affiliated International School of Shenzhen University, Shenzhen 518083, China

Abstract. Historically, financial crises have crippled individuals, businesses and global economies; identifying prospective threats accurately can mitigate their repercussions. This paper examines the annual economic statistics in fourteen developed countries from 1870 to 2008. We demonstrate the variations of credit and money aggregates over time, analysing the reasons behind those changes in light of macroeconomic history. We build OLS and logit models to determine the underlying link between financial instability and major macroeconomic indicators, proving that growth in credit aggregates is a salient indicator for a higher likelihood of a financial crisis. We compare the predictive power of GDP, money and credit growth in different eras, taking the Second World War and the 1980s as turning points. The results confirm the significance of credit in forecasting. These findings contribute to the discussion of the predictability of financial crises and provide valuable insights for economic agents.

Keywords: Financial Crises · Forecasting · Predictive Regressions · Credit

1 Introduction

Before and after World War II, many emerging market countries experienced severe financial crises, including the famous Great Depression and the recent financial crisis of 2008–2009. Nowadays, more and more government officials and scholars have begun to pay attention to crises, and people have begun to discuss their impacts and methods that can help predict or even prevent damage. Scholars and research institutions also made continuous attempts to establish the crisis early warning system (EWS). The IMF initiated the study on the crisis early warning model of emerging markets very early and made many valuable research results.

This paper builds on the extensive body of research, presenting a data set of nearly 140 years for 14 developed countries. Different countries have varying trends in money and credit aggregates and respond to finical crises differently. Therefore, when establishing the financial risk early warning model of these countries, how to choose the early warning indicators has become a problem. This paper focuses on several relatively effective early warning indicators. We use discrete dependent variable models to establish a crisis early

S. Tehseen et al. (Eds.): ICEDBC 2023, AEBMR 258, pp. 53–70, 2024.
https://doi.org/10.2991/978-94-6463-246-0_7

warning system, and further study the predictive effect of various warning indicators on crises. We introduce OLS and logit models for long-term prediction of each indicator to improve the out-of-sample prediction ability of the model.

2 Exploratory Data Analysis

2.1 Data Description and Data Preprocessing

This paper uses the data from *Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008*, authored by Moritz Schularick and Alan Taylor. The dataset contains annual economic statistics in fourteen developed countries over a span of 138 years, from 1870 to 2008. Countries in the study include the United States, the United Kingdom, Japan, France, Italy, Spain, Canada, Denmark, Sweden, Australia, the Netherlands, Germany, Norway and Switzerland. The dataset centred particularly around the statement of the financial position of banks. It is also supplemented with information on price levels, narrow money (M0 or M1), broad money (M2 or M3), and real GDP.

The most pivotal concepts are banks and bank loans. Total bank loans are the totality of all outstanding domestic currency loans lent out to domestic households and non-financial firms by domestic banks at the end of each year (excluding lending within the financial system). Total bank assets refer to the valuable items owned by domestic banks [1].

Table 1. Annual Summary Statistics by Period

	Pre-World War 2			Post-World War 2		
	N	mean	s.d.	N	mean	s.d.
Broad Money/GDP	742	0.5343	0.207	834	0.6458	0.4239
Assets/Broad Money	617	0.7132	0.4453	828	1.0135	0.6688
Loans/Broad Money	665	0.4217	0.3582	831	0.5470	0.4239
Δ log Real GDP	868	0.0148	0.0448	854	0.0270	0.0253
Δ log CPI	826	−0.0002	0.0568	852	0.0452	0.0396
Δ log Narrow Money	787	0.0278	0.0789	825	0.0780	0.0717
Δ log Broad Money	741	0.0365	0.0569	833	0.0857	0.0552
Δ log Loans	652	0.0416	0.0898	833	0.1094	0.0749
Δ log Assets	607	0.0433	0.0691	825	0.1048	0.0678
Δ log Loans/Broad Money	626	0.0017	0.0729	825	0.0222	0.0643
Δlog Assets/Broad Money	573	0.0043	0.0452	820	0.0182	0.0595

Notes: Loans denote total bank loans. Assets denote total bank assets. The sample's time frame is 1870–2008. War and aftermath periods are excluded. From "Credit Booms Gone Bust", by Moritz Schularick and Alan M.

Table 1, the annual summary statistics by period, demonstrates stark differences before and after World War II. The first three ratios, namely broad money/GDP, assets/broad money and loans/broad money, all saw a rise in their means. The growth rates shown in the lower panel also leapt after the Second World War: the ratio of assets to broad money quadrupled from a low of 0.43% to 1.82%; log real GDP increased from 1.48% to 2.7%; log total bank assets elevated from 4.33% to 10.48%; log loans expanded from 4.16% to 10.94%. More strikingly, the log of loans/broad money rocketed by a whopping 13-fold, from 0.17% to 2.22%. Plus, price levels grew over time, as the log CPI growth rates stood at negative 0.02% in the pre-World War 2 era, and the figure turned to positive 4.52% during the post-WW2 period.

2.2 Statistical Analysis and Visualisation

To further explore the time series data, Fig. 1 exemplifies the visualisation of aggregate bank loans and aggregate bank assets to GDP ratios in 4 selected nations respectively. The green line represents bank assets over GDP, whereas the red line denotes bank loans over GDP. Due to substantial missing values and data volatility, we decided not to fill up those omitted values. Besides, statistics in wartime, between 1914 and 1917, as well as 1939 to 1947, are not included. This is because amidst war economies struggled to operate properly, and monetary and fiscal policies adopted to bail out economies will massively impact the data [2], creating numerous outliers.

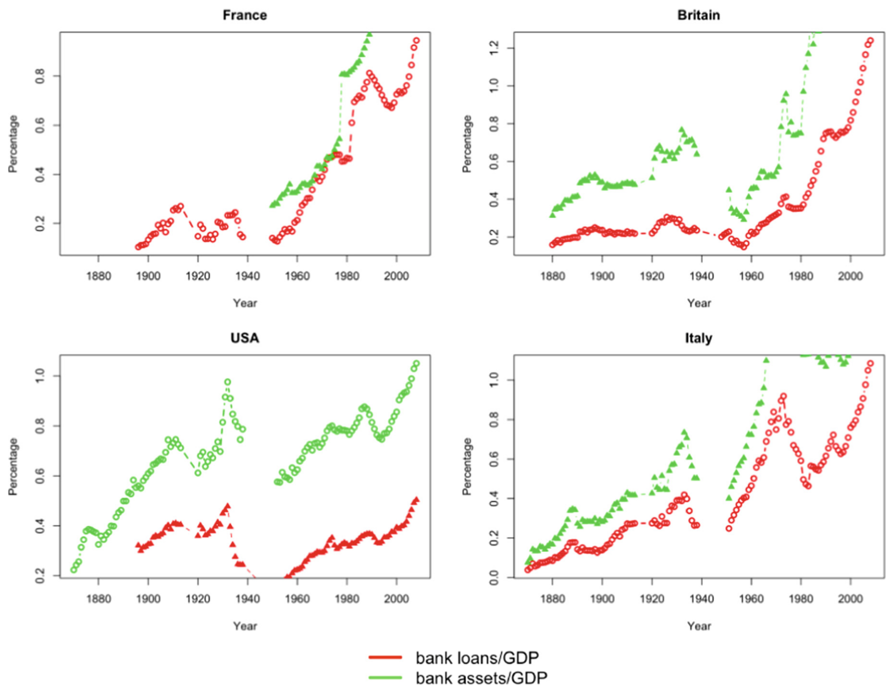

Fig. 1. Bank Loans/GDP & Bank Assets/GDP (By Countries)

Overall, Fig. 1 depicts a generally upward trend and several features. First, bank assets consistently exceeded bank loans throughout the period, so banks were able to cover loans. Second, after 2000, countries witnessed noticeable surges in ratios of bank loans and assets to GDP. Additionally, figures shot up in 1910 and 1930.

2.3 Differences Between Pre and Post-2nd World War

Factors changed drastically before and after World War II. WW2, starting in 1939 and ending in 1945, partitioned trends in Fig. 1. Before that, the bank loans/GDP and bank assets/GDP were at a relatively lower level.

The most overt variations lay in the 1930s when the world was mired in the Great Depression. Before this downswing, the globe saw hikes in both ratios fuelled by excessive production, risk-taking optimism, and overextended loans [3]. Also, the prevalent notion of "buying on margin" seduced a flurry of frenetic retail investors to use leverage to trade stocks [4]. Such a speculative bubble eventually burst in 1929, leading to a stock market meltdown and widespread panic. A massive exodus of savers caused bank failures and dragged economies into the Great Depression. Consequently, the ratios of bank assets and loans plummeted simultaneously.

It was a different story after WW2. Countries started with even lower ratios in the aftermath of the war. The subsequent rebound in ratios was quite strong, soaring at a more rapid rate compared to previous jumps. Notwithstanding a few key points on the line where ratios sank slightly, the trend stayed upward overall.

In 1944, at the end of World War II, the Bretton Woods system was established, which symbolised the advent of a more stable regime. The new international monetary system aimed to provide a stable and predictable monetary environment that would support post-war global economic growth and development. Such a fixed exchange rate stabilised economies and promoted economic prosperity in the post-war era; it was conducive to growth in loans and assets as well, which had been increasing until around 1970.

The stagflation of the 1970s, featuring high inflation and rising unemployment rates, was mainly caused by oil price hikes and monetary instability. The driving force behind the staggering climb in the costs of oil was the collective power of OPEC [5], which acted as a cartel. Meanwhile, failing to detect the potential economic turbulence, the Fed adopted an expansionary monetary policy at the initial stage [6], which exacerbated the pressing issue of inflation. As a result of the costly inflation, real interest rates fell below zero, engendering massive outflows of deposits. Therefore, since 1970, the ratios of bank loans and assets to GDP slumped. Another notable peak happened around 1990. It was the consumption shock that arose from animal spirits that mostly caused this time's economic downturn [7].

Recovering from the 1990–1991 recession, total bank loans/GDP and assets/GDP ratios went up spectacularly as the world economy started booming. For one thing, the march of globalisation has accelerated, increasing the volume of international trade and investment [8]. For another, commencing in the 1990s, the global interest rate has been declining [9]. Pursuing loose monetary policies, central banks were intended to stimulate lending and investment, which was a boon for banking systems.

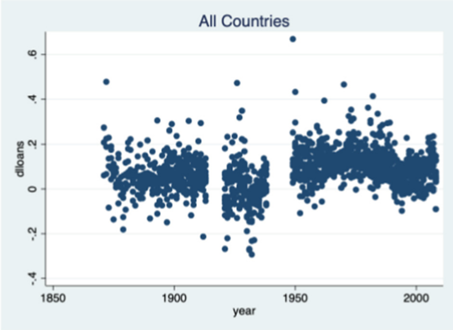

Fig. 2. Growth Rates of Log Total Bank Loans (All Countries)

Moving to Fig. 2, we construct time series models to inspect variations due to exogenous shocks. The stationary variables are the growth rates of log total bank loans. The data prove stationarity because the result of the Augmented Dickey-Fuller (ADF) test suggests that there is strong evidence against the null hypothesis of a unit root in the time series data (p-value = 0.01). Growth rates were higher in the post-WW2 era as points clustered around 0.1% before WW2, doubling that afterwards (0.04%). Being buffeted by the Great Depression in the 1930s, the growth rates slowed down remarkably. The expansions in bank loans and assets quickened after WW2, and the 1970s and the 1980s observed the fastest growth rates in these nations.

On the whole, there are essential differences in the data set's variables between pre-WW2 and post-WW2 eras, as the world economy underwent structural shifts politically and economically. The most fundamental transformation is the replacement of the gold standard with fiat money. In the wake of the war, most countries abandoned the gold standard and adopted fiat currencies [10], shifting from the fixed exchange rate regime to floating exchange rate systems. Such a reform allowed banks to hold more diversified assets. Additionally, purchasing goods and services on credit became prevalent. The resultant escalating consumer credit led to a more powerful role for banks in providing consumer loans and a corresponding jump in the size of loans on banks' balance sheets. Furthermore, the post-war epoch saw the founding of several international organisations like the United Nations (UN), and the International Monetary Fund (IMF). These institutions have facilitated capital flows both within and among countries by easing trade barriers, promoting multinational cooperation, and fostering economic growth. Consequently, the aforementioned changes reinforced one another, collectively fuelling greater growth in total credits, real GDP and money aggregates than in the pre-war era. Nonetheless, these transformations brought some detrimental side effects, toppling financial stability; the world after WW2 witnessed more frequent occurrences of banking failures and their impacts were severer, albeit more active monetary policies [1]. The credit boom thus fed asset bubbles, ultimately spelling the global financial crisis of 2007–2009.

3 Probabilistic Models of a Financial Crisis

3.1 OLS Linear Probability Model

Factors that Help Predict a Financial Crisis. To test for this link between macroeconomic indicators and the probability of a financial crisis, we propose utilizing a fundamental forecasting framework. We aim to answer the simple yet crucial question: does a nation's recent credit growth history predict the occurrence of the financial crisis? Further, we want to investigate if this relationship remains stable across various specifications. To achieve this, we created three different OLS Linear Probability models with simple pooled data and panel data to estimate this relationship. The forms of three specifications are:

Model specification 1:

$$P = \beta 0 + \beta 1(L)DlogLOANS + \beta 2(L)X + e \tag{1}$$

Model specification 2:

$$P_i = \beta 0_i + \beta 1(L)DlogLOANS_i + \beta 2(L)X_i + e_i \tag{2}$$

Model specification 3:

$$P_{it} = \beta 0_i + \beta 1(L)DlogLOANS_{it} + \beta 2(L)X_{it} + e_{it} \tag{3}$$

The LOANS variable is defined as the total amount of bank loans deflated by CPI to eliminate the disturbance of inflation. Letter L is the lag operator. To make the lag structure reasonable, we involved five annual lags of any covariance. The vector X contains other macroeconomic indicators that are also informative in predicting the financial crisis, including real GDP, broad money, and CPI price level, which we will discuss later. The dependent variable P is a dummy when equal to one indicating a financial crisis in country i in year t and otherwise zero. The error is assumed to be well-behaved.

Model specification 1 is constructed based on simple pooled data. To account for individual differences between countries, we added the country-fixed effect in the second model specification. However, it was shown not to be statistically significant using the ANOVA test (Table 2). On this basis, we include the year-fixed effect into the model to see if the time is informative, which is shown to be highly significant on 0.01 level. The addition of the year fixed effect improved the adjusted R^2 by 43% to 0.043, indicating the difference in financial condition before and after World War II plays a significant role in affecting the probability of occurrence of the financial crisis.

The result of all three OLS Linear Probability models in Table 2 demonstrates that a higher real growth rate of bank loans two years ago increases the probability of a future financial crisis. Doubling the real bank loans growth rate increases the probability of financial crisis by 25%, as found in our analysis. Since financial crises are very rare (sample frequency under 4%), this demonstrates a high sensitivity of crisis to plausible loan growth disturbance. These findings align with the idea that financial crises are 'credit booms gone wrong' [1].

Table 2. Financial Crisis Prediction – OLS

		(1)	(2)	(3)
Estimation Method		Pooled OLS	Panel OLS	Panel OLS
Fixed Effects		None	Country	Country + Year
Coefficient (Standard error)	$\Delta\log(\text{loans}/P)_{i,t-1}$	0.043 (0.090)	0.050 (0.090)	0.063 (0.090)
	$\Delta\log(\text{loans}/P)_{i,t-2}$	0.257***(0.091)	0.261***(0.091)	0.269*** (0.090)
	$\Delta\log(\text{loans}/P)_{i,t-3}$	0.054 (0.091)	0.056 (0.091)	0.067 (0.091)
	$\Delta\log(\text{loans}/P)_{i,t-4}$	0.005 (0.091)	0.004 (0.091)	0.017 (0.090)
	$\Delta\log(\text{loans}/P)_{i,t-5}$	0.065 (0.089)	0.063 (0.089)	0.076 (0.088)
Observations		1,246	1,246	1,246
Residual standard error		0.199(df = 1220)	0.199(df = 1207)	0.197(df = 1206)
Test for country fixed effects		–	0.5235	–
Test for year fixed effects		–	–	2.699e−05 ***
R^2		0.050	0.060	0.073
Adjusted R^2		0.031	0.030	0.043
F statistics		2.583***(df = 25;1220)	2.015***(df = 38;1207)	2.446***(df = 39;1206)
Notes: *p < 0.1; **p < 0.05; ***p < 0.01; Standard error in parentheses				

Are there any other indicators that can be informative aside real growth rate of bank loans? We examined the relationships between real GDP growth rate, CPI price level growth rate, real broad money growth rate and the probability of a financial crisis.

Table 3 displays a significant positive relationship between the real broad money growth rate one year ago and the probability of a financial crisis. Suggesting a double in the broad money growth rate could result in a 21.8% higher likelihood of a financial crisis, which, combined with the finding above about the real growth rate of banks loans, challenges the pre-crisis new Keynesian consensus that money and credit have no constructive role to play in monetary policy.

Moving along the table, the link between CPI price level growth rate and the occurrence of a financial crisis is explored. The significant lagged variants suggest a positive relationship between the continuous inflation rate two years before the crisis explosion and the probability of a financial crisis. It may give us some insight that a continuously high inflation growth rate signals an impending crisis.

Table 3. Financial Crisis Prediction – OLS

		Broad Money/CPI	Replaced with CPI	Replaced with Real GDP
Estimation Method		Panel OLS	Panel OLS	Panel OLS
Fixed Effects		Country + Year	Country + Year	Country + Year
Coefficient (Standard error)	$\Delta\log(\text{Broad Money }/P)_{i,t-1}$	0.218* (0.110)	0.190** (0.060)	−0.200(0.169)
	$\Delta\log(\text{Broad Money}/P)_{i,t-2}$	−0.021(0.111)	0.172**(0.061)	−0.125 (0.171)
	$\Delta\log(\text{Broad Money}/P)_{i,t-3}$	−0.013 (0.111)	0.061 (0.012)	−0.486** (0.171)
	$\Delta\log(\text{Broad Money}/P)_{i,t-4}$	−0.120 (0.110)	0.025 (0.061)	−0.022 (0.170)
	$\Delta\log(\text{Broad Money}/P)_{i,t-5}$	−0.158 (0.109)	−0.081 (0.061)	−0.229 (0.166)
Observations		1,246	1,246	1,246
Residual standard error		0.199(df = 1220)	0.199(df = 1207)	0.197(df = 1206)
R^2		0.050	0.060	0.073
Adjusted R^2		0.031	0.030	0.043
F statistics		2.583***(df = 25;1220)	2.015***(df = 38;1207)	2.446***(df = 39;1206)
Notes: *p < 0.1; **p < 0.05; ***p < 0.01; Standard error in parentheses				

Regarding the real GDP growth rate, we found a negative relationship between the growth rate of real GDP three years ago and the probability of a financial crisis. This variable has the largest absolute value of coefficient among all the variables examined so far, indicating its crucial role in estimating the likelihood of the explosion of a financial crisis.

Upon comparing the coefficient of the real bank loans growth rate (0.269***) to that of real GDP growth rate (−0.486**), it becomes evident that an increase of roughly one percent in the real GDP growth rate could counteract the heightened probability of a financial crisis resulting from a two percent increase in the growth rate of real bank loans. This inference suggests that maintaining a reasonably balanced pace between credit growth and real GDP growth rate could mitigate the risk of financial crises, underscoring the crucial role of real GDP growth rate as a potent stabilizer of financial instability.

Model Checking. During the model checking stage, we test the data set to see to what extent our data set satisfied the statistical assumption of the OLS Linear Probability model. Our analysis reveals that the OLS model is not appropriate for this task. From Fig. 3, we can see that the assumption of linearity, normality, constant variance of the

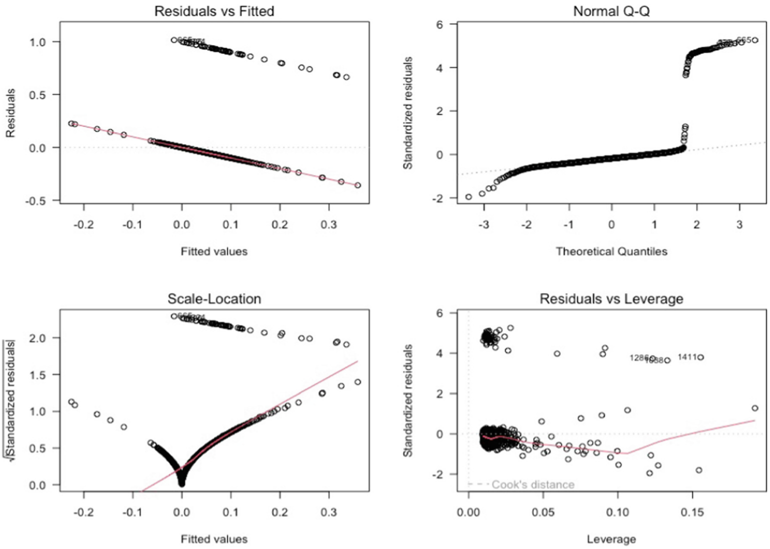

Fig. 3. OLS Model Checking

data set are all rejected. Besides, clear outliers are seen that indicate the poor predicting power of our OLS Probability model.

The failure in meeting the statistical assumption for the OLS model seems to make sense as it has some well-known problems in dealing with such a binomial classification task, chief among which is the fact that the domain of its fitted values is not restricted to the unit interval pertinent to a probability result [1]. Therefore, we switch to logit models in the following section.

3.2 Logistic Regression

Factors that Help Predict a Financial Crisis. In this section, we switch to Logit models. At the very beginning, on the basis of our findings in previous sections, we look into whether the so-called "leverage" is the culprit of a financial crisis. We do the estimation in one of two forms respectively:

$$\text{Pooled: } p_{it} = \frac{e^{\alpha+\beta(L)Dlog\left(\frac{Loans}{P}\right)_{it}}}{1+e^{\alpha+\beta(L)Dlog\left(\frac{Loans}{P}\right)_{it}}} \tag{4}$$

$$\text{Panel with fixed country effect: } p_{it} = \frac{e^{\alpha_i+\beta(L)Dlog\left(\frac{Loans}{P}\right)_{it}}}{1+e^{\alpha_i+\beta(L)Dlog\left(\frac{Loans}{P}\right)_{it}}} \tag{5}$$

The variables used are the annual growth rate of log of bank loans deflated by the CPI (Table 4). All forms of models display that a boom in borrowing would largely contribute to a heightened risk of a financial crisis. Through the diagnostic tests, it is shown that the five lags are all significant at the 1% level; the regression overall test statistics are also significant. The sum of lag coefficient is about 10, which is still statistically significant.

In addition, we look into the effects of fixing country effects into models. By comparing model specification (1) with (2). It is found that using panel logit models does not significantly enhance the predictability power of the models, so the Hausman test has been done and the result suggests that the panel model outweighs the pooled. Thus, we select model specification 2 as our baseline model.

We also aim to figure out whether other important indicators of financial stability also point towards this "credit view". To do this, we replace total loans in the baseline model with other credit-related indicators, including loans-to-GDP and loans-to-money ratios [11]. Model specifications (3) and (4) show the results. Having significant sums of lag coefficients which are close to that of the baseline model, these various scalings of loans and credit generally demonstrate a similar picture as total loans, in spite that they are less significant. The relative volume between credit and GDP has a better predictive power than that between credit and money, as the logs of loans-to-GDP-ratio growth rate is shown to be more significant in diagnostic tests. It also outperforms its counterparts in overall test statistics. From the results, we may conclude that these credit-based indicators are good predictive symbols of rising financial crisis risk as well.

Examination of the Model with Pre and Post WW2 Samples.
In Chapter 2, we have already understood that many aggregates and monetary responses have demonstrated quite distinctive trends in the eras before and after WW2. Therefore, we continue to test the variants with pre-1945 and post-1945 samples, respectively using AUROC (Area under ROC curves) comparison tests along with Kolmogorov Smirnov tests of the difference in the distributions under each outcome [1] to find out the favoured predictor in two epochs. The variables investigated into are growth rates of loans, real GDP and broad money. Looking at Fig. 4, it shows that before WW2 (N = 474), three ROC curves are very close to one another, and the hypothesis testing that suggests there are equal AUROCs between the GDP, money and loans models passes. ROC curves of pre-1945 loans and pre-1945 broad money demonstrate high similarity, almost overlapping with each other, while that of pre-1945 GDP model is lower than the other two curves at almost every point. This further reflects a weaker predictive capability of GDP. In addition, the results generated by K-S tests suggest that models all generally have a maximum height that is far much greater than the diagonal, in comparison to zero, except for GDP model. However, after-WW2 (Observations: N = 694), the ROC curve of money largely deviates from that of loans. With the exception of a few points between the (0,0) and (1,1) points, the money model ROC is below the loans model ROC curve virtually everywhere, having smaller AUROC value and hence weaker predictive ability. Three AUROCs are different, among which those of GDP and money models shrink to a level below 0.7. The disparities between AUROCS values of loans and broad money models expand dramatically. The post-WW2 money model also fails the Kolmogorov-Smirnov test.

This finding actually strengthens the statement that we have discussed in Chapter 2. Before the Great Depression, regardless of the volatility of credit, it has maintained a roughly stable size in relative to the money supply. However, due to a more aggressive monetary response and faster capital accumulation and transfers after WW2 [12], the

Table 4. Financial Crisis Prediction – Logit Estimates with various scalings of loans volume

		(1)	**(2) Baseline Model**	**(3) Replace loans with loans-to GDP ratio**	**(4) Replace loans with loans-to-money ratio**
Estimation Method		Pooled Logit	Panel Logit	Panel Logit	Panel Logit
Fixed Effects		None	Country	Country	Country
Coefficient (Standard error)	$\Delta\log(\text{loans}/P)_{i,t-1}$	−0.331 (2.10)	−0.457 (2.14)	1.087 (1.67)	0.158(1.95)
	$\Delta\log(\text{loans}/P)_{i,t-2}$	6.853***(2.33)	7.036***(2.66)	3.965*** (1.74)	3.604 (2.23)
	$\Delta\log(\text{loans}/P)_{i,t-3}$	1.151 (2.92)	0.964 (3.04)	3.777 (2.44)	4.552* (2.36)
	$\Delta\log(\text{loans}/P)_{i,t-4}$	0.310 (1.31)	0.210 (1.41)	0.625 (1.42)	0.218 (1.73)
	$\Delta\log(\text{loans}/P)_{i,t-5}$	1.978 (1.62)	1.828 (1.65)	2.903** (1.46)	1.850 (2.12)
Observations		1,253	1,253	1,244	1,223
Groups		–	14	14	14
Sum of lag coefficients		9.962***	9.582***	12.357***	10.383***
Standard error		2.592	2.908	2.893	3.369
Test for all lags = 0		24.19***	16.90***	22.85***	13.29***
p value		0.0002	0.0047	0.0004	0.0208
Test for country effects = 0		–	7.65	8.69	9.36
p value		–	0.8656	0.7961	0.7427
R^2		0.0425	0.0615	0.0777	0.0579
Pseudolikelihood		−210.2	−205.2	−202.1	−199.7
Overall test statistics		24.19***	35.55***	41.34***	25.3
p value		0.0002	0.0081	0.0014	0.1169

Note: Reported "test for all lags", "test for country effects", and "overall test statistics" are $\chi 2$ for logit regression. Reported "R^2" is Pseudo R for logit regression. Standard errors in parentheses. Logit standard errors are robust. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

mismatch between credit growth and money supply growth started to appear. During the process of decoupling, credit has gradually become the decisive factor that triggered the accumulation of a financial crisis risk, and had a profound impact on macroeconomic performance. By contrast, the indicative ability of money supply is getting less and less.

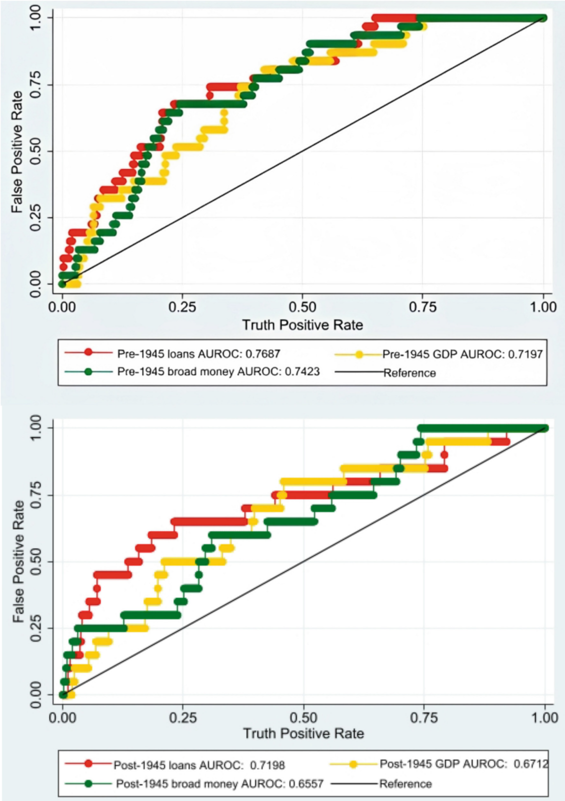

Fig. 4. ROC comparisons of loans, GDP and money as predictors: pre-1945 vs. post-1945

Beyond that, panel logit models with fixed-country effects are run respectively with pre-WW2 and post-WW2 samples. The results are presented in Table 5. A large difference can be observed in terms of the correlation degree between real GDP growth rate and financial crisis risk in two eras. Before the war, 1% increase in the real GDP growth rate would be offset by 1% increase in real loans growth rate. However, in the post-WW2 epoch, 1 unit increase in real GDP growth rate could reduce the probability of a financial crisis by about 18 unit. We may infer that output growth has turned to be far more "useful" after the Great Depression in maintaining a stable economy. This finding might also have potential policy implications. Before 1945, GDP would be an important factor that represented the banks' ability to meet payment obligations. However, in the post-war era, the stagnant real incomes and discouraged aggregate demand have been largely offset by lax monetary policy, which raised the leverage and credit, and pushed the economy to the edge of a financial crisis [13].

Examination of the Model with Pre and Post 1980 Samples. Beyond this traditional view that WW2 made a large difference, we assume that the circumstances before and after 1980 were quite different. That is because of the globalization, which gradually turned the exchange of imports and exports into flow of financial capital. To investigate

Table 5. Examination of the model with pre and post 1945 samples

		(1) pre-WW2 samples	(2) post-WW2 samples
Estimation Method		Panel Logit	Panel Logit
Fixed Effects		Country	Country
Coefficient (Standard error)	$\Delta\log(\text{loans/P})_{i,t-2}$	7.871*** (2.922)	9.672*** (2.999)
	$\Delta\log(\text{real GDP})_{i,t-3}$	−7.083 ** (3.428)	−18.346*** (6.617)
	$\Delta\log(\text{broad money/P})_{i,t-3}$	3.975 (2.862)	4.258* (2.341)
Observations		538	722
Groups		14	13
Sum of lag coefficients		4.763	−4.416
Standard error		3.589	7.32
Test for all lags = 0		19.12***	16.74***
p value		0.0003	0.0008
Test for country effects = 0		9.21	5.06
p value		0.7566	0.956
R^2		0.1208	0.0864
Pseudolikelihood		−109.1	−83.5
Overall test statistics		32.60***	38.63***
p value		0.0084	0.0007

Note: Robust standard errors in parentheses. Logit standard errors are robust. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. In the post war samples, a country is dropped from the logit regression because there are no crises in the sample, so N = 13 for these cases

into these differences, we at first, use AUROC comparison tests to find a preferred model for its binary classification ability. The results are presented with Fig. 5. Unlike what we have found when 1945 is viewed as a turning point, the scenario, in this case, shows that the AUROCs of three models all ascend after 1980, demonstrating a stronger predictive ability. In addition, the closeness and relative position of the three ROC curves do not change dramatically.

Panel Logit models with pre and post 1980 samples are examined further (Table 6). The models are both significant at the 1% level, with the post-1980 models having a higher R^2. The parameters indicate that the effect of the increase in real loans growth rate and broad money growth rate on the crisis risk got magnified in the post-1980 era. The same percentage increase in these two variants would double the risk level of a financial crisis after 1980. This, once more, strengthens the opinion that the credit booms should undertake greater responsibility for the outbreak of a financial crisis, especially in the recent era as globalisation got complex. By sharp contrast, the GDP growth has experienced a deteriorated deterring ability for a financial crisis.

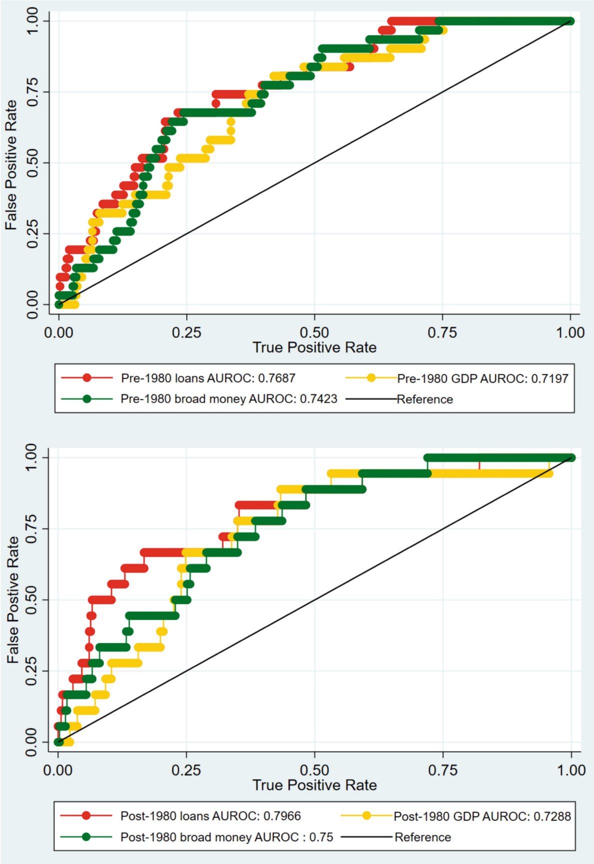

Fig. 5. ROC comparisons of loans, GDP and money as predictors: pre-1980 vs. post-1980

4 Limitations

Although our models provide constructive insights into projecting financial crises, several limitations influence their validity and reliability. Firstly, the data set has approximately 8% of missing values, and collecting thorough and complete statistics across all countries and centuries can be a daunting challenge. Hence, the existing data may fail to generalise all situations. Secondly, definitions of credit and money are different in different countries, and these concepts have evolved over time, making cross-national and cross-temporal comparisons excruciatingly problematic.

Moreover, when we divide samples into groups according to the time, the sample size might get quite small, potentially weakening the model's performance and leading to inaccuracy of the results. In addition, we want to discuss the feasibility of implementing a logit model with year effects. The results are presented in Table 7. The lagged bank loans growth rate is still adopted as the variant to keep the structure straightforward. We adopt Column 3, the model with country effects and time effects to compare it with the

Table 6. Examination of the model with pre and post 1980 samples

		(1) pre-1980 samples	(2) post-1980 samples
Estimation Method		Panel Logit	Panel Logit
Fixed Effects		Country	Country
Coefficient (Standard error)	$\Delta\log(\text{loans}/P)_{i,t\text{-}2}$	6.831**(2.775)	15.073*** (2.999)
	$\Delta\log(\text{real GDP})_{i,t\text{-}3}$	−15.293*** (3.323)	−1.388** (15.727)
	$\Delta\log(\text{broad money}/P)_{i,t\text{-}3}$	2.541 (2.888)	7.234 * (3.150)
Observations		911	364
Groups		14	13
Sum of lag coefficients		4.763	16.927
Standard error		3.589	7.32
Test for all lags = 0		21.63***	20.47***
p value		0.0001	0.0001
Test for country effects = 0		8.72	6.78
p value		0.794	0.8719
R^2		0.097	0.1404
Pseudolikelihood		−134	−61.6
Overall test statistics		34.68***	41.23***
p value		0.0044	0.0003

Note: Robust standard errors in parentheses. Logit standard errors are robust. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. In the post-1980 samples, a country is dropped from the logit regression because there are no crises in the sample, so N = 13 for these cases

other two columns. The results show that fixing time-effects into the model deteriorates the panel dataset, collapsing our number of observations from 1,253 to only 330. This will lead to imprecisely estimated parameters. Still, the fitting effects and explanatory power of the model have been improved dramatically. The diagnostic tests report that the five lags are much more significant (at the 1% level). The regression $\chi 2$ also gets more significant with a large increase in R square value. The sum of lag coefficients surges to around 20, which is also far more significant than that of the other two forms of models. However, given the effectiveness of fixing time effects into models, this technique is not appropriate for our panel data set. That is because in our data set, there are small N and large T. It is a narrow panel which means the incidental parameters problem afflicts the T dimension, and we have consistency in N. We, thus, keep the model with country effects but not year effects as our baseline model.

Table 7. Financial Crisis Prediction – Logit Estimates with Loans

		(1)	(2) Baseline Model	(3)
Estimation Method		Pooled Logit	Panel Logit	Panel Logit
Fixed Effects		None	Country	Country + year
Coefficient (Standard error)	$\Delta\log(loans/P)_{i,t-1}$	−0.331 (2.10)	−0.457 (2.14)	−1.601(2.351)
	$\Delta\log(loans/P)_{i,t-2}$	6.853***(2.33)	7.036***(2.66)	11.284*** (3.055)
	$\Delta\log(loans/P)_{i,t-3}$	1.151 (2.92)	0.964 (3.04)	1.299 (2.700)
	$\Delta\log(loans/P)_{i,t-4}$	0.310 (1.31)	0.210 (1.41)	3.142 (2.463)
	$\Delta\log(loans/P)_{i,t-5}$	1.978 (1.62)	1.828 (1.65)	5.424* (2.823)
Observations		1,253	1,253	330
Groups		–	14	14
Sum of lag coefficients		9.962***	9.582***	19.549***
Standard error		2.592	2.908	5.129
Test for all lags = 0		24.19***	16.90***	26.89***
p value		0.0002	0.0047	0.0001
Test for year effects = 0		–	–	45.76**
p value		–	–	0.0135
Test for country effects = 0		–	7.65	22.87**
p value		–	0.8656	0.0432
R^2		0.0425	0.0615	0.2914
Pseudolikelihood		−210.2	−205.2	−103.1
Overall test statistics		24.19***	35.55***	96.60***
p value		0.0002	0.0081	0.0000

Note: Reported "test for all lags", "test for country effects", "test for year effects" and "overall test statistics" are $\chi 2$ for logit regression. Reported "R^2" is Pseudo R for logit regression. Standard errors in parentheses. Logit standard errors are robust. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

5 Conclusion

The paper aims to look for variables that are suitable for financial crisis prediction. Using macroeconomic indicators and microfinancial institution indicators, we examine the actual effect of the Logit model's in-sample prediction in the crisis early warning process, and also the OLS model to make short-term prediction for each crisis early warning index. The disparities between different epochs are also examined. We came to the following conclusion: From the out-of-sample prediction results of Logit model, we find that that loans, GDP and money, are important predictor, among which credit is the superior one.

Acknowledgements. To clarify, Wen Dang, Jiayi Peng, Ruidan Fan, and Ziefei Wang contributed equally to this work and should be considered co-first authors.

We would like to take this opportunity to express our heartful appreciation to our instructor, Prof Donald Robertson, for his support and encouragement throughout this research. His profound knowledge of data analysis and statistical learning has provided us with new insight into these fields. His lectures have ignited our interest in furthering our exploration of Econometrics. We also benefited significantly through his generous support and self-devotion at the research stage. We also thank our teaching assistant Sir Boyu Han for his helpful suggestions and valuable research assistance.

References

1. Schularick, M., & Taylor, A. M. (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870–2008. American Economic Review, 102(2), 1029–1061. https://doi.org/10.1257/aer.102.2.1029
2. Eichengreen, B., El-Erian, M., Fraga, A., Ito, T., Pisani-Ferry, J., Prasad, E., ... & Yu, Y. (2011). Rethinking central banking: committee on international economic policy and reform. Brookings Institution.
3. Wheelock, D. C. (1992). Deposit insurance and bank failures: New evidence from the 1920s. Economic Inquiry, 30(3), 530-543.
4. Nolan, J. (1995). Boom and Bust in the 1920s. Vital Speeches of the Day, 62(4), 124.
5. Barsky, R., & Kilian, L. (2000). A monetary explanation of the great stagflation of the 1970s. https://doi.org/10.3386/w7547
6. McCallum, B. T. (2000). Alternative monetary policy rules: a comparison with historical settings for the United States, the United Kingdom, and Japan.
7. Blanchard, O. (1993). Consumption and the Recession of 1990-1991. The American Economic Review, 83(2), 270-274.
8. Anderson, E., & Obeng, S. (2021). Globalisation and government spending: Evidence for the 'hyper-globalisation' of the 1990s and 2000s. The World Economy, 44(5), 1144-1176.
9. Gamber, E. (2020). The Historical Decline in Real Interest Rates and Its Implications for CBO's Projections. Congressional Budget Office.
10. Mitchener, K. J., & Weidenmier, M. D. (2015). Was the classical gold standard credible on the periphery? Evidence from currency risk. The Journal of Economic History, 75(2), 479-511.
11. Kelly, R. J., McQuinn, K., & Stuart, R. (2013). Exploring the Steady-State Relationship Between Credit and GDP for a Small Open Economy: The Case of Ireland. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2240169
12. Tiejun, W., & Springerlink (Online Service. (2021). Ten Crises: The Political Economy of China's Development (1949–2020). Springer Singapore.
13. Davies, H. (2014). The Financial Crisis : Who is to Blame. Wiley.