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Prediction for Financial Crisis Based on Data from 14 Developed Counties

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Abstract: This article provides an analytical process for predicting a financial crisis. The article mainly adopt the regression method of limited probability model and logit model on the panel data from 14 developed countries from 1870 to 2008. Cau-sality problems have also been condidered when translating the regression output. The core finding of our research is that our model has a relatively weak ability to predict financial crises due to their low frequency, so the focus should lie on how to make policies to minimize the consequence of financial crises rather than trying to prevent them in advance. A very important assumption within our analysis is that it ignore the spillover effect of the financial crisis between countries, which may simplify our model but is not appropriate in the real world.

Keywords: Prediction for financial crisis, Limited dependent model, Logit model, Causality, Policy suggestion.

1. Introduction

At the beginning of the research, we undertook some background research on financial crises. We found the earliest reported financial crisis is the tulip mania associated with the importing of tulips from the Netherlands that caused a bubble economy. However, some scholars argue that a bubble economy does not result in a true financial crisis because the infection and the damage to the whole economic framework are not suitable with calling it a crisis. In other words, they think the tulip mania was ranged too concetrated and had a tiny impact. Then we looked into the latest financial crises. Surprisingly, we found that actually the latest crisis is the era we are living through—the Covid period. During the first year of the outbreak of the Covid, most countries' GDPs had fallen by 20% to 30%. However, in less than two years, the GDP of almost every developed country has recovered gradually, and finally, GDP had recovered to suppase the pre-covid level. From our perspective, that is because corresponding adjustment and optimization measures have been undertaken by various countries and these make the economic status of most countries more stable.

With the globalization process, the world is becoming more and more co-integrated. Thus the consequences of financial crises may become more serious through this joined mechansim. Therefore,

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if we could determine a model using the data at hand and successfully predict a financial crisis, it would help to prevent some losses in advance.

2. Literature Review

We investigated factors that may lead to a financial crisis. Benmelech and Eyal Dvir (2011) compared and analysed the dataset of 359 banks [1]. They concluded that short-term debt was a symptom of weak financial institutions rather than the reason for their demise [1]. In their essay, Efraim Benmelech and Eyal Dvir applied mathematical formula verification rigorously, and the data is fully verified from trusted sources. Yet, the data in this paper are mostly from Southeast Asian countries with underdeveloped industries and simple economic typologies that are not representative of the whole economical system. Moreover, the data are mostly from 1997–1998, the economic structure from which does not match the current pattern in which the service sector is challenged by internet-connected industries.

The second paper, from Borio and Disyatat (2010), states that the main macroeconomic cause of the financial crisis in 2008 was not "excess saving" but the "excess elasticity" of the international monetary and financial system [2]. The paper argues that it is the excess of savings over investment in some countries that causes significant downward pressure on world interest rates [2]. This diminution, in turn, helped to fuel the credit boom in major advanced economies, particularly the USA, which sowed the seeds of the recent global financial crisis [2]. The authors illustrated and analyzed the connection between the ES View and the Determination of the Interest Rate with trustworthy and abundant data sources, and proposed a hypothesis of financial crisis due to the excess elasticity via the analysis of the bank credit of US banks, which is a perfect example of the economic pattern in a developed country [2]. However, the model studied is limited to a well-structured economy and neglects the developing economic system.

3. Materials and Methods

We assume our data follows the assumptions of the classical linear regression model. The Gauss-Markov theorem suggests that Ordinary Least Squares (OLS) is the best linear unbiased estimator if the data meet certain requirements [3]. In other words, OLS will give us the best linear unbiased estimator.

OLS is a linear least squares method in statistics are used to estimate unknown parameters in linear regression models. OLS regression aims to estimate some unknown, dependent variable by minimizing the squared differences between observed data points and the best linear approximation of the data points [3].

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i + \varepsilon_i \tag{1}$$

However, if the data has some outliers, they will have a disproportionate effect. This is because OLS uses the square of the offset rather than the absolute value of the offset. Outliers with higher offsets have a greater impact on the line than points closer to the line [3].

The limited probability model (LPM) is a special form of OLS, where LPM looks at binary rather than continuous outcomes. We are still assuming that $E(u|\boldsymbol{x}) = 0$.

$$E(Y|X) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i + \varepsilon_i \tag{2}$$

And, since $y = 1$ or 0, we can write that:

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$$P(Y=1|X)=E(Y|X)=\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_iX_i+\varepsilon_i \tag{3}$$

βj measures the change in the probability of y taking the value 1 owing to a one unit change in X_j:

$$P(Y=1|X)=E(Y|X)=\beta_0+\beta_jX_j \tag{4}$$

In this report, the linear probability model was used as the underlying analytical method for the regression of the data because our regression model has a binary dependent variable. We adopted this model due to its relatively ease for intepretaing and including like square terms. The main advantage of LPM is that the parameter estimates can be interpreted directly as the "average marginal effect" of the covariates on the outcome. However, in addition to sharing the same drawbacks as OLS, another drawback of LPM is that the true relationship between the binary outcome and the continuous explanatory variables is inherentl nonlinear. This means that the functional form of the LPM is misrepresented, which can lead to misestimation of some key parameters [4]. Besides, as a dependent variable can only take on two values, the exact meaning of goodness of fit in this case is uncertain. The regression R-squared is therefore difficult to interpret. Here, we will use another two measurements to evaluate the fitness and predictive power of LPM model (details below). Lastly, if the probability of occurrence of an event is predicted using LPM, it is not ensured that the predicted probability is between 0 and 1. Further specific evaluation with empirical data will be provided later.

$$P(Y=1|X)=G(\beta_0+X\beta_j) \tag{5}$$

For the reasons mentioned above, the report also uses (binary) logistic models to analyze the data to enable the model fit the data better. A logistic model is a statistical model in which the logarithm of an event is a linear combination of one or more independent variables in a statistic, which reflects the likelihood of an event (in both options) occurring. In binary logistic regression, the dependent variable is a dummy variable with two values, "0" and "1", while the independent variable can be binary or continuous. This forces the output to assume only values between 0 and 1. The G(·) in the output of logit model is the cumulative distribution of logistic distribution function. And the marginal effect could be intepreted as:

$$\frac{\partial P(Y=1|X)}{\partial X_j}=(exp(\beta_0+X\beta)/[1+\exp(\beta_0+X\beta)]^2)\beta_j \tag{6}$$

In many ways, logistic regression is very similar to linear regression. The main difference between logit models and LPM is that logit predictions are always between 0 and 1 due to the property of logistic ditribution. However, a disadvantage of the logistic regression model is that it is more difficult to interpret because the average partial effect (APE) and parital average effect (PAE) are not the same. The marginal effect of X_j is different across range of X.

4. Data Analysis

The data set is directly derived from Schularick and Taylor [5], which contains data from 14 countries over the years 1870 to 2008. Since the data has already been cleaned and modified, we didn’t make any changes to the dataset. The countries include the United States, Canada, Australia, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom. Our dependent variable is CrisisST, which is a dummy variable, which shows if there is a financial crisis happens during such a year, the value would be 1. Else, it would be 0. We let the core

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definitions be consistent with the definitions from Schularick and Taylor (2012): “Total lending, or bank loans, is defined as the end-of-year amount of outstanding domestic currency lending by domestic banks to domestic households and non-financial corporations” [5]. Below are the first log difference of loansgdp, the first log difference of credit and the first log difference of lpc. All the explanatory variables have been normalized with GDP before transformation and we take the log first difference of them. Here we use a table to summarize them.

Table 1: Overall discription.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Obervations	Assignment	mean	sd	min	max
year	1,736	Time	1,940	42.18	1,870	2,008
crisisST	1,736	Financial crisis	0.0449	0.207	0	1
ccode	1,736	Country code	7.500	4.032	1	14
loansgdp	1,496	Bank loans/gdp	0.491	0.401	0.0157	2.504
credgdp	1,445	Bank assets/gdp	0.885	0.602	0.0550	4.460
moneygdp	1,576	Broad money/gdp	0.593	0.232	0.180	1.458
loansmoney	1,475	Bank loans/broad money	0.803	0.472	0.0478	2.410
credmoney	1,417	Bank assets/broad money	1.453	0.696	0.169	4.217
lloansmoney	1,475	Log of loans/money ratio	-0.412	0.665	-3.042	0.880
lcredmoney	1,417	Log of credit/money ratio	0.254	0.512	-1.777	1.439
lm	1,596	Log of broad money	6.871	4.300	-2.579	18.87
lnm	1,635	Log of narrow money	5.520	4.320	-3.650	17.77
lloans	1,506	Log bank loans	6.574	4.387	-2.581	18.71
lcred	1,455	Log bank assets	7.411	4.391	-2.198	19.14
pre45	1,736	Dummy for pre 1945	0.508	0.500	0	1
post45	1,736	Dummy for post 1945	0.492	0.500	0	1
lrgdp	1,736	Log real gdp	8.678	0.891	6.603	10.34
lpc	1,696	Log of CPI price level	1.495	4.874	-25.22	5.245
DL_loansgdp	1,454	Log first difference of loansgdp	0.0216	0.0752	-0.310	0.438
DL_cred	1,416	Log first difference of cred	0.0784	0.0745	-0.256	0.563
DL_pc	1,654	Log first difference of pc	0.0220	0.0532	-0.218	0.331

From table 1, we were able to find similar features to those in Schularick and Taylor [5]. The mean ratio of credit to GDP or money and the mean ratio of loans to GDP or money have all increased after World War Two (WW2). The growth rate of the credit to GDP ratio increased from 4. 19% before WW2 to 10.5% after WW2, and the growth rate of the ratio of loans to GDP ratio increased from 1.47% before WW2 to 2.7% after WW2. When comparing these two, we can see that credit grew much more rapidly than loans. Other than loans and credit, we found that the growth rate of GDP increased from 1.48% per cent to 2.67 per cent. Inflation increased from almost -0.2% to 5.5%. The findings are consistent with Schularick and Taylor’s (2012) conclusion that the world’s behaviour toward money and loans notably changed after WW2 [5]. A more detailed analysis of the change before and after WW2 is found below.

We have calculated the mean of the variables from these 14 countries for each year and then plotted the results. These figures show more detailed features of how loans, credit, and money flows. Here we created two graphs: figure 1 contains the data of loans to GDP ratio, credit to GDP ratio, and money to GDP ratio, and figure 2 contains the data of log of loans to money ratio and log of credit to money ratio. From the graph, we see that all three ratios increased steadily and relatively slowly until the credit boom and the Great Depression. Starting from the 1930s, credit and loans collapsed. Although we don’t have the data from WW1 and WW2, we can see that both the growth rate of loans and credit to money ratio decreased to negative before 1950. After WW2, the banking system has

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changed after the collapse, which results in a rapid increase in loans and credit to GDP ratios until 2008, while the money to GDP ratio remains relatively steady. We can see from the second graph that the loans and credit to money ratio reached a higher level than pre-1945. Because of that, we decided to make 1945 a separate point to divide our data into two parts. This provides a more detailed picture of how banks' loans and credit flows and enables a closer examination as to why statistics were so different before and after WW2. We want to see which variable caused financial crises and whether it is the same for pre and post-1945.

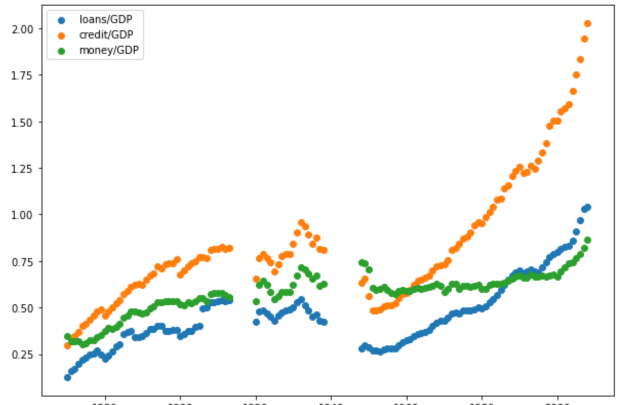

Figure 1: loans/GDP & credit/GDP & money/GDP.

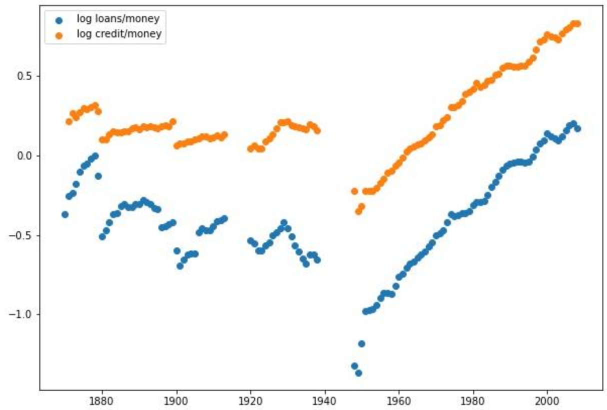

Figure 2: log loans/money & log credit/money.

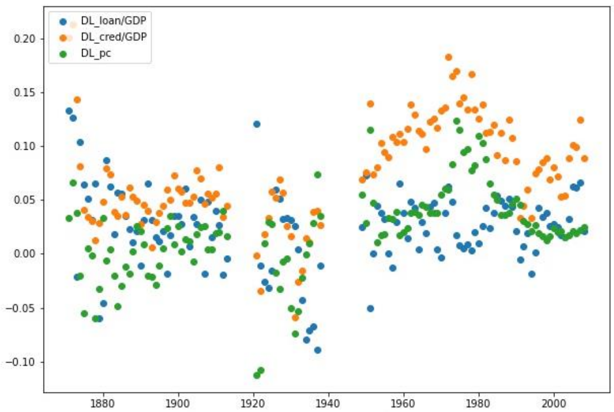

Figure 3: DL_loan/GDP & DL_cred/GDP & DL_pcf.

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Here, we also plot figure 3, which is the growth rate of loans to GDP ratio, credit to GDP ratio, and inflation,. It further explains the difference between the two periods. The graph has shown that pre-1945 the growth rate of credit to GDP ratio and inflation are lower than post-1945. The growth rate of loans to GDP ratio is similar to pre-1920 and post-1945 and for most of the years the growth rate is above 0, but it is lower between WW1 and WW2. All the increases after WW2 were because of the effect of the Bretton-Woods System, which was launched in 1946, and ideas from neoliberalism. Both of these promote globalization and free trade, which result in a huge increase in credit and loans. All of these may be the reason for different banking systems before and after WW2. However, does such change also affect how we predict financial crisis? Therefore, as we proceed in this paper, we will create the same model for pre- and post-1945 to investigate such differences.

5. Model Construction

Our analysis contains two models: pooled LPM model and the logit model. An important assumption we made here is there is no spillover effect of the financial crisis between countries. For our model, the main existing paper we used for reference is from Schularick and Taylor [5], 'Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870——2008'. We followed the same principle of choosing five lags of our core explainatory variables.

This is the basic layout of our first model, the pooled LPM model.

$$P(crisisST = 1|x)_{it} = \alpha_{0i} + \beta_1 L1.DL_{loansgdp_{it}} \dots + \beta_5 L5.DL_{loansgdp_{it}} + \beta_6 L1.DL_{loansgdp_{it}} + \cdots + \beta_{10} L5.DL_{loansgdp_{it}} + \beta_{11} DL_{pc_{it}} + \cdots + \beta_{15} L5.DL_{pc_{it}} \quad (7)$$

We made some transformations to the explanatory variables at hand. Firstly, we take the log first difference of our variable. We all know that after taking the first difference, the meaning of macroeconomic variables will become the 'growth rate', which is easy for us to interpret. The second point is that we take five lags of the transformed variable respectively. This is because the financial crisis is an economic-financial phenomenon which may last for several periods of time, and it is quite reasonable for us to take the past few periods into account [5]. We evaluated our first LPM. We define a prediction estimator as $\tilde{y}$, and our fitted value $\hat{y}$.

$$\begin{aligned} if\ \hat{y} &\geq 0.5, \tilde{y} = 1 \\ if\ \hat{y} &< 0.5, \tilde{y} = 0 \end{aligned} \quad (8)$$

Here is our outcome for the overall model:

Table 2: overall fitness.

crisisST	success_LPM		
	0	1	Total
0	1106	552	1658
1	45	33	78
Total	1151	585	1736

In the above table 2, the vertical axis is our binary explanatory variable, the horizontal axis is our newly defined prediction estimator, named success_LPM. Through this table, we can calculate that the fitness for '0' is 1106/1658=66.7%, fitness for '1' is 33/78=42.3%, and the overall goodness of fit is (1106+33)/1736=65.6%.

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Following the same procedure, we also calculated our model's fitness for our sub-samples, which respectively use the year 1945 and year 1980 as a dividing line.

Table 3: fitness under different senarios.

results	pre1945	post1945	pre1980	post1980
ability to predict success	0.569	0	0.55	0.11
ability to predict failure	0.468	0.863	0.57	0.818
overall prediction ability	0.475	0.843	0.569	0.785

At first glance, as shown in table 3, we may feel our model has relatively good predictive power as more than half of the above scenarios have over a 50% prediction correctness. However, there still exist some problems.

Table 4: fitness for post1945 LPM model.

crisisST	success_LPM		
	0	1	Total
0	720	114	834
1	20	0	20
Total	740	114	854

Table 5: frequency for dependent variable after 1945

crisisST	Frenquency	percent
0	834	97.66
1	20	2.34
Total	854	100

The first one lies in the significant differences between our data for the crisis. In 1,736 statistical items, the crisis only occurs 78 times, which has quite low frequency compared to the situation when a crisis does not happen. As a result, the accuracy between these two comparing scenarios may differ considerably.

Secondly, according to table 4, we notice that in our post-1945 model, our model's ability to correctly predict crisis happening is 0, which gives no contribution to our prediction analysis, and that there exist 114 wrongly predicted crisis when crisis actually did not happen. Digging into the data, in table 5, we can see that the frequency percentage (i.e. unconditional probability) of crisis that happened is quite low, about 2.34%. This may help explain why the overall predictive power can be quite distorted. What is more, there are also some problems with the distribution of our fitted values.

The second problem is the natural disadvantage of the LPM model originating from its inherent functional form assumption, where we assume a fixed marginal effect. After calculation, there is about 33.7% of the fitted value that is higher than 1 and 10.7% that is lower than 0. This will lead to some trouble for our analysis because we know that probability could only take the value with the range from 0 to 1.

So we move on to our next model, the logit model. Here is the basic layout:

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$$logit(P(crisisST = 1|x))_{it} = \alpha'_{0i} + \beta'_1 L1.DL_{loansgdp_{it}} + \cdots + \beta'_5 L5.DL_{loansgdp_{it}} + \beta'_6 L1.DL_{loansgdp_{it}} + \cdots + \beta'_{10} L5.DL_{loansgdp_{it}} + \beta'_{11} DL_{pc_{it}} + \cdots + \beta_{15}{}' L5.DL_{pc_{it}} \quad (9)$$

With the help of the non-linear transformation undertaken on our dependent variable, we are confident that its value is constrained between 0 and 1. We also give our second model an evaluation, through the ROC curve.

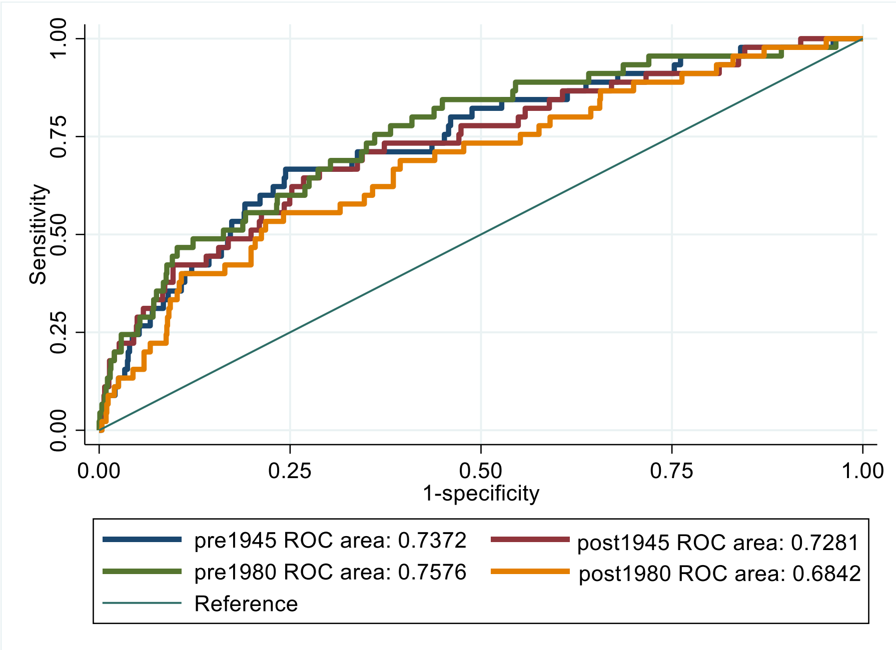

Figure 4: ROC curves for 4 sub-sample logit models.

As can be seen from figure 4, there are four ROC curves. The blue one represents our model using data on the period before 1945 and the red one after 1945. The green and orange ones stand for data before and after 1980 respectively. Put simply, we could specify the value ‘area under the ROC curve’ as an indicator for the appropriateness of the fit for each model. For example, the model based on data after 1980 has the poorest predictive power because it is the lowest lying amongst these four curves. This may be due to issues with data, such as structural breaks or lower frequency of crisis after 1980.

6. Regression results (1945 as a diving line)

First, we analyzed the data set through visualized illustrations to find the variables that may have influenced financial crises before and after World War II. One important conclusion from the data set is that there is a significant change before and after WW2. In figure 5, the ratio of loans to GDP rises rapidly after WW2. The ratio of loans to GDP is a measure of bank assets, and the lower the ratio of loans to GDP, the lower the confidence in investment of the lending parties within the country. We interpret this change in the data being due to the reduced confidence of most countries' in investment due to the impact of World War II on their economies.

The log first difference of bank assets is used to measure the growth rate of bank assets, and figure 6 shows that the growth rate of bank assets increased significantly after WW2. Since bank assets are heavily dependent on uninsured funds, they became more volitile after WW2.

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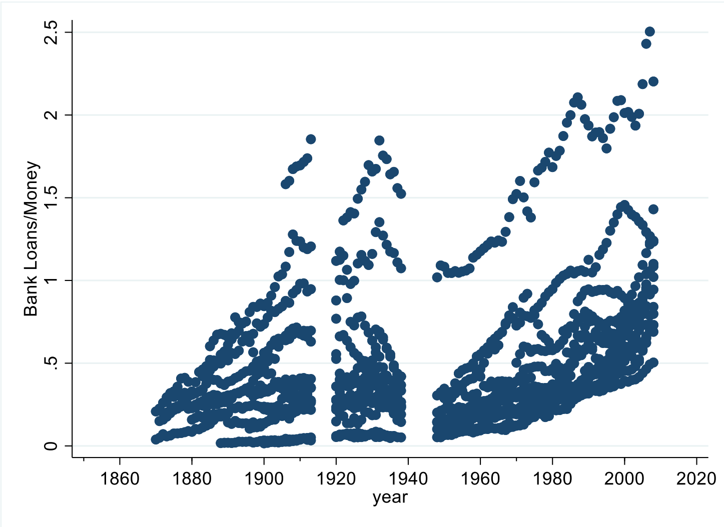

Figure 5: ratio of loans to GDP.

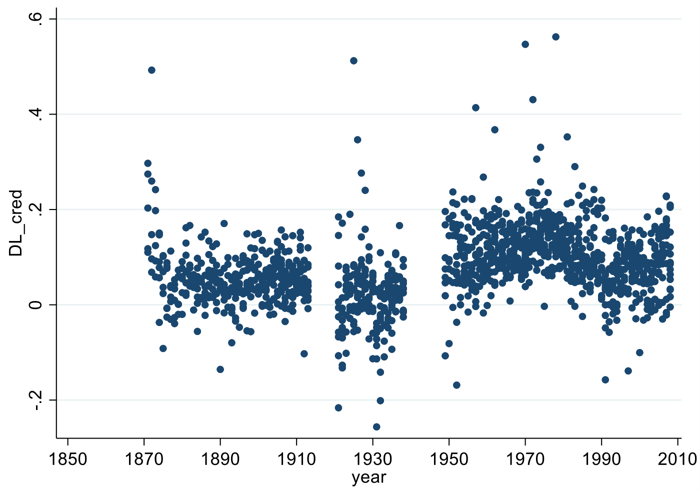

Figure 6: growth rate of bank assets.

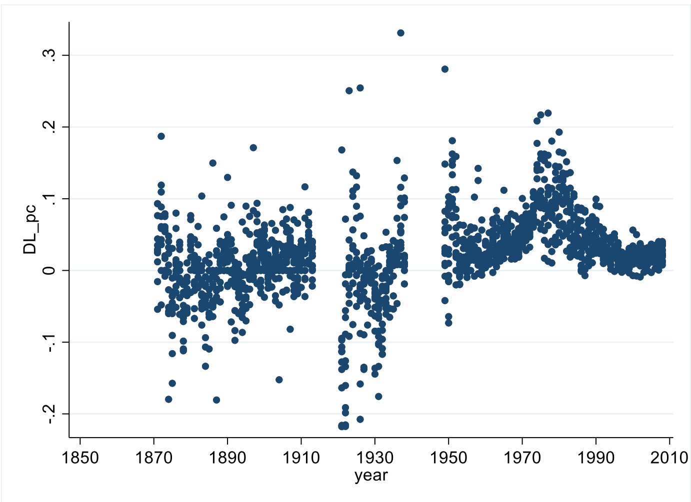

Figure 7: log first difference of the CPI price level.

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The log first difference of CPI price level is often used as a measure of inflation. We can see that after 1950, inflation existed most of the time rather than deflation. In figure 7, the log first difference of the CPI price level is significantly higher after WW2 than before WW2. We think that it is likely that aggressive monetary policy after WW2 caused the rise in inflation.

To examine the different predictive ability of variables towards financial crises before and after WW2, we split the data into 2 sub-samples, using year 1945 as a dividing line. Here is the result.

Table 6: LPM and Logit regression result using 1945 as dividing line.

	LPM before 1945	LPM after 1945	Logit before 1945	Logit after 1945
VARIABLES	crisisST	crisisST	crisisST	crisisST
L.DL_loansgdp	-0.028	0.038	0.443	1.290
	(-0.14)	(0.32)	(0.11)	(0.28)
L2.DL_loansgdp	0.042	0.274**	-0.156	7.926*
	(0.21)	(2.30)	(-0.04)	(1.87)
L3.DL_loansgdp	0.356*	0.240**	7.171*	7.326*
	(1.81)	(2.02)	(1.79)	(1.72)
L4.DL_loansgdp	0.132	0.058	2.969	1.024
	(0.67)	(0.50)	(0.77)	(0.24)
L5.DL_loansgdp	0.127	0.103	2.002	5.085
	(0.68)	(0.91)	(0.55)	(1.16)
L.DL_cred	-0.294	0.018	-3.502	0.287
	(-1.03)	(0.15)	(-0.60)	(0.06)
L2.DL_cred	0.961***	0.145	21.240***	4.347
	(2.94)	(1.18)	(3.17)	(1.10)
L3.DL_cred	-0.156	-0.029	-4.192	0.185
	(-0.48)	(-0.24)	(-0.66)	(0.04)
L4.DL_cred	0.152	-0.002	2.901	1.573
	(0.49)	(-0.02)	(0.49)	(0.36)
L5.DL_cred	0.186	-0.276**	3.188	-11.525**
	(0.65)	(-2.37)	(0.59)	(-2.30)
L.DL_pc	0.193	0.140	1.846	3.455
	(0.47)	(0.43)	(0.21)	(0.28)
L2.DL_pc	-0.277	-0.082	-4.750	-6.559
	(-0.67)	(-0.21)	(-0.51)	(-0.41)
L3.DL_pc	-0.184	0.350	-4.567	15.350
	(-0.45)	(0.94)	(-0.55)	(1.06)
L4.DL_pc	0.208	0.041	2.399	1.412
	(0.57)	(0.11)	(0.34)	(0.10)
L5.DL_pc	-0.693**	-0.128	-11.994**	-7.869
	(-2.23)	(-0.47)	(-2.10)	(-0.69)
Constant	0.013	0.009	-4.429***	-4.468***
	(0.60)	(0.61)	(-7.38)	(-6.78)
Observations	411	740	411	740
R-squared	0.077	0.040		
F test	0.00647	0.0131	0.00469	0.0393
r2_a	0.0415	0.0199	.	.
F	2.184	2.002	.	.

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0. 1

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In Table 6, considering financial crises as cumuliative effects, lag operations have been performed. We use up to five annual lags for each variable to maintain an appropriate lag structure. There are on average 411 pre-WW2 observations and 740 post-WW2 observations in this panel.

Taking the sub-sample before 1945 as an example, our key finding is that the results we have obtained are not very consistent in both models. Firstly, the signs of the estimated coefficients in most cases are different. Even under the circumstances that the sign is the same, the magnitude of the coefficients differs greatly. But one thing that needs to be stated is that almost all the results from the same period across different models share the same significance level, except for the constant term. Quite similar results could be found in the sub-sample of post-1945, but with greater differences. If we take the logit model output as a more reliable result, credit is usually defined as total bank loans deflated by the consumer price index (CPI).

Second, let's focus on the coefficient of L5.DL_pc. It has a negative effect on the happening of the financial crisis, and the effect becomes weaker after WW2, although the latter result is not statistically significant. We assume that this is likely to massive printing of money by governments after WW2 and aggressive monetary policies that led to the rise in inflation. This indicates that the direct relationship between inflation and financial crises is not strong.

Moreover, according to the change of the coefficient of L5.DL_cred, the effect of the growth rate of normalized bank assets is to lower the probability of a financial crisis or, let's say, that the change in the coefficients of L2.DL_cred, the growth rate of bank assets, would not contribute to the occurance of a financial crisis as much as before. According to a study, there is a substantial negative association between inflation and the number of bank assets at low to moderate inflation rates [6]. The number of bank assets declined after WW2 due to rising inflation.

Even though we found in the previous analysis that both models had some predictive power, the model results illustrate the risk of mixing pre-1945 and post-1945 data in trying to build a model. The mechanisms linking our variables, and the financial crisis themselves, do not look very similar in the pre-1945 and post-1945 periods. Therefore, it is risky to include pre-1945 data when predicting future financial crises because the mechanisms that caused them have changed. If the data used includes pre-1945 data, the model will likely be contaminated because of the different economic and financial structures.

7. Regression Results (1980 as a dividing line):

We also ran the same regression but used 1980 as the timepoint to separate the dataset. As we know that during the 1980s the idea of neoliberalism was introduced, we wanted to see whether such a change also affected how we predicted the financial crisis. The table 7 shows the result of our LPM and logit regression. In terms of significance before 1980, the growth rate of loans to GDP ratio at the third lag, the growth rate of credit to GDP ratio at the second lag, and inflation at 5th lag are all statistically significant at less than a 5% significance level. We can therefore determine that all three variables contribute to predicting a financial crisis to some extent. It was interesting that inflation was insignificant until it reaches the 5% significance at the 5th lag, which satisfies the idea that moderate inflation in the short term may decrease bank loans, which decreases the chance of a financial crisis, but when high inflation occurs over the long term it may result in a severe financial crisis.

After 1980, only the growth rate of the loans to GDP ratio at the second lag is statistically significant, which may be interpreted as the loans to GDP ratio being more significant when predicting a financial crisis in such a case. The significant coefficient is completely different pre- and post-1980, due to the banking system being completely different within these time frames. We know that during the 1980s the ideas of neoliberalism were introduced, and that the global market and free trade has been promoted. This resulted in more transactions between countries and more loans being created compared to GDP. Also, as inflation also goes up, peoples' standards of living rise. Therefore,

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people start to borrow more, which causes loans to be even higher. This may be the reason why loans take on such an important role after 1980. Thus, we can say that all three variables contribute to financial crises to some extent before 1980, and that loans take on a much more significant role after 1980. We can also see a similar situation in the sum of five lags regression, which implies that no matter the time, loans are always one of the major variables to be considered when thinking about a financial crisis. In a similar manner as to the pre/post-1945 split, if we want to use such data to predict future financial crises, we can not assume that the banking system is the same before and after 1980, and we must take neoliberalism into account.

Table 7: LPM and Logit regression result using 1980 as dividing line.

VARIABLES	LPM before 1980 crisisST	LPM after 1980 crisisST	Logit before 1980 crisisST	Logit after 1980 crisisST
L.DL_loansgdp	0.033	-0.163	3.444	-6.052
	(0.29)	(-0.71)	(0.98)	(-0.99)
L2.DL_loansgdp	0.121	0.494**	2.943	12.709**
	(1.02)	(2.21)	(0.86)	(2.23)
L3.DL_loansgdp	0.278**	0.336	7.669**	5.570
	(2.36)	(1.50)	(2.15)	(1.10)
L4.DL_loansgdp	0.114	0.035	3.563	0.589
	(1.00)	(0.16)	(1.04)	(0.10)
L5.DL_loansgdp	0.179	0.046	4.954	3.635
	(1.63)	(0.22)	(1.47)	(0.56)
L.DL_cred	-0.236*	0.214	-8.441*	6.272
	(-1.73)	(0.93)	(-1.84)	(1.02)
L2.DL_cred	0.397**	0.168	10.659***	3.984
	(2.52)	(0.78)	(2.80)	(0.66)
L3.DL_cred	-0.217	0.167	-6.422	7.462
	(-1.38)	(0.77)	(-1.28)	(1.46)
L4.DL_cred	0.001	0.094	1.538	4.360
	(0.01)	(0.43)	(0.35)	(0.81)
L5.DL_cred	-0.033	-0.341	-2.588	-11.247*
	(-0.23)	(-1.59)	(-0.57)	(-1.66)
L.DL_pc	0.176	0.098	8.228	-3.215
	(0.72)	(0.13)	(1.13)	(-0.17)
L2.DL_pc	-0.179	-0.221	-5.207	-7.442
	(-0.68)	(-0.24)	(-0.64)	(-0.28)
L3.DL_pc	-0.041	0.293	-3.424	4.987
	(-0.16)	(0.33)	(-0.43)	(0.19)
L4.DL_pc	0.216	0.546	4.145	15.413
	(0.92)	(0.64)	(0.63)	(0.65)
L5.DL_pc	-0.491**	-0.889	-12.486**	-24.243
	(-2.46)	(-1.47)	(-2.40)	(-1.48)
Constant	0.032**	0.010	-3.827***	-4.564***
	(2.52)	(0.42)	(-9.05)	(-5.79)
Observations	745	406	745	406
R-squared	0.047	0.070		
F test	0.00191	0.0178	0.00294	0.0165
r2_a	0.0279	0.0339	.	.
F	2.422	1.949	.	.

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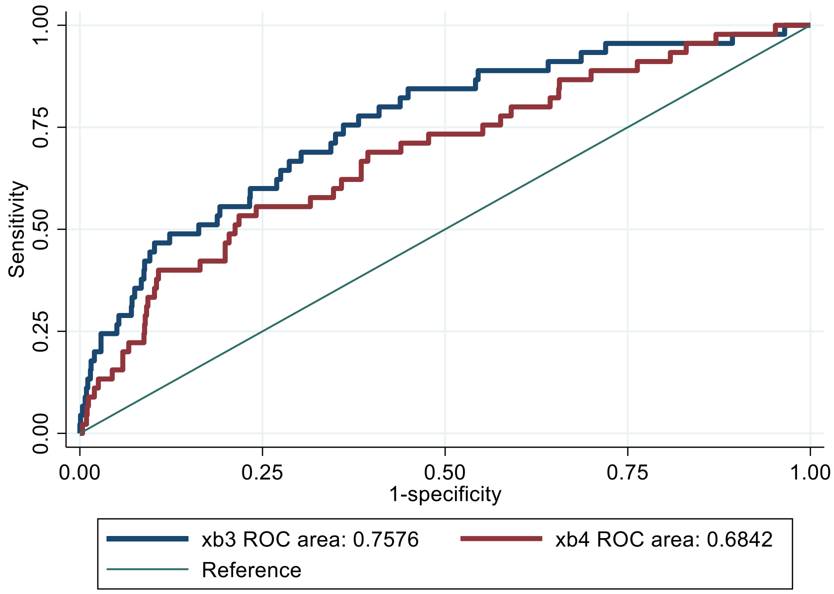

Figure 8: ROC curves for sub sample using 1980 as dividing line.

To determine the predictive power of the model, we've created the graph of the area under the ROC curve for our logit model that we have introduced before. The figure 8 above shows us the model prediction power for data before and after 1980s. For the data before 1980, the AUROC value is 0.7526, and for the data after 1980, AUROC value is 0.7051. What this graph shows is that for both models, the predictive performance of a classifier is better than coin toss (0.5), but it's still far from perfect model (1). The pre-1980 model has better predictive performance than the post-1980 model. This may be due to the fact that only a few financial crises happen after 1980: and there is much less observance of them than pre-1980. However, when comparing the predictive performance for the model pre- and post-1945, the post-1980 model was not a failure. Although we may not use such model as prediction model for financial crisis in the future, it still contains reference value.

8. Discussion

However, it has to be acknowledged that our models have some limitations. First, as we all know, the factors that cause financial crises are very complex, and when constructing the model, we have only chosen three variables that are relatively important in predicting a financial crisis. There are thus some omitted variables, which may have a great impact on the accuracy of our model. Secondly, some important information about a particular country or region may be missing in the aggregated model. For example, the political situation or the legal system of a country may lead us to underestimate the likelihood of a crisis. Thirdly, in analyzing the impact of globalization on the prediction model, we chose data for the periods 1870–1980 and 1980–2008. The reason for choosing data between 1870–1980 instead of 1945–1980 is because a financial crisis itself is a low probability event, and the period 1945–1980 has less data: some countries did not experience a financial crisis between 1945 and 1980. However, the years 1870–1980 included the Second World War. Based on previous analysis of the model results, we know that the mechanisms linking our variables and financial crises are not similar before and after the war and it is risky to mix pre-1945 and post-1945 data. Therefore, the model pre-1980 is likely to be contaminated by different structures of data.

Finally, financial crises have a time effect and often involve multiple countries. Thus when a financial crisis occurs, there is propagation from country to country. Since there is no way to predict

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this time effect in advance, we ignore the time effects of financial crises and the interactions between countries when building our model.

We would like to also give some consideration to the causality problems in our analysis. Since we cannot ensure that the data we have is derived from a randomized experiment, we could not say with one hundred per cent certainty that the explanatory variables we have chosen will affect the probability of the occurrence of a financial crisis. What is more, another issue that casts a shadow on our analysis is reverse causality. Take the variable of the inflation rate as an example: we do not know whether the high rate of inflation will cause a financial crisis or the financial crisis will increase a country's inflation level. Finally, we are not sure about whether inflation could be a proxy for some other factor, such as competitiveness or exchange rate voltality, which also adds some uncertainty to the intepretation of the results. These are the problems that remain to be solved in the future.

9. Conclusion

Although some variables do have a great impact on increasing the risk of a financial crisis, we can not say that we can predict it. Because the financial is a random event, it is not possible to precisely take into account all the variables and use the accurate format of mathematical methods.

Relevant policy advice can be found in some literature. An article written by Villacorta and Unite in a PASCN(i.e. Philippine APEC Study Center Network) Discussion Paper published in 1999 mentioned a related concept to APEC (i.e. Asia-Pacific Economic Cooperation): the ECOTECH, which focuses on human resources development, technological upgrading and infrastructure improvements, and wider outreach to SMEs (i.e. small and medium enterprise) [7]. The ECOTECH is designed to strengthen APEC's resilience and competence in restoring regional stability and trust. Aside from creditworthiness and political concerns, a lack of experience in administering these approaches is a barrier that several developing economies have in implementing this new system [7]. ECOTECH activities can help less-developed economies take advantage of private-sector resources for financing developmental projects by exchanging experiences, best practices, and policy dialogues [7]. A similar policy could be adopted to enhance the knowledge and experience transmission between economic groups to alleviate the consequences of financial crises.

The second method is through creating a new liquidity tool like the Term Auction Facility, a new liquidity facility introduced by the Federal Reserve, that greatly reduced the stresses in the money market, especially by reducing banks' liquidity concerns [8]. However, its impact on counterparty risk premiums has been minimal [8].

Another study carried out by Alfaro and Chen [9] looked at how businesses responded differently to the global financial crisis, with a focus on the significance of foreign ownership [9]. They explored how multinational subsidiaries around the world responded to the crisis in comparison to local establishments, using a global establishment panel dataset [9]. The paper determined that on average multinational subsidiaries outperformed local counterfactuals with similar economic features [9]. Also, among multinational subsidiaries, those with deeper vertical production and financial ties to their parent companies fared better [9]. Consequently, policymakers could think of suggestions like enhancing foreign direct investment to establish some factories in foreign countries to alleviate the consequences of the financial crisis.

However, it can be hard for policymakers to relieve the consequences of a financial crisis. Because the crisis has been viewed heterogeneously in different contexts and has been objectively extremely different in nations – like Germany and Sweden when compared to the United States – the varying starting places for the various regimes mean that policy and governance options available to them, as well as the expectations placed on them, are vastly different. Lastly, there is also a lack of new ideas when faced with the emergence of new paradigms [10].

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