What is really common in the run-up to banking crises?

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\textbf{ABSTRACT}

Arguing that crises are similar if they are predictable from historical experience, we employ panel logit models to examine similarities in the run-ups to the current global financial crisis and historical banking crises. Asset bubbles are the most common precursors.

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1. Introduction

Attempts to find the causes of the global financial crisis and to address the urgent policy issues associated with it have often looked back in history to find the “common” factors that triggered previous financial crises. An early inquiry was made by Reinhart and Rogoff (2008) (henceforth RR)\textsuperscript{1} immediately after the signs of the US subprime market collapse in late 2007. They found that post-war advanced economy banking crises share striking similarities in the run-up of GDP growth, asset prices, public debt and capital flows. Other analyses followed as the subprime crisis deepened in 2008 and similar systemic crises appeared in other countries (see Roubini and Mihm, 2010, and references therein).

Indeed, an understanding of the similarities of historical financial crises led a few researchers to see the current episode before the fact. For example, Shiller (2005, pp. xiii–xiv and ch. 2, 7) argued that similar to the recent historical financial booms in many countries, including Japan, Finland, Norway and Sweden in the late 1980s, the most recent equity and housing booms in the United States and other countries, not being supported by real fundamentals, would also implode. But this time it would result in a world-wide recession that might last as long as Japan’s “lost decade”.

This paper examines similarities of the current global crisis and historical banking crises. It is motivated by the analyses of RR (2008, 2009), inter alia, and the lack of strong statistical evidence in the literature for the robustness of comparisons of alleged similarities. Arguing that crises are similar in a robust sense if they are predictable from similar histories, we employ panel logit models in order to examine both similarity and predictability of banking crises. In this, we follow the literature on predicting banking crisis by Demirguc-Kunt and Detragiache (1998), Davis and Karim (2008) and others.

In Section 2, we propose two important criteria for demonstrating crisis similarity. In Section 3, we employ panel logit models and examine, based on the same criteria, the robustness of crisis similarities that RR (2008, 2009) and others suggest.

2. Criteria for crisis similarity

2.1. Criterion 1: conditional probability of a certain behavioral pattern given a crisis

While examining crisis similarity with an indicator, the primary question is whether the indicator has similar “run-ups” to most...
currencies. For example, soaring house prices might be quite common over a few years before most banking crisis episodes. This, of course, amounts to asking: what is the probability “conditional” on a crisis that an indicator would behave in a certain way in a given period prior to a crisis?

2.2. Criterion 2: conditional probability of a crisis given a certain behavioral pattern

To understand the similarities (or dissimilarities) of the underlying dynamics that triggered the crises, it is also important to know how the same indicators generally behave in a relatively tranquil period. If an apparent behavioral pattern over a few years prior to the crises is more frequent in relatively tranquil periods, then we are unable to infer a distinctive similarity across crisis incidents based on that pattern. Thus, we should also ask: what is the conditional probability of a crisis given a certain behavioral pattern of an indicator?

2.3. Similarity and predictability

The literature on predicting financial crises suggests that Criterion 1 and Criterion 2 for inferring crisis similarity are also two essential criteria for the predictability of crises. Kaminsky et al. (1998), Berg and Pattillo (1999), and several other authors examine predictability of currency crises. On the other hand, Demirguc-Kunt and Detragiache (1998) and Davis and Karim (2008), inter alia, examine the predictability of banking crises. The most important criteria for assessing an early warning system adopted in the literature are:

(i) Percentage of observations in a reference period prior to a crisis correctly identified.

(ii) True alarms as a percentage of total alarms for a crisis.

To understand these are also Criterion 1 and Criterion 2 conditional probabilities discussed above, we note that a high percentage of observations in a given reference period prior to a crisis will be correctly identified if, equivalently, an identified behavioral pattern of an indicator (or the combined effect of certain changes of a set of indicators) prior to a crisis is common enough so that the conditional probability of such a behavioral pattern given a crisis is high. Also, true alarms as a percentage of total alarms will be high if, equivalently, the chances of a crisis are high after such a behavioral pattern (upon which an alarm is issued) is observed.

2.4. Choice of model

It follows that the robustness of crisis similarities should be inferred based on their predictability. Thus, to see if the apparent similarities of crises are robust, we first need to choose an early warning system for financial crises. We choose the approach based on logit and probit models, since some recent findings (e.g. Berg and Pattillo, 1999 and Davis and Karim, 2008) suggest that among several alternatives, this approach yields relatively greater prediction accuracy with cross-country data. This is, therefore, our approach in the next section to answer the main question asked in this paper.

3. Are the current global crisis and historical banking crises similar?

3.1. Model and evaluation criteria

Following Demirguc-Kunt and Detragiache (1998) and Davis and Karim (2008), we adopt, in particular, logit models\(^2\) to test predictability – and hence similarities – of banking crises. Adopting the same reference period as in RR (2008, 2009), we ask if such a crisis can be predicted to occur within a period of four years. Accordingly, we label the four observations immediately preceding any crisis episode as “pre-crisis” observations and all other observations as “tranquil”. The dependent variable representing crisis probability takes on the actual value one when the observation is “pre-crisis” and zero when the observation is “tranquil”. In a prediction exercise, we classify an observation as “pre-crisis” (i.e., a crisis is predicted to occur in four years) if the estimated crisis probability exceeds a pre-specified threshold value. An observation is classified as tranquil otherwise. In order to avoid any potential bias toward predictability of either pre-crisis or tranquil observations, we choose the threshold value as 50%.

Indeed, an alarm can be true or false. If a crisis follows an alarm within four years then the alarm is true. Otherwise, an alarm is false. Hence, in light of the discussion in Section 2, the prediction accuracies are determined by:

(i) Percentage of “pre-crisis” years correctly called.

(ii) False alarms as a percentage of total alarms.

3.2. Data and sample

We consider the same post-war historical crisis episodes in advanced countries as in RR (2008), and estimate several bivariate and multivariate panel logit models and check the accuracy of within sample (1967–1994) predictions. Then, similarities of the current global crisis and historical crises are inferred by how accurately the current episode is predicted out of sample. For this purpose, we consider a representative sample consisting of the severe and systemic crises in the US, UK, Spain and Ireland during 2007–2008. Since the last historical crisis episode was in 1995 (UK), the period for out of sample forecasts should be 1996–2007.

While we select the variables with reference to the emerging literature on the causes of the global financial crisis and the literature on predicting banking crisis, our choice, nonetheless, is limited by the availability of data for countries in the sample. We consider six indicators: (i) current account as a percentage of GDP (CA); (ii) public debt as a percentage of GDP (PD); (iii) growth rate of per capita real GDP (GGDC); (iv) real interest rate (RINT); (v) real share price (RSP); and (vi) real house price (RHP).

All data are annual. Due to missing observations, in order to eliminate any potential bias from any particular country data, we make the sample distribution symmetric by including only ten observations prior to any crisis episode in the estimation sample. Further, to eliminate issues of scale across crisis experiences, the data is normalized so that the observations related to any crisis range from zero to one.

3.3. Results and discussion

The results from bivariate and multivariate logit model specifications, where the dependent variable is the probability of crisis, are reported in Table 1. In the bivariate specifications (1 through 6), all indicators have the expected signs, and all coefficients, except that of PD, are significant in lesser or greater measure. We note that this is consistent with the general findings in the literature on predicting banking crisis (see Section 2.3), where INT and GGDC are found to be contributing to the probability of banking crisis and variables similar to PD are found to be insignificant. Considering the fact that the formation and inflation of a housing bubble is closely associated with increase in private sector debt, the significance of RHP herein parallels a similar finding by Demirguc-Kunt and Detragiache (1998) that an increase in the ratio of private sector debt to GDP\(^3\) raises the probability of banking crisis.

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\(^2\) The logit model better captures non-Gaussian processes with fat tails. We also examined several probit specifications and the results were very similar.

\(^3\) As in RR (2008), we did not include this variable due to insufficient data for most countries in the sample.
Table 1
Panel logit model: coefficient estimates (P-values in parentheses) and within sample and out of sample prediction performance.

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<tr>
<td>Coefficient estimates</td>
<td>-</td>
<td>-0.54 (0.07)</td>
<td>-</td>
<td>-1.31 (0.00)</td>
<td>-1.91 (0.00)</td>
<td>-1.96 (0.00)</td>
<td>-5.50 (0.00)</td>
<td>-4.23 (0.00)</td>
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<tr>
<td>Constant</td>
<td>-</td>
<td>-0.54 (0.07)</td>
<td>-</td>
<td>-1.31 (0.00)</td>
<td>-1.91 (0.00)</td>
<td>-1.96 (0.00)</td>
<td>-5.50 (0.00)</td>
<td>-4.23 (0.00)</td>
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<tr>
<td>Current account as a percentage of GDP (CA)</td>
<td>-0.54 (0.05)</td>
<td>1.55 (0.05)</td>
<td>0.80 (0.27)</td>
<td>0.79 (0.27)</td>
<td>1.55 (0.05)</td>
<td>0.80 (0.27)</td>
<td>0.79 (0.27)</td>
<td>1.55 (0.05)</td>
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<tr>
<td>Public debt as a percentage of GDP (PD)</td>
<td>0.47 (0.33)</td>
<td>-2.10 (0.02)</td>
<td>-2.21 (0.01)</td>
<td>-2.10 (0.02)</td>
<td>-2.21 (0.01)</td>
<td>-2.10 (0.02)</td>
<td>-2.21 (0.01)</td>
<td>-2.10 (0.02)</td>
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<tr>
<td>Growth rate of per capita real GDP (GGDC)</td>
<td>-0.33 (0.20)</td>
<td>-2.10 (0.02)</td>
<td>-2.21 (0.01)</td>
<td>-2.10 (0.02)</td>
<td>-2.21 (0.01)</td>
<td>-2.10 (0.02)</td>
<td>-2.21 (0.01)</td>
<td>-2.10 (0.02)</td>
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<tr>
<td>Real interest rate (RINT)</td>
<td>-2.10 (0.02)</td>
<td>-2.21 (0.01)</td>
<td>-2.10 (0.02)</td>
<td>-2.21 (0.01)</td>
<td>-2.10 (0.02)</td>
<td>-2.21 (0.01)</td>
<td>-2.10 (0.02)</td>
<td>-2.21 (0.01)</td>
</tr>
<tr>
<td>Real share price (RSP)</td>
<td>1.97 (0.00)</td>
<td>3.50 (0.00)</td>
<td>3.50 (0.00)</td>
<td>3.50 (0.00)</td>
<td>3.50 (0.00)</td>
<td>3.50 (0.00)</td>
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<tr>
<td>Real house price (RHP)</td>
<td>3.50 (0.00)</td>
<td>4.61 (0.00)</td>
<td>4.61 (0.00)</td>
<td>4.61 (0.00)</td>
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<tr>
<td>Log likelihood</td>
<td>-102.09</td>
<td>-101.87</td>
<td>-103.15</td>
<td>-95.56</td>
<td>-82.29</td>
<td>-82.96</td>
<td>-59.28</td>
<td>-61.22</td>
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<tr>
<td>Sample size</td>
<td>150</td>
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**Within sample prediction**

Threshold probability = 50%

| Percentage of pre-crisis years correctly called | 0 | 0 | 0 | 47 | 66 | 67 | 75 | 75 |
| True alarms as a percentage of total alarms   | No alarms | No alarms | No alarms | 58 | 72 | 65 | 81 | 81 |

**Out of sample prediction**

Threshold probability = 50%

| Percentage of pre-crisis years correctly called | 0 | 0 | 0 | 13 | 100 | 94 | 100 | 100 |
| True alarms as a percentage of total alarms   | No alarms | No alarms | No alarms | 88 | 37 | 88 | 40 | 42 |
Looking at the in-sample prediction results, \textit{RINT} predicts only 47\% of the pre-crisis periods with 58\% true alarms, while \textit{CA}, \textit{PD}, and \textit{GGDC} completely fail to generate any alarm. In contrast, for the same within sample exercise, \textit{RSP} and \textit{RHP} correctly predict 66\%–72\% of the pre-crisis years and generate alarms that are true 65\%–72\% of the time. Thus, of all indicators recently examined in the literature on global financial crisis, only \textit{RSP} and \textit{RHP} demonstrate robust similarities in the run-up to historical crises, while \textit{RINT} is somewhat important in this respect. In other words, prior stock and housing bubbles – often caused by wishful thinking of unending price increases – are common to most banking crises. This is also suggested by Shiller (2005) and the historical account of Kindleberger and Aliber (2005).

The out-of-sample prediction results with specifications 1 through 6 suggest that the current global crisis and historical banking crises are also most similar in terms of prior stock and housing bubbles. Again, no alarms are generated with specifications 1–3. And, here, specification 4 also fails almost completely. But, specifications 5 and 6 correctly predict 94\%–100\% of the pre-crisis years. However, since the percentage of true alarms, 88\%, with specification 6 is much higher than that with specification 5, 37\%, the case for \textit{RHP} as the predominant indicator for crisis similarity is indeed much stronger.

Specification 7 of the multivariate model retains significance and signs of all coefficients from the bivariate specifications, except that of \textit{CA} which now has the wrong sign. We find that \textit{CA} and \textit{RHP} are strongly correlated (the ratio being −0.50), indicating a potential multicollinearity problem. Granger causality test results suggest that if there is any causality in this regard for any country, it runs from \textit{RHP} to \textit{CA} rather than in the reverse direction. Thus, the increasing \textit{RHP}, and not a negative and falling \textit{CA}, is the primary factor for most banking crises—contrary to what many have suggested. This conclusion is confirmed by specification 8—despite \textit{CA} being excluded, the signs and significance of other coefficients and the prediction accuracies are essentially the same as those of specification 7.

The within sample prediction results from specifications 7 and 8 are better than those from the bivariate specifications, indicating that the confluence of several adverse forces explains the historical crises better. We find that 75\% of the pre-crisis years are correctly called by both specifications, while 80\%–83\% of the alarms are true. However, in the out of sample exercise, while 100\% of the pre-crisis years are correctly identified by both specifications, only 40\%–42\% of the alarms are true—much smaller than what was obtained with specification 6 and almost the same as that obtained with specification 5. These results, therefore, unambiguously speak for our earlier conclusion: prior housing bubbles, and to a lesser extent prior stock bubbles, make the current global financial crisis look like the historical banking crises. This, of course, confirms Shiller’s (2005, pp. xiii–xiv and ch. 2, 7) prescience regarding the global financial crisis that followed from the observations of rapid surges of home prices of the early 2000s in the US and other countries and of the historical boom–bubble–bust cycles of asset markets.

\textbf{Acknowledgment}

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\textbf{Appendix. Supplementary data}

Supplementary material related to this article can be found online at doi:10.1016/j.econlet.2011.07.007.

\textbf{References}


