Banking crises: Identification, propagation, and prediction
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Document Version
Publisher's PDF, also known as Version of record

Publication date:
2015

Link to publication in University of Groningen/UMCG research database

Citation for published version (APA):

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Chapter 6

Conclusions

This thesis focuses on the identification, propagation, and prediction of banking crises and on the relationship between banking and currency crises. In particular, the thesis addresses the following four research questions:

1. How to identify a (systemic) banking crisis timely using higher-frequency data than usually analysed in the literature?

2. What is the lead-lag relationship between currency and banking crises? And does the usage of different proxies affect the conclusion?

3. Is the spread of financial turbulence in the banking system across countries due to spillover or interdependence effects?

4. What type of model predicts bank failures more correctly, the logit model or data mining models?

Chapter 2 answers the first research question and constructs a Money Market Pressure Index to identify banking crises. In our view, the advantages of such an index are that it is less subjective, available at a higher frequency (several countries are not included in the most widely used crises databases) and timelier (as it relies on less information). We modify the Von Hagen-Ho index and apply it to a large set of countries, excluding countries with a repressed financial system. The main change is that in our modified index nominal interest rates are used instead of real interest rates as the former better capture money market stress, notably in developing
countries. To avoid sample selection bias, our sample includes not only countries that suffered from one or more banking crises but also includes countries without banking crises. Our sample consists of 109 countries (21 industrial economies and 88 developing economies). We employ the database of banking crises of Laeven and Valencia (2010) for comparison purposes. Our findings suggest that our preferred index outperforms the index of Von Hagen and Ho (2007). The crises identified by our MMPI are more in line with the crises identified by Laeven and Valencia (2010), while the index also gives fewer ‘false alarms’. This conclusion is robust when we use different groups of countries, different periods and different time windows. We also find that money market pressure indexes, be it the original index of Von Hagen and Ho (2007) or our modified index, suggest many more banking crises than those included in the database of Laeven and Valencia (2010). We argue that most of the ‘false alarms’ are crises missed by Laeven-Valencia, crises not severe enough to be considered as systemic by Laeven-Valencia, or reflect stress in the banking sector. Finally, we show that the 98.5% threshold used in the Von Hagen and Ho decision rule corresponds to a policy maker who dislikes ‘false alarms’ relative to ‘missed crises’.

Chapter 3 addresses the second research question and investigates the dynamic relationship between currency and banking crises in 94 developing and emerging countries using quarterly data from 1980 to 2010. Quarterly data enable to clarify the lead-lag relationship even when the two crises occur in the same year. The novelty of this chapter is that we proxy the two crises in four ways. First, we use two continuous variables, namely the Exchange Market Pressure Index (EMPI) and the modified Money Market Pressure Index (MMPI) of Chapter 2, to proxy currency and banking crises, respectively. Then, we convert the two continuous variables into multi-categorical variables, distinguishing very deep crises, deep crises, mild crises and tranquil periods. Third, we convert EMPI and MMPI into dummy variables, adopting the decision rules of Eichengreen, Rose and Wyplosz (1996a) for currency crises and of Von Hagen and Ho (2007) for banking crises. Finally, we use the Laeven-Valencia database as an alternative proxy of banking crises in combination with the dummy variable based on EMPI for currency crises. For sensitivity tests, we added time fixed effects variables and split the sample into emerging and developing
countries. The results show that in most cases currency crises tend to lead banking crises and vice versa which is robust for using different periods and different samples of countries. This conclusion differs from those of most previous studies, but is similar to that of Kaminsky and Reinhart (1999). However, lagged banking crises do not lead currency crises robustly when we proxy the banking crises by dummies based on the market pressure index. The reason might be that the dummy based on MMPI can identify the onset of a banking crisis, but fails to identify for how long the crisis lasts. For instance, the average length of each banking crisis identified by the dummy based on MMPI is 1.28 quarters which is far shorter than the 10.85 quarters identified in the Laeven-Valencia database. In addition, currency crises have strong state dependence, indicating that countries which experienced a currency crisis in the past are more likely to face another currency crisis, but this does not hold for banking crises.

For policy implications, policy measures for avoiding a banking (currency) crisis have the additional benefit of decreasing the probability of the other crisis. In other words, steps to enhance the stability of banking sector may reduce the probability of a currency crash; measures used for promoting exchange rate stability may support a stable banking system.

Chapter 4 focuses on the third research question and investigates interdependence and spillover effects of financial turbulence across countries during the last decade. Since propagation is characterized by spatial dependence, we apply a spatial panel data model with spatial fixed effects to investigate the propagation of the two effects across countries. In this chapter, three transmission channels are considered, namely trade, foreign claims, and distance. Our sample contains annual data of 40 countries from 2003 to 2010. Our results suggest that financial turbulence has a significant interdependence effect across countries through the trade and distance channels, while a significant spillover effect through the capital flows channel is also identified. Our results also suggest that the capital flows channel issues a better description than the other two channels of financial turbulence propagation. Finally, the economic fundamentals considered also have robust spillover effects across countries but no interdependence effects. Notably foreign inflation has robust spillover effects on domestic financial turbulence through all three channels.
Chapter 5 focuses on the final research question and compares the performance of the logit model and data mining models in predicting bank failures in the United States during 2002 to 2010. In the empirical investigation, we start with 16 financial ratios and 16 corresponding rates of change. We collect 293 bank failures in the United States during 2002 to 2010 and then create a match-pair sample by the selection rules: (1) near in asset size [-30%, 30%] to the bank that failed in the quarter of failure and (2) located in the same state. We use the data from 2002 to 2009 as the ex post sample, and the data for 2010 as the ex ante sample.

Empirical results show that between the two data mining models, support vector machines predict bank failures better than neural networks. For all three models, the logit model issues more missed failures and false alarms ex post than data mining models, but issues fewer missed failures and false alarms ex ante. This conclusion is robust if we choose another match-pair sample based on the same selection rules. Moreover, the logit model predicts bank failures with accuracy higher than 96%, and predicts banks that did not fail with accuracy higher than 83%.

Economically, the logit model offers a better understanding of the relationship between financial variables and bank failures than the data mining models which enables bank supervisors to supervise banks more efficiently. In addition, the logit model has a higher ability to predict bank failures reducing the expected bailouts cost and minimize the cost to the public. Therefore, the logit model can be used as a decision support tool for detecting bank problems.