Chapter 1

Introduction

1.1 Background and motivation

The past several years have witnessed a very disruptive financial crises that originated in the United States in 2007. Although financial crises are not a new phenomenon, the frequency of financial crises has doubled since the collapse of the Bretton Woods system (Bordo et al., 2001). Notably after the financial liberalization during the 1990s, the intensity of financial crises has increased.

In general, three types of financial crises can be distinguished: banking crises, currency crises and debt crises. Figure 1.1 shows the frequency of three types of crises starting in a given year since 1970 including the recent Global Financial Crisis. The frequencies of all three types of crises are high during the 1976–2000 period and decrease at the beginning of the 21st century. Since 2007 banking crises have become more prominent than the other two types of crises. There is peak in 2008 when 22 countries suffered from a banking crisis.

Recent research suggests that financial crises may have a permanent effect on potential output (Furceri and Mourougane, 2012). Laeven and Valencia (2013) compare the output losses across three types of crises and find that the output losses associated with a banking crisis and a debt crisis are not statistically different, but banking and debt crises are associated with statistically larger output losses than currency crises. Although currency and debt crises are still attracting scholars’ attention, research on banking crises has become more important than before.
Conceptually, definitions of banking crises have been proposed by many scholars (see Chapter 2 for a literature review). However, a serious methodological challenge which researchers face is the identification of (systemic) banking crises. Most studies identify a (systemic) banking crisis based on exceptional events or policy interventions, such as bank closures, deposit freezes and government rescues (cf. Laeven and Valencia, 2008; 2010; 2013; and Reinhart and Rogoff, 2009), which is referred to as the events method. But this methodology may be biased for several reasons (Von Hagen and Ho, 2007). For example, government rescues mostly occur when a crisis has a serious impact on the financial system implying that the start of the banking crisis may have been identified too late.

The proper identification of banking crises hinders research on the causes of banking crises. One important example is the lead-lag relation between currency and banking crises which has attracted a lot of attention since the Asian financial crisis in 1997. Previous papers on this topic (see Chapter 3 for a literature review) typically employ dummy variables as proxies for the occurrence of crises, where 1 denotes a crisis, and 0 a tranquil period. These dummies are derived from a so-called exchange market pressure index or currency depreciation exceeding a particular threshold for currency crises and the events method for banking crises. However, dummy variables may not fully capture the relationship between banking and cur-
rency crises, because there may also be a relationship between the two crises during the process of risk accumulation prior to the crises. In addition, most studies apply annual data and low frequency data makes it difficult to determine which type of crisis occurs earlier if a currency crisis and a banking crisis occur in the same year.

Different from earlier crises, Figure 1.1 shows that banking crises not only affected many countries but also did so within a short period during the Global Financial Crisis. Banking crises spread across countries more easily via strong trade or capital linkages between countries than before with the development of economic and financial globalization. Employing a spatial approach seems to be a suitable approach to investigate the spread of banking crises which can explain how the occurrence of a banking crisis in one country is affected by the occurrence of banking crises in other countries (more details can be found in Chapter 4).

Two mechanisms can explain banking crises propagation, namely spillover effects and interdependence. Forbes (2012) defines spillover effects as a significant increase of the linkages across countries (or markets) after a shock in one country (or market), whereas interdependence is defined as strong linkage between two countries (or financial markets) that exist at all times. To the best of our knowledge, previous research has not analyzed the spread of banking crises differentiating between these propagation mechanisms.

Finally, one important feature of a banking crisis is that many banks are in trouble or are nationalized (Demirgüç-Kunt and Detragiache, 1998). If bank regulators detect problems in individual banks in advance and take timely actions to prevent problem banks from failing, a banking crisis may be mitigated or circumvented. Up to now, various studies have focused on predicting bank failures, but few studies have compared the prediction performance of the logit model and advanced data mining models, such as neural networks and support vector machines. In addition, most studies split the sample into in-sample and out-of-sample randomly. However, prediction models typically use past information to predict bank failures in the future. Thus, ex post and ex ante samples should be distinguished, where ex post stands for past information and ex ante represents future information.
1.2 Research questions

This thesis tries to deal with the limitations in the literature outlined above and contributes to the literature by extending the analysis of identification, propagation, and prediction of banking crises. Specifically, four research questions are investigated in this thesis:

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?

1.3 Methods description

Various methods are employed in this thesis for answering these four research questions. In Chapter 2, we construct a money market pressure index (MMPI) based on central bank reserves and the short-term nominal interest rate to identify banking crises, thereby extending the index of Von Hagen and Ho (2007). Then, we employ the loss function approach of Demirgüç-Kunt and Detragiache (2000) to find out the optimal decision rule in identifying banking crises using our preferred MMPI.

In Chapter 3, we apply continuous variables, namely an Exchange Market Pressure Index (EMPI) and a Money Market Pressure Index (MMPI) to proxy currency and banking crises, and employ Granger causality tests in a fixed effects dynamic panel setting to investigate their dynamic relationship. Then, we summarize the two continuous variables into multi-categorical data, distinguishing between very deep crises, deep crises, mild crises and tranquil periods, and employ fixed effects ordered logit models to analyze the relationship between the two crises. Third, we convert
the two pressure indexes into binary dummy variables, adopting the decision rules provided by Eichengreen, Rose and Wyplosz (1996a) for currency crises and those of Von Hagen and Ho (2007) for banking crises, and employ the logit model with fixed effects to re-examine the relationship between the two crises. Finally, to compare our outcomes with previous research, we use the banking crises database of Laeven and Valencia (2013) in combination with EMPI-based dummies for currency crises and employ the fixed effects logit model to investigate their lead-lag relationship.

The propagation of financial turbulence is characterized by spatial dependence, which is a special case of cross-sectional dependence, in the sense that the structure of the correlation or covariance between observations with different linkages is derived from a specific ordering, determined by the relative position of the observations in trade, capital flows or geographic space. In Chapter 4, we apply a spatial panel data model with spatial fixed effects to investigate spillover and interdependence effects of financial turbulence in the banking system, distinguishing three transmission channels, namely trade, capital flows and distance.

In Chapter 5, we apply the logit model, neural networks, and support vector machines to predict bank failures in the United States from 2002 to 2010. We split the sample into an ex post sample covering data from 2002 to 2009 and an ex ante sample covering data in 2010. Then, we estimate the parameters of the three models on the basis of the ex post sample and evaluate the models’ prediction performance.

1.4 Outline of the thesis

The rest of this thesis is structured as follows. Chapter 2 applies an index to identify (systemic) banking crises. Chapter 3 and Chapter 4 analyze the causes of banking crises from domestic and international perspectives. Chapter 5 investigates the prediction performances of bank failures using the logit model and data mining models. Chapter 6 concludes.

We start with the identification of banking crises as this research question is crucial for further research on banking crises. Without a proper identification of crises, research on the determinants or consequences of crises will be rather futile. Von
Hagen and Ho (2007) claim that the events method is biased and apply real interest rates and central bank reserves to construct a Money Market Pressure Index (MPI) for identifying banking crises based on the idea of liquidity shortages in the money market. However, liquidity shortages affect nominal short-term market rates (Cecchetti and Disyatat, 2010). In addition, existing research suggests that, if anything, inflation has a positive impact on banking crises (cf. Demirgüç-Kunt and Detragiache, 1998) instead of a negative impact as implied by the index of Von Hagen and Ho. Chapter 2 answers the first research question by constructing a money market pressure index (MMPI) based on central bank reserves and the nominal money market interest rates which is different from the index proposed by Von Hagen and Ho (2007). 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. Then, we use the Laeven-Valencia (2010) database of banking crises as a benchmark and compare the performances of two indexes in 109 countries from 1970 to 2010. Results show that the crises identified by MMPI are more in line with the benchmark, and it also identifies fewer banking crises that are not listed in the benchmark than the index of Von Hagen and Ho. Finally, we investigate the banking crisis decision rule with a utility function framework with different weights for missed crises and false alarms.

Chapter 3 deals with the second research question and investigates the lead-lag relationship between currency and banking crises. Davis and Karim (2010) argue that before the outbreak of a crisis, risk is generally being build up. Thus, dummy variables may not fully capture the relationship between banking and currency crises. In this chapter, we use quarterly data for a sample of 94 emerging and developing countries during 1980–2010. Different from earlier studies, we proxy the two types of crises by continuous, multi-categorical and dummy variables based on market pressure indexes, and a dummy variable from the Laeven-Valencia banking crises database to investigate whether the lead-lag relationship between the two types of crises depends on the choice of proxies. In addition, the quarterly data makes it possible to determine which type of crisis occurs earlier if a currency and a banking crisis occur in the same year. Results suggest that in most cases currency crises tend to lead banking crises and vice versa. However, lagged banking crises
do not lead currency crises robustly when we proxy the banking crises by dummies based on the market pressure index. In addition, currency crises have strong state dependence, indicating that countries which have experienced a currency crisis in the past are more likely to face another currency crisis, but this does not hold for banking crises. As sensitivity tests, we added time fixed effects variables and split the sample into emerging and developing countries, but this does not affect our conclusions in this chapter.

Chapter 4 focuses on the propagation of financial turbulence in the banking system across countries during the Global Financial Crisis. Similar to the arguments in Chapter 3, the dichotomous nature of crisis dummies implies loss of information. We use the ratio of non-performing loans to total gross loans as dependent variable. Moreover, we consider three transmission channels: (i) the trade channel, measured by exports and imports between countries; (ii) the capital flows channel, measured by bank lending in one country to residents in other countries; and (iii) distance, calculated by the distance between the capitals of two countries. 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. In addition, the capital flows channel issues a better description than the other two channels in financial turbulence propagation. Finally, foreign inflation has robust spillover effects on domestic financial turbulence through all three channels.

Chapter 5 addresses the final research question and investigates which type of models can predict bank failures better. In this chapter, we split the sample into an ex post part and an ex ante part, where ex post stands for the past information and ex ante represents future information. This chapter applies the logit model, neural networks, and support vector machines to predict bank failures based on 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 define the sample from 2002 to 2009 as the ex post sample to estimate models, and the data in 2010 as the ex ante sample
for out-of-sample tests. Empirical results show that support vector machines predict bank failures ex ante better than neural networks. Moreover, the logit model predicts bank failures less precisely ex post than data mining models, but more precisely ex ante. Specifically, the logit model issues fewer missed failures and false alarms than data mining models ex ante. Finally, the logit model predicts bank failures with accuracy higher than 96% and predicts banks that do not fail with accuracy higher than 83%, indicating that the logit model can be a helpful tool for bank supervisors.

Chapter 6 summarizes the main findings.