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Published in:
International Review of Economics and Finance

DOI:
10.1016/j.iref.2020.03.013

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2020

Link to publication in University of Groningen/UMCG research database

Citation for published version (APA):
de Haan, J., Fang, Y., & Jing, Z. (2020). Does the risk on banks' balance sheets predict banking crises? New evidence for developing countries. *International Review of Economics and Finance*, *68*, 254-268. https://doi.org/10.1016/j.iref.2020.03.013

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Download date: 23-01-2025

International Review of Economics and Finance 68 (2020) 254–268

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Does the risk on banks' balance sheets predict banking crises? New evidence for developing countries

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ARTICLE INFO

JEL classification:
C33
F30
G21

Keywords:
Banking fragility
Balance sheet pro-cyclicality
Early warning models

ABSTRACT

Simulation results of our theoretical model for banks' risk-taking behavior suggest that during booms banks have high non-core liabilities, high leverage and few liquid assets, while the reverse holds during busts. We investigate the predictive power of these bank balance sheet variables for future banking crises using monthly data of 147 developing countries for the period 1980–2016. Our results suggest that low levels of liquid assets and domestic financial liabilities, high levels of foreign liabilities and high financial leverage increase are leading indicators of banking crises. Results are robust when we use different (lags of) dependent variables and control variables.

1. Introduction

Important lessons of the Global Financial Crisis are that the banking sector is pro-cyclical and that its risk-taking behavior during booms sows the seeds for future banking crises (Boissay, Collard, & Smets, 2016; Hahm, Shin, & Shin, 2013). Consistent with Minsky's financial instability hypothesis (Minsky, 1992), empirical evidence suggests that banking crises generally occur after a credit boom (Borio & Drehmann, 2009; Schularick & Taylor, 2012).

Several papers have estimated early warning models for banking crises using credit growth and various other macroeconomic indicators, such as economic growth, interest rates, inflation, the exchange rate, debt ratios, and capital flows (Claessens, Dell'Ariccia, Igan, & Laeven, 2010; Davis, Karim, & Liadze, 2011, Davis & Karim, 2008; Frankel & Rose, 1996; Klomp, 2010; Milesi Ferretti and Tille, 2011; Pedro, Ramalho, & Silva, 2018; Reinhart & Rogoff, 2009; Rose & Spiegel, 2011, 2012; Roy & Kemme, 2012). Other papers focus on the predictive power of bank-level indicators based on the asset side of the bank balance sheet, such as capital adequacy, liquidity and default risk (Barrell, Davis, Karim, & Liadze, 2010; Caggiano, Calice, & Leonida, 2014; Carmona, Climent, & Momparler, 2019; Wong, Wong, & Leung, 2010).

In contrast to the studies listed above, Shin & Shin (2011) use indicators based on the liability side of the bank balance sheet to predict financial fragility in Korea. They find that a high growth rate of bank liabilities is closely related to the depreciation of the Korean Won and the increase of the credit spread. Chung, Lee, Loukoianova, Park, & Shin (2015) categorize liabilities on the bank balance sheet into core and non-core liabilities. Core liabilities are mainly retail deposits from the household sector which generally grow in line with the economy (Shin & Shin, 2011). Non-core liabilities are other sources of funding. As core liabilities do not increase sufficiently to

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https://doi.org/10.1016/j.iref.2020.03.013
Received 28 May 2019; Received in revised form 31 December 2019; Accepted 26 March 2020
Available online 9 April 2020
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finance credit growth in a boom, banks will raise non-core liabilities. As a consequence, a high proportion of non-core liabilities can be a good early warning indicator of financial fragility. Some recent studies provide support for this. For instance, Hahm et al. (2013) investigate the predictive performance of non-core liabilities for a sample of 80 developed and developing countries over the period January 2000 to December 2010. They find that non-core liabilities (notably the banking sector's foreign liabilities) have significant predictive power for crises. Similarly, Pedro et al. (2018), who focus on the determinants of banking crises in OECD countries, report that banks' indebtedness, as measured by the average ratio of banks' non-deposit debt to total liabilities and equity, is an important determinant of banking crises.

In this paper, we investigate the pro-cyclicality of the banking sector based on banks' risk-taking behavior in a more comprehensive way. We pose that banks' pro-cyclical behavior is not only reflected in credit growth and non-core liabilities but also in liquid assets and leverage. During a boom period, banks accelerate credit growth by shifting funds from liquid assets (like government bonds) to high-profit assets. By using funds received by selling liquid assets to provide credit, banks increase profits because the return on liquid assets is lower than that on loans during the boom period. Likewise, high leverage during the boom period increases the fragility of the banking system.[1]

We contribute to the literature in the following ways. Firstly, we develop a theoretical model to show the correlation between the business cycle and bank behavior as reflected in the banking sector balance sheet. For that purpose, we extend the model of Hahm et al. (2013) - most importantly, we divide bank assets into liquid assets and risky assets (loans) and take the relationship between macro-economic risk and liquid assets holdings and leverage into account - and calibrate the parameters in the model to offer simulations of bank behavior during different phases of the business cycle. In our model, banks seek sources to fund credit growth during the boom not only by increasing non-core liabilities, but also by holding fewer liquid assets and by increasing leverage.

Secondly, we examine whether banks' risk-taking behavior, as captured by some bank balance sheet variables, has predictive power for future banking crises. It turns out that these indicators issue warning signals early enough for policymakers to take effective policy measures. More specifically, our results suggest that low levels of liquid assets and domestic financial liabilities, high levels of foreign liabilities and high financial leverage are leading indicators of banking crises. These results are robust when we use different (lags of) dependent variables and control variables.

Thirdly, we extend the empirical literature on predicting banking crises in two ways. In the first place, risk taking by banks is commonly regarded as one of the main drivers of banking crises (Boissay et al., 2016; Danielsson, Valenzuela, & Zer, 2018). In general, risk taking behavior occurs via the change of the banking balance sheet. In other words, determinants of banking crises, like economic growth, interest rates, inflation, the exchange rate, and capital flows, affect the probability of a banking crisis via the banking balance sheet. Therefore, our indicators drawn from the banking sector balance sheet reflect the health of a banking system more directly than macroeconomic indicators.

In the second place, the selection of indicators in predicting banking crises in previous studies is mostly based on empirical evidence (see, e.g., Lee, Posenau, & Stebunovs, 2020; Eijffinger & Karataş, 2019). Different from the literature, leading indicators chosen in this paper are based on a theoretical framework, and have a solid micro-level theoretical basis. To be precise: our paper is not a study of comparing the predictive power of various leading indicators, but we focus on the risk-taking behavior of banks and check whether this kind of behavior may lead to a banking crisis in the future. We lag our proposed indicators from 6 to 48 months with a step of 6 months to investigate whether these indicators have long-run predictive power.

The outline of the paper is as follows. Section 2 summarizes our model for bank credit supply. (The full model is available in the online appendix.) Section 3 describes the data and methodologies used, while Section 4 presents our estimates of a panel logit model for the occurrence of a banking crisis. Finally, Section 5 concludes.

2. Pro-cyclicality of the banking system

The main purpose of our paper is to empirically investigate whether banks' balance sheet structures (liquid assets, non-core liabilities and leverage) are related to the occurrence of banking crises. However, it is crucial to have a theoretical analysis to offer solid fundamentals for the empirical investigation. Therefore, we construct a theoretical model to guide our empirical analysis.

Our theoretical model suggests that not only non-core liabilities, documented by Hahm et al. (2013), but also liquid assets and leverage are correlated with future crises. The model is an extension of the model of Hahm et al. (2013) who show the relationship between non-core liabilities and crises. We extend their model in several directions. Most importantly, we divide bank assets into liquid assets and risky assets (loans) and take the relationship between macro-economic risk and liquid assets holdings and leverage into account. Moreover, we introduce more benefits of holding liquid assets and more costs of holding non-core liabilities. Because there is no analytical solution for the bank's optimization problem, we apply simulations to show the relationship between banks' behavior and macro-economic risk in Section 2.2.

As the model is rather complicated, we describe its main mechanisms and the main simulation results in this section and present the full model in Appendix 1.

[1] Adrian and Shin (2014) show that leverage is pro-cyclical, while Duarte and Eisenbach (2018) find that leverage increases during a credit boom. During a recession, high leverage causes fire sales leading to large spillover losses (Tepper & Borowiecki, 2014).

2.1. Theoretical analysis

Banks' funding sources include: (1) equity E, which is assumed to be fixed, (2) deposits D, which are exogenous and have a zero-interest rate, and (3) non-core liabilities N, which are endogenous and have an interest rate f. At the asset side of the balance sheet, there are two kinds of assets, namely liquid assets (B) and risky assets (L). Liquid assets are composed of government bonds, which are assumed to have neither default risk nor liquidity risk. Risky assets consist of various loans, which originate at date 0 and are repaid at date 1. We assume that credit risk determines the amount of credit provided (cf. Hahm et al., 2013).

We assume equity to be fixed following Hahm et al. (2013), who show that the 2-year change in equity is always around zero. Furthermore, we assume that deposits are cheaper than non-core liabilities, thus banks prefer deposits to non-core liabilities for funding. But banks cannot obtain unlimited deposits. Deposits from the household sector increase in line with economic growth (Shin & Shin, 2011). So, in a boom when credit grows rapidly, deposits do not increase sufficiently to fully fund the rapidly growing credit demand. Banks have to raise more non-core liabilities than usual. In our model, we focus on non-core liabilities and set deposits as an exogeneous variable to simplify the model following Hahm et al. (2013).

We measure the total riskiness of a bank using VaR (Value at Risk). We set the probability of bankruptcy of a bank exogenously at a particular percentile of the VaR constraint. Using the VaR constraint, we can calculate whether the realized value of credits is enough to repay the bank's liabilities. In other words, we can obtain the ratio of net liabilities to credit, i.e. the adjusted leverage. This adjusted leverage is similar to the ratio of liabilities to assets.[2]

Although the return on liquid assets is low, banks hold liquid assets for potential liquidity demand. Assets are valued not only for their returns, but also for their liquidity services (Duffie, Gârleanu, & Pedersen, 2005; Rocheteau & Wright, 2013). The liquidity benefits function in our model has three features. Firstly, the more liquid assets a bank holds, the higher the liquidity benefits it gets, but the marginal benefits of holding liquid assets decrease. Secondly, the higher the macro-economic risk faced by a bank, the more benefits the bank receives from holding liquid assets. The reasoning here is that during a boom, loan risk will be low and banks will garner high profits from their loans, allowing them to bear less liquidity risk and obtain fewer liquidity benefits from the liquid assets than is typically the case.[3] However, during the downturn, credit risk will increase, and the liquidity benefits of holding risk-free assets will increase in turn. Thirdly, when a bank has no risk-free assets, it cannot obtain liquidity benefits. Therefore, the liquidity benefits function is a non-linear function.

The liquidity costs function also has three features. Firstly, the liquidity costs are positively correlated to the volume of non-core liability holdings. If a bank holds a high proportion of non-core liabilities, default risk will increase and the bank will bear high liquidity risk as well. In addition, the marginal liquidity costs will increase with the volume of non-core liabilities. Secondly, liquidity costs are positively correlated with macro-economic risk. During a credit boom, systemic risk will be low, and a bank will have high profits and low default risk. Thus, a bank's counterparties will unlikely withdraw their funding and the bank will face low liquidity risk as a result. However, this situation reverses during an economic downturn when the bank faces high liquidity costs. Thirdly, when a bank has no non-core liabilities, it will bear no liquidity costs. Therefore, the liquidity costs function is also a non-linear function.

As both the liquidity benefits function and liquidity costs function are non-linear, it is difficult to obtain the analytical solution of the optimal holdings of credits, liquid assets, non-core liabilities and leverage during different stages of the business cycle (reflected by the value of the macro-economic risk). We therefore apply simulations using parameters based on calibration to show the relationship between a bank's balance sheet structure and macro-economic risk in Section 2.2.

Our model focuses on liquid assets ratio, non-core liabilities ratio and adjusted leverage, and their correlation with macro-economic risk. Adjusted leverage is defined as: $(D+N)/(B+L)$. During a boom, characterized by low macro-economic risk, a bank will prefer to issue more loans in order to obtain higher profits. As retail deposits grow in line with economic growth, banks increase funding through other sources, increasing both the non-core liabilities ratio and adjusted leverage. In addition, banks will hold fewer liquid assets to finance its credit. During the subsequent economic recession, characterized by higher macro-economic risk, banks prefer to hold a high proportion of liquid assets for both liquidity and safety reasons, by decreasing their non-core liabilities ratio and adjusted leverage. Therefore, liquid asset holdings are positively related to macro-economic risk. The non-core liabilities ratio and adjusted leverage, on the other hand, are negatively related to macro-economic risk. Table 1 summarizes the balance sheet structure variables and their theoretical correlation with macro-economic risk.

2.2. Parameter calibration and simulation

In this section, we use simulations to show the correlation between macro-economic risk and bank balance sheet variables. In principle, the theoretical model identifies the optimal level of credit, liquid assets and non-core liabilities during different stages of the business cycle (reflected by the value of macroeconomic risk) based on the maximization of bank profits.

For convenience, we set equity equal to 1, and the volume of core liabilities D is calculated as

[2] There are two reasons for moving the liquid assets to the numerator to get net liabilities instead of total liabilities. First, liquid assets have high liquidity and can repay liabilities in time. Thus, a bank's liquidity risk mainly stems from its net liabilities. Second, if we keep liquid assets and credit together, the distribution of assets may be different from that of credit in which case we cannot apply the credit risk model of Vasicek (2002). We apply the traditional leverage measure in the simulation and empirical investigations.

[3] This is very similar to the portfolio channel of monetary policy transmission (Dell'Ariccia et al., 2017; Jimenez, Ongena, Pedro, & Saurina, 2014). As policy rates increase, banks may seek to rebalance their portfolios to safer assets, with the opposite happening as policy rates decrease.

Table 1
Definition of balance sheet structure variables.

	Liquid assets ratio	Non-core liabilities ratio	Adjusted leverage
Bank balance sheet	Asset side	Liability side	Asset and liability side
Measurement	$B/(B+L)$	$N/(N+D+E)$	$(D+N)/(B+L)$
Correlation with macro-economic risk	Positive	Negative	Negative

$$Core\ liabilities\ (Deposits) = \frac{Equity}{(RCA*(1 + Non - core\ liabilities\quad ratio))} \tag{1}$$

Where the *RCA* is the ratio of bank capital to assets, which is closely related to the leverage ratio. Credit supply is driven by the business cycle. Liquid assets are calculated as the difference between the sum of equity, deposits and non-core liabilities, and the amount of credit. Therefore, if non-core liabilities and *RCA* are known, we can obtain the holdings of liquid assets. Thus, non-core liabilities and *RCA* are the two key parameters.[4]

The simulation is done as follows. First of all, we apply actual data to calculate the ratio of non-core liabilities to core liabilities and *RCA*, as well as the funding costs, liquid asset returns, and loan returns. Secondly, we set (combinations of) the parameters in the liquidity benefits function and liquidity costs function such that non-core liabilities ratio and *RCA* correspond to their actual values as closely as possible. Finally, based on the values of all parameters obtained in the first two steps, we simulate the theoretical model to calculate the correlations between macro-economic risk and bank balance sheet variables during different stages of the business cycle. Appendix 1 provides more details about the simulations.

As to non-core liabilities, we use data for emerging and developing countries selected on the basis of data availability. We divide non-core liabilities into two parts namely foreign liabilities and liabilities to other domestic financial institutions. Using data from the IMF' *International Financial Statistics database* during 1980M1 to 2016M10, the averages of foreign liabilities and domestic financial liabilities are 0.66 and 0.02, respectively. Therefore, the ratio of non-core liabilities to core liabilities is 0.68.

Next, we collect data for the *RCA*. Based on the statistics in Table 2 in the following section, the median of leverage, defined by total debts to total assets, is 0.981. Thus, the value of *RCA* is 0.019 (=1–0.981). Given the assumption that equity equals to 1, the volume of core liabilities D is 31.328.

In the simulations, non-core liabilities ratio is 0.6793 and *RCA* at 1.98%. These values are very close to the dataset's real values of 0.68 and 1.90%.

The calibration for the funding costs, liquid asset returns, and loan returns are obtained using the WIND database,[5] for the period 1986M1 to 2015M12. As to the funding cost, because foreign liabilities are comprised primarily of non-core liabilities, we choose the three-month LIBOR (in US dollars) as the funding costs for non-core liabilities. Average funding costs amount to 3.87%. As to the returns on liquid assets r_f, we choose the data for some BRICS countries as a proxy. Because Russia and Brazil have high rates of inflation, we choose the average return of three-month government bonds in China, South Africa, and India as a proxy. The average return is 6.74%. Similarly, the loan interest rate r is measured by the average of the loan interest rates in China, South Africa, and India; its average is 12.22%.

Next, because the probability of defaulting on a loan is higher than the insolvency probability of a bank, we set $\varepsilon = 0.01,\ \alpha = 0.001$the former probability at 0.01 and the latter probability at 0.001.

Fig. 1 presents the relationship between liquid assets, non-core liabilities, leverage, and the business cycle (macroeconomic risk)ρ. The upper panel of Fig. 1 shows that liquid assets have a non-linear correlation with macro-economic risk. Liquid assets and macro-economic risk have a negative correlation when the parameter ρ ranges from 0.1 to 0.48, and a positive correlation when ρ ranges from 0.48 to 0.88. The reason may be that at low ρ (i.e. the economy is in a boom), banks provide many loans and for regulatory reasons should have a sufficiently high ratio of liquid assets to core liabilities. When the economy continues to prosper, default risk is perceived to be lower and banks will be inclined to decrease their holdings of liquid assets. However, when asset prices start to bubble banks will increase their liquid asset holdings again. Thus, we find a U-shaped correlation between liquid asset holdings and macro-economic risk.

The middle panel shows that non-core liabilities and macro-economic risk have a negative correlation. Similarly, leverage and macro-economic risk also have a negative correlation, as shown in the bottom panel of Fig. 1.

So, our model captures the pro-cyclical behavior of banks, consistent with the financial instability hypothesis of Minsky (1992), and suggests that bank balance sheet indicators have predictive power for future banking crises. In the next section, we investigate whether this implication of our model is supported by the data.

Our simulations show that, during a boom, a bank will prefer to hold fewer liquid assets and more non-core liabilities and to have

[4] In the literature, *RCA* is applied more frequently than the capital adequacy ratio (*CAR*) for the following reasons. First, in theoretical analyses, *RCA* is often preferred over *CAR*. For example, Tressel (2010) applies *RCA* instead of *CAR* to construct a banking network model. The author poses that based on the *CAR* indicator many large financial institutions appeared to be well capitalized from a regulatory perspective before the 2008 crisis, while they were very fragile during the Global Financial Crisis. In this case, *CAR* does not correctly capture risk-taking behavior of banks. Second, in empirical research *RCA* performs better in predicting bank distress than *CAR* (Blundell-Wignall & Roulet, 2012; Gerhardt & vander Vennet, 2017;). Therefore, in this paper we apply the *RCA* instead of the *CAR* for simulations.

[5] WIND is the leader in China's financial information services industry and offers comprehensive financial data as well as economic data of most countries in the world.

Table 2
Summary statistics.

Variable	Obs.	Mean	SD	Max	Min	Median
Liquid assets	22812	0.176	0.158	0.851	0.000	0.134
Foreign liabilities	47385	0.661	4.238	107.878	−0.060	0.136
Domestic financial liabilities	14761	0.021	0.061	0.904	0.000	0.000
Leverage	13777	1.059	0.413	6.867	0.302	0.981
LIBOR	66300	0.052	0.042	0.207	0.002	0.053
Commodity price inflation	44550	0.004	0.044	0.116	−0.211	0.008
Credit-to-GDP	54120	0.452	0.456	20.662	−1.147	0.369
World GDP growth	64950	0.029	0.011	0.046	−0.017	0.030
Banking crises	66300	0.058	0.235	1.000	0.000	0.000

Note: This table summarizes the variables used, indicating the number of observations (Obs.), mean, standard deviation (SD), minimum, maximum and median.

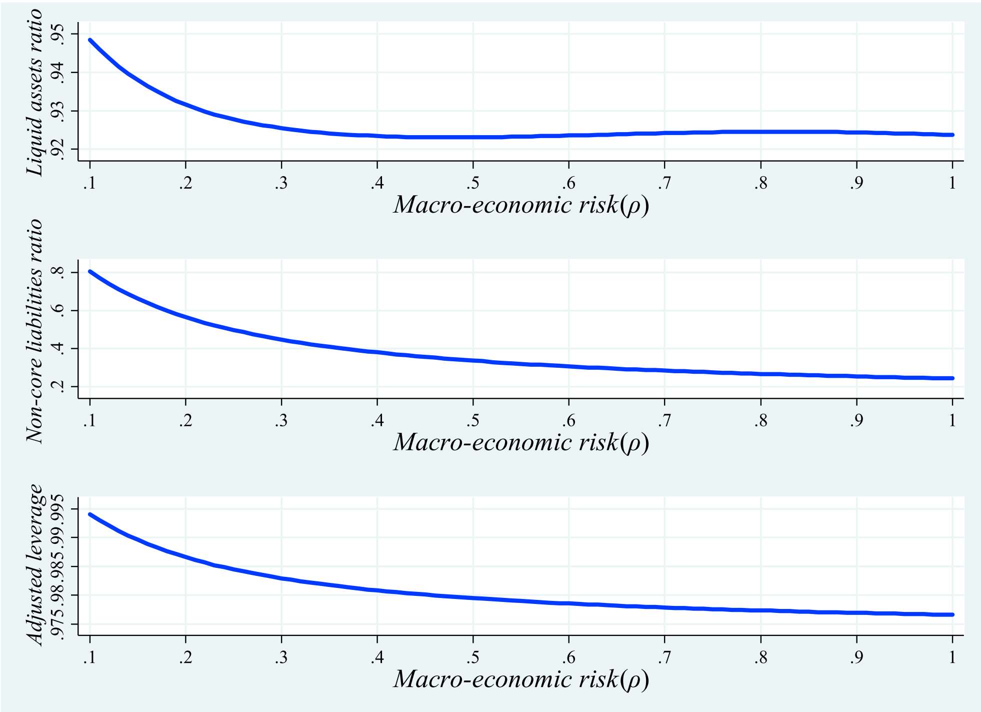

Fig. 1. Correlations between balance sheet indicators and macro-economic risk. Note: The horizontal axis shows the values of macro-economic risk. The vertical axis shows the values of correlation coefficients between the macro-economic risk and liquid assets, non-core liabilities and leverage (which are the indicators of interest) in the upper, middle, and bottom panels, respectively.

higher leverage. This increases a bank's fragility and leads to a higher probability of bankruptcy. In other words, if a bank would have more liquid assets, fewer non-core liabilities and lower leverage, it would be less risky and less likely to be involved in a government bailout during crisis periods.

In the past decade, governments frequently bailed out distressed banks thereby reducing their fragility via the channels outlined above. Firstly, in order to increase banks' holding of highly liquid assets, governments usually replaced risky and low-quality assets by high-quality assets. In 2008, for instance, the US Treasury Secretary set up the Troubled Asset Relief Program (TARP). Under this program, the U.S. government bought up to $700 billion of illiquid mortgages from the financial system. Therefore, asset relief helped the banking system to hold more liquid assets instead of risky assets.

Secondly, in order to decrease the funding risk incurred by non-core liabilities, many, in particular European, governments introduced debt guarantees for distressed banks (König, Anand, & Heinemann, 2014). In September 2007, Northern Rock in the United Kingdom experienced a bank run. Different from other mortgage banks, Northern Rock was heavily relying on non-core liabilities, which made up 77 percent of its total liabilities (Shin, 2009). To bailout this bank and mitigate spillover effects to other banks, the UK government announced that it would guarantee all deposits in Northern Rock and injected £10 billion into the money market to maintain the high liquidity in the interbank market (Goldsmith-Pinkham & Yorulmazer, 2010).

Finally, in order to decrease banks' leverage, governments ejected equity. For instance, in October 2008 the U.S. Treasury bought shares of nine major banks for $145 billion. Later, Citigroup and Bank of America received a second round of government assistance. Similarly, European governments injected €413.2 billion (3.2% of EU 2012 GDP) in undercapitalized banks in the period 2008–2012.

Some recent studies obtain findings which are similar to our simulation results. Based on a sample of 114 aided and 212 non-aided banks in 22 European countries, Gerhardt & vander Vennet, 2017 find that banks with a higher leverage ratio, measured as total equity/total assets, are more likely to be bailed out by the government. Similarly, Betz et al. (2014) find that banks with lower leverage and a larger share of deposit funding are less likely to experience a bailout based on the sample of 546 banks with a minimum of €1 billion in total assets during the period 2000Q1 and 2013Q2 in EU countries. Abreu, Alves, and Gulamhussen (2019) find that banks with illiquid problems are more likely to receive state interventions. In the concluding section, we tie our results to the Basel III regulation.

3. Data and methodology

3.1. Data

We focus on the banking sector in emerging and developing countries using monthly data during the period 1980M1-2016M10. The data is mainly from the International Monetary Fund's *International Financial Statistics* database. We not only collect data for countries which experienced a banking crisis during the period, but also for countries which did not experience a banking crisis, thereby avoiding the problem of selection bias. Our final sample includes 147 emerging and developing countries with the number of observations ranging from 4379 to 26,753 depending on the availability of data for different variables.[6]

Laeven and Valencia (2013) identify 147 systemic banking crises from 1970 to 2011 based on certain events, such as bank runs and banking policy interventions. We draw our banking crises dummy variable from this database; our sample covers 110 banking crises.[7] Our banking crises dummy is 1 during a crisis period, and 0 otherwise. The Laeven-Valencia database consists of annual data while this paper is based on monthly data. Following Jing (2015), we assume that if there is a banking crisis in one specific year in the Laeven-Valencia database, all 12 months in this year are having a crisis.

Our key indicators are the balance sheet structure variables, i.e. the ratio of claims on central and general government to assets (Liquid assets), the ratio of liabilities to other financial institutions to core liabilities (Domestic financial liabilities), the ratio of foreign liabilities to core liabilities (Foreign liabilities), and the leverage ratio (Leverage), which is the ratio of the sum of core and non-core liabilities to total assets. Domestic financial liabilities and foreign liabilities are non-core liabilities. Core liabilities are the sum of time, saving, and foreign deposits, demand deposits, and restricted deposits. Assets is the sum of claims on the government, claims on the private sector, claims on other banking or other financial institutes, and claims on public non-financial corporations.

We include the credit-to-GDP ratio (Credit-to-GDP) as control variable, as Borio and Lowe (2004) find that this ratio is a good indicator of banking crises. In the robustness section, we replace the credit ratio by the credit gap, i.e. the difference between the credit-to-GDP ratio and its long-term trend. This indicator has been widely adopted as a reference in regulations on countercyclical capital buffers (Caggiano et al., 2014). In addition, we add the London interbank offer rate for 1-month (LIBOR), commodity price inflation and world GDP growth to control for international macroeconomic developments. All variables are monthly data except for the credit-to-GDP ratio and the world GDP growth, which we linearly interpolate into monthly data following Hahm et al. (2013).

Table 2 shows summary statistics for all variables used. On average, one fifth of total assets of banks consist of government bonds. Banks have very few liabilities to other financial corporations (almost 2% of core liabilities), while they have many foreign liabilities (66% of core liabilities), indicating that banking systems in emerging and developing countries are highly dependent on international financing.

There are outliers for several variables. It turns out that these outliers reflect characteristics of some specific countries.[8] To control for these characteristics, we include country fixed effects in our regressions. In addition, we find that our results are robust if we exclude these countries.

Table 3 shows the correlation matrix of our four key banking indicators. The correlation between foreign liabilities and leverage is 0.215. This indicates that high leverage is associated with high foreign liabilities. Interestingly, the correlation between leverage and domestic financial liabilities is negative (−0.145); the same holds for the correlation between leverage and liquid assets. This indicates that if a bank is highly levered, it holds low levels of liquid assets and domestic financial liabilities. In general, the results of the correlation matrix show that the correlation between the balance sheet variables is rather low.

3.2. Methodology

First, we apply an event study to investigate banks' behavior during crises episodes. Following Gourinchas and Obstfeld (2012), we apply a regression model to illustrate how the variable of interest, $\theta_{i,t}$, behaves during a crisis, compared to a "tranquil period" which

[6] Countries are listed in Table A2.1 in Appendix 2.

[7] Chaudron and de Haan (2014) compare three widely used databases on banking crises and find that the Laeven-Valencia database is the most reliable one in identifying and dating crises. We therefore use the Laeven-Valencia database.

[8] For example, the average and maximum of the ratio of foreign liabilities to core liabilities in Bahamas is 30.465 and 107.878, respectively. This suggests that there is always a high level of foreign liabilities in Bahamas. Likewise, there is a high level of foreign liabilities in Zimbabwe while Libya has a negative credit-to-GDP ratio from 2004 to 2012.

Table 3
Correlation matrix of banking indicators.

	Liquid assets	Foreign liabilities	Domestic financial liabilities	Leverage
Liquid assets	1.000			
Foreign liabilities	−0.131	1.000		
Domestic financial liabilities	0.048	0.057	1.000	
Leverage	−0.098	0.214	−0.145	1.000

Note: This table shows the correlations between four balance sheet variables.

serves as a benchmark, where $\theta_{i,t}$ is the holdings of liquid assets, foreign liabilities, domestic liabilities or leverage of the banking system. The subscript i refers to country i and subscript t refers to time. The fixed-effects panel regression is:

$$\theta_{i,t} = \alpha_i + \beta_{i,s} d_{i,s} + \varepsilon_{i,t} \tag{2}$$

where $d_{i,s}$ indicates a dummy variable equal to 1 when country i is s months prior to a banking crisis at time t. We set the window around a banking crisis to 49 months (24 months before the crisis data, the crisis date, and 24 months thereafter) following Gourinchas and Obstfeld (2012). The parameter α_i captures country fixed effects and $\varepsilon_{i,t}$ is the error term. The coefficient $\beta_{i,s}$ measures the behavior of $\theta_{i,t}$ over the crisis event window -24 (months) $\leq s \leq 24$ (months) compared to the non-crisis period.

Next, we employ a discrete-choice model to investigate whether balance sheet structure indicators can predict banking crises. Following Demirgüç-Kunt and Detragiache (2000), we employ a multivariate logit model as the logistic distribution in a logit model has wider tails than the normal distribution in a probit model. In addition, the logistic distribution is preferable if an event (i.e. a crisis) has a very low frequency (Manasse, Roubini, & Schimmelpfennig, 2003). We include country fixed effects.

The logit model is written as

$$P(y_{i,t} = 1 | Z_{i,t}) = \frac{1}{1 + e^{-Z_{i,t}}}, \quad Z_{i,t} = a + \rho X_{i,t-1} + \delta C_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

Where $y_{i,t}$ is a dummy variable that takes the value of one when a banking crisis occurs in country i at time t and zero otherwise; a_i is the country-specific intercept; $X_{i,t-1}$ is a vector of lagged balance sheet structure indicators and $C_{i,t-1}$ is a vector of lagged control variables; ρ and δ are coefficients of explanatory and control variables, respectively; $\varepsilon_{i,t}$ is the error term.

The estimated coefficients in the logit model reflect the impact of the explanatory variables on the probability that a banking crisis occurs by $\ln[P(\cdot)/(1 - P(\cdot))]$ which depends on the initial probability $P(\cdot)$.

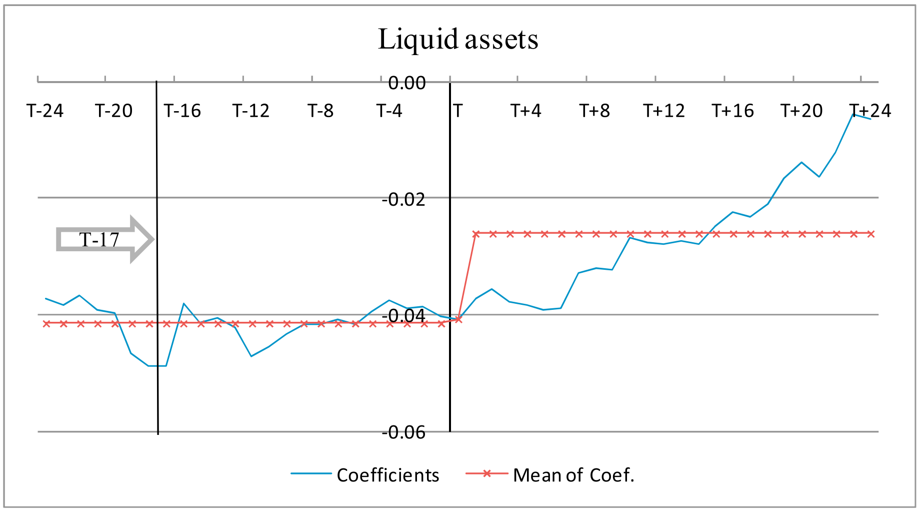

Fig. 2. The behavior of liquid assets around a crisis period. Notes: This figure shows how liquid assets behave before, during, and after a banking crisis, compared to a "tranquil period" which serves as a benchmark. The Y axis shows the change of holdings of liquid assets compared to a "tranquil period", and the X axis shows the time window. "T" stands for the onset of a banking crisis, "T-a" stands for a months before a banking crisis, and "T+b" stands for b months after the occurrence of a banking crisis.

4. Empirical results

4.1. Banking behavior around crisis episodes

In this section, we examine banks' behavior before a banking crisis. Specifically, we examine whether key indicators of our model change sharply before crises. If so, then this would suggest that these indicators could predict banking crises and if they do so early enough policymakers could act.

Following Gourinchas and Obstfeld (2012), we estimate Equation (2) for this purpose. Figs. 2–5 show the behavior of various balance sheet indicators around crisis episodes. In each figure, the solid line shows the indicator over the event window, the solid line with a fork is the mean before and after the crisis. The vertical axis at date T is the beginning of a banking crisis.

Fig. 2 shows that the holdings of liquid assets in the months preceding a banking crisis are lower than those during a non-crisis period. The mean before the crisis is significantly lower than that after the crisis (*t*-test = 7.0465 and P value = 0.000). After a crisis, the average of liquid assets holdings is still lower than that in tranquil periods (i.e. outside the 49 months-window). The reason may be that all banks seek for safe assets within a short time while the supply of liquid asset is limited. In addition, we find that liquid assets increase sharply around 17 months prior to a crisis, indicating that banks may have realized a high level of fragility and begin to hold more liquid assets. Therefore, this indicator could issue a signal almost one and a half years ahead of a potential banking crisis.

Fig. 3 shows the behavior of foreign liabilities around crisis episodes. Banks tend to hold more foreign liabilities 14 months before the banking crisis. However, the mean before the crisis does not differ significantly from that after the crisis (*t*-test = 0.7621 and P value = 0.775). The reason is that the holdings of foreign liabilities is low before the date of T-14. Specifically, 14 months prior to a banking crisis, this indicator increases significantly, indicating that holding a high proportion of foreign liabilities signals a banking crisis 14 months later. Finally, this indicator is significantly above the trend in the months before and after a banking crisis relative to normal periods, indicating that banks hold more foreign liabilities around a banking crisis than during a tranquil period.

As shown in Fig. 4, domestic financial liabilities behave similar to liquid assets. Banks have few liabilities to other financial corporations, indicating that in our sample banks seldom borrow money from other financial institutions and the main purpose of this funding may be to get liquidity, which would explain why domestic financial liabilities behave similar to liquid assets. The mean of the coefficients before the crisis is significantly lower than that after the crisis (*t*-test = 4.5334 and P value = 0.000).

In addition, we find that this indicator increases sharply 16 months prior to a crisis, indicating that banks may have realized their fragility and begin to increase interbank funding for liquidity. Therefore, this indicator could issue a signal almost one year and a half ahead of a potential banking crisis.

Fig. 5, showing the behavior of leverage around the crisis episode, indicates that leverage is significantly above the trend in the months prior to a banking crisis relative to normal periods, suggesting that high leverage exists before a banking crisis. The mean of the coefficients before the crisis is significantly higher than that after the crisis (*t*-test = 4.6018 and P value = 0.000). However, leverage begins to decrease significantly 12 months prior to a banking crisis, indicating that this indicator could issue a signal about one year ahead of a potential banking crisis.

In sum, we find that balance sheet variables behave significantly different before and after a banking crisis, indicating that these indicators could be useful for predicting future banking crises. In addition, all four indicators can issue signals at least one year before a banking crisis indicating that they have ability to predict banking crises and do so sufficiently ahead of the crisis for policymakers to act.

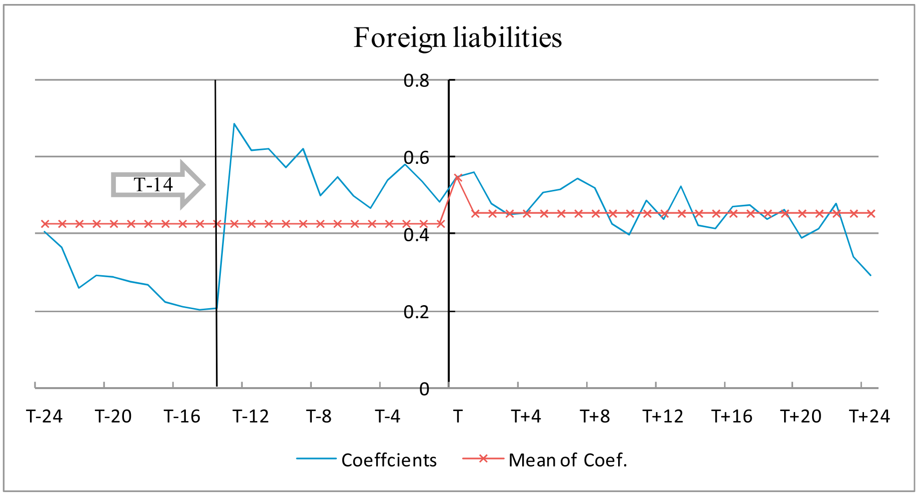

Fig. 3. The behavior of foreign liabilities around the crisis period. Notes: This figure shows how foreign liabilities behave before, during, and after a banking crisis, compared to a "tranquil period" which serves as a benchmark. Y axis stands for the change of holdings of foreign liabilities compared to a "tranquil period", and X axis stands for the time window during a banking crisis. "T" stands for the onset of a banking crisis, "T-a" stands for *a* months before a banking crisis, and "T+b" stands for *b* months after the occurrence of a banking crisis.

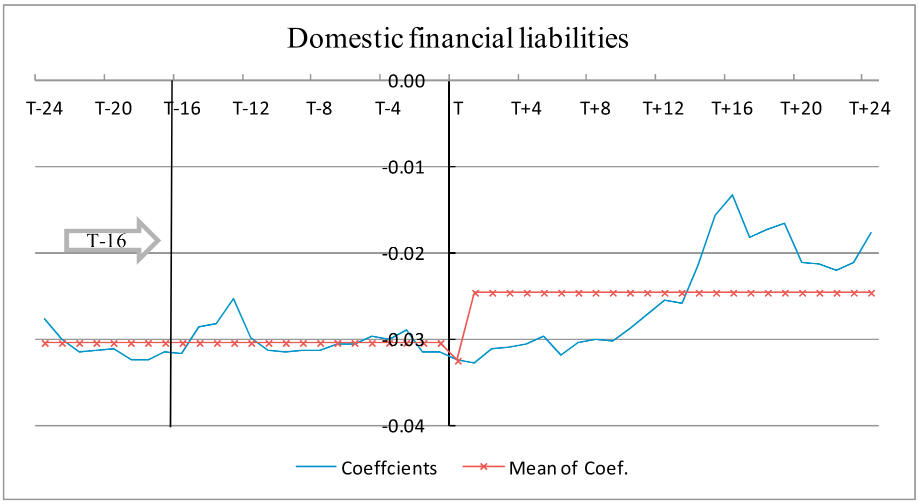

Fig. 4. The behavior of domestic financial liabilities around the crisis period. Notes: This figure shows how domestic financial liabilities behave before, during, and after a banking crisis, compared to a "tranquil period" which serves as a benchmark. The Y axis shows the change of holdings of domestic financial liabilities compared to a "tranquil period", and the X axis shows the time window. "T" stands for the onset of a banking crisis, "T-a" stands for a months before a banking crisis, and "T+b" stands for b months after the occurrence of a banking crisis.

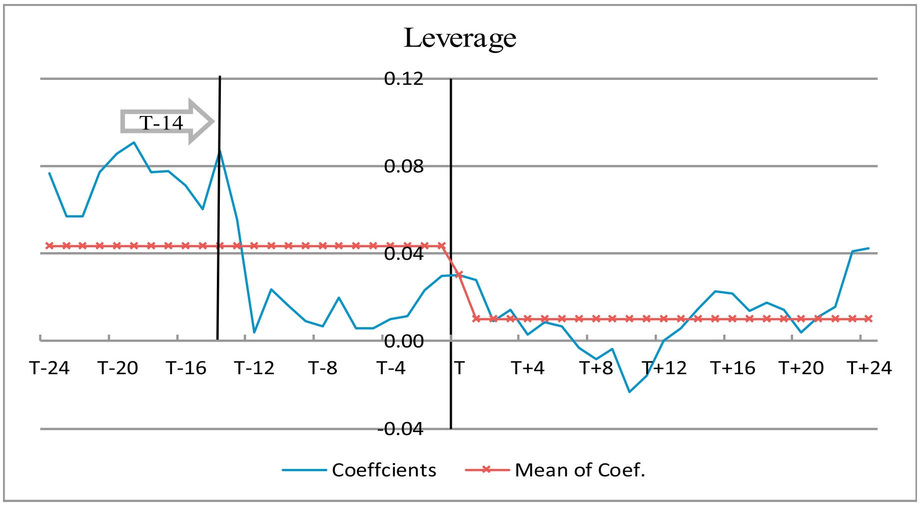

Fig. 5. The behavior of leverage around the crisis period. Notes: This figure shows how leverage behaves before, during, and after a banking crisis, compared to a "tranquil period" which serves as a benchmark. The Y axis shows the change of leverage compared to a "tranquil period", and the X axis shows the time window. "T" stands for the onset of a banking crisis, "T-a" stands for *a* months before a banking crisis, and "T+b" stands for *b* months after the occurrence of a banking crisis.

4.2. Logit estimation results

The results in the previous section suggest that banking crises are preceded by changes in the risk-taking behavior of banks as reflected in liquid assets, domestic financial liabilities, foreign liabilities and leverage. In this section, we estimate a panel logit model with country fixed effects to explore these indicators' predictive power for banking crises (random effects are rejected by the Hausman test). However, logit estimation with fixed effects will omit all countries without banking crises , and this would produce a bias sample. Therefore, we also estimate a pooled logit model (which includes all countries) as a robustness check.

Demirgüç-Kunt and Detragiache (2000) and Bussière and Fratzscher (2008) argue that the behavior of the explanatory variables may be affected by the crisis itself after the onset of a banking crisis, and these feedback effects would muddle the true relationship between predictors and crises. However, eliminating all observations following a crisis would result in a very small number of crisis observations. For example, if we apply leverage as the explanatory variable, our whole sample has 13,777 observations, but there are only 27 crisis-month observations. A similar problem exists if we use domestic financial liabilities as explanatory variable. A large proportion of non-crisis observations would lead to an estimation bias. Therefore, in the basic model, we include all crisis-month observations in the sample following Hahm et al. (2013), and later we only keep the first month of a banking crisis and exclude the following observations to avoid the estimation bias discussed in Bussière and Fratzscher (2006). In addition, we lag all variables one month in view of the feedback effects mentioned above.[9]

Table 4 reports the base line results of the logit model with country fixed effects. In Panel A, we show the marginal effect at the mean along with White-robust standard errors. Columns (1) to (4) show the univariate regression results. We find that all coefficients are significant at the 1% confidence level. Thus, a banking system holding low liquid assets, low domestic financial liabilities, high foreign liabilities and high leverage is very prone to a banking crisis. In addition, the P-values in all five models are lower than 1%, indicating that these indicators have predictive power for banking crises. This conclusion is consistent with the results of our theoretical model and the event study presented in the previous sections.

Column (5) in Panel A of Table 4 reports the results including all bank balance sheet structure variables. The final sample includes 5779 observations and the p-value (0.000) indicates that this model has a good fit. The coefficients on all four balance sheet structure variables are significant at the 1% confidence level and have the same signs as those in columns (1) to (4).

Panel B of Table 4 reports the change in the probability of a banking crisis resulting from a one standard deviation increase in each indicator. Here the measurement of ΔP equals $SD(x_i)$*Marginal effect,* where the standard deviation is calculated for the estimation sample. As shown in column (1), a one standard deviation increase in liquid assets causes the probability of a banking crisis to decrease by 0.054. Similarly, a one standard deviation increase in foreign liabilities increases the probability of a banking crisis by 0.051 (column (2)), a one standard deviation increase in domestic financial liabilities decreases this probability by 0.092 (column (3)), and a one standard deviation increase in leverage raises it by 0.0.048 (column (4)). So, the effect of these indicators on the probability that a banking crisis occurs is also economically significant.

Next, we include control variables in the model. Following previous studies, we consider four variables, namely 1-month LIBOR, commodity price inflation, the world GDP growth rate, and the credit-to-GDP ratio. The first two variables are monthly data; the latter two variables are quarterly and are linearly interpolated into monthly data. Table 5 shows the estimation results.

The results in Panel A of Table 5 show that the coefficients on all four balance sheet indicators remain significant except for the coefficient on foreign liabilities which is insignificantly negative in the final column. Moreover, the marginal effect of liquid assets is only significant when all variables are included. In general, these results are consistent with the findings shown in Table 4. As to the control variables, we find that a high interest rate, a high credit-to-GDP ratio and low world GDP growth are positively related to the probability of a banking crisis, and this conclusion is consistent with results of previous studies. Commodity price inflation has a significant negative coefficient in the first two columns but it becomes insignificant in the last two columns.

Panel B of Table 5 reports the change in the probability of a banking crises resulting from a one standard deviation increase in each indicator. Generally speaking, the economic significance of the bank balance sheet indicators decreases when we include control variables.

4.3. Robustness checks

In this section, we test the robustness of our conclusions by changing the dependent variable, the construction and lags of independent variables, and including different control variables.

Firstly, we retain the observations at the onset month of a banking crisis and exclude all post-crisis observations to avoid an estimation bias. The results without control variables as presented in Table 6 are similar to those in Table 4. Likewise, the sign of the marginal effects is consistent with the theoretical model and the results reported in the previous section. However, some of the marginal effects are insignificant, but this may be due to the limited number of crisis-months in the sample. Table A2.2 in Appendix 2 shows the marginal effects and changes of probability of the four bank balance sheet indicators when we include our four control variables. The significance of the estimated coefficients is lower than those in Table 5, but the sign of the coefficients for each variable is consistent with the results shown in the previous section.

Secondly, Drehmann and Tsatsaronis (2014) argue that the gap between the credit-to-GDP ratio and its long-term trend provides robust signals for a potential banking crisis. Thus, we replace the credit-to-GDP ratio by the credit gap and re-run the model. Table A2.3 in Appendix 2 shows the estimation results. Once again, the sign and significance of the marginal effects are consistent with the theoretical model and the results reported in Table 5. Thus, replacing the credit-to-GDP by the credit gap variable does not affect our results.

Next, we use lags for all balance sheet structure variables ranging from 6 to 48 months, while keeping the lag of all control variables at 1 month. Table A2.4 in Appendix 2 presents the results. Liquid asset has a significantly negative marginal effect in all models, suggesting that if banks hold few liquid assets, banking fragility increases in the long run. Likewise, a low level of liabilities to other financial institutions, a high level of foreign liabilities and high leverage increase the probability of future banking crises.

So far, the control variables used are motivated by the work of Hahm et al. (2013). Other studies come up with other drivers of banking crises. For instance, Klomp (2010) shows that high credit growth, low GDP growth and a high interest rate are the most important determinants of a banking crisis. Pedro et al. (2018) conclude that a high level of non-deposit liabilities and low GDP growth rate are the major causes of a banking crisis. We therefore use the real GDP growth rate, CPI inflation, the exchange rate, and money market interest rate as control variables to re-estimate our model. However, we exclude the one-month LIBOR and commodity price inflation in view of their overlap with money market interest rate and inflation, respectively.

[9] We use lags of 6 months or longer in the robustness checks and the results (available on request) are similar.

Table 4
Panel logit estimation-basic results (Sample: 1980M1-2016M10).

	(1)	(2)	(3)	(4)	(5)
Panel A: Marginal effects					
	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x
Liquid assets	−0.383***				−0.840***
	(0.0628)				(0.0911)
Foreign liabilities		0.0172***			0.273***
		(0.00232)			(0.0295)
Domestic financial liabilities			−1.099***		−0.822***
			(0.173)		(0.169)
Leverage				0.244***	0.248***
				(0.00828)	(0.0359)
P-value	0.000	0.000	0.000	0.000	0.000
Observations	10,901	26,753	6687	5779	5779
Panel B: Changes of probability due to increase with one S.D.					
	ΔP	ΔP	ΔP	ΔP	ΔP
Liquid assets	−0.054				−0.113
Foreign liabilities		0.051			0.090
Domestic financial liabilities			−0.092		−0.073
Leverage				0.048	0.049

Notes: Panel A shows the marginal effects of a panel logit model with country fixed effects. The dependent variable is a banking crises dummy based on the Laeven-Valencia banking crises data set. All explanatory variables are lagged 1 month. Standard errors are shown in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Panel B reports the change in the probability of a banking crisis resulting from a one standard deviation increase in each indicator. Here, the standard deviation is calculated for the estimation sample.

Table 5
Panel logit estimation results with control variables (Sample: 1980M1-2016M10).

	(1)	(2)	(3)	(4)	(5)
Panel A: Marginal effects					
	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x
Liquid assets	−0.039				−0.072***
	(0.067)				(0.021)
Foreign liabilities		0.005***			−0.013
		(0.002)			(0.010)
Domestic financial liabilities			−1.416***		−0.299***
			(0.165)		(0.077)
Leverage				0.056***	0.079***
				(0.016)	(0.013)
LIBOR	14.480***	13.370***	6.333***	0.758**	0.807***
	(0.325)	(0.275)	(0.585)	(0.295)	(0.224)
Commodity price inflation	−0.398***	−0.411***	−0.185*	−0.034	−0.039
	(0.150)	(0.116)	(0.109)	(0.022)	(0.024)
World GDP growth rate	−19.620***	−20.120***	−7.328***	−1.040**	−0.831***
	(0.751)	(0.456)	(1.099)	(0.442)	(0.296)
Credit-to-GDP	0.003	0.022***	0.657***	0.081***	0.143***
	(0.007)	(0.007)	(0.037)	(0.027)	(0.031)
P-value	0.000	0.000	0.000	0.000	0.000
Observations	6442	13,313	4103	3435	3435
Panel B: Changes of probability due to increase with one S.D.					
	ΔP	ΔP	ΔP	ΔP	ΔP
Liquid assets	−0.005				−0.010
Foreign liabilities		0.015			−0.003
Domestic financial liabilities			−0.141		−0.032
Leverage				0.012	0.017
LIBOR	0.280	0.271	0.117	0.014	0.015
Commodity price inflation	−0.018	−0.018	−0.008	−0.002	−0.002
World GDP growth	−0.201	−0.208	−0.073	−0.010	−0.008
Credit-to-GDP	0.003	0.014	0.176	0.021	0.038

Notes: Panel A shows the marginal effects of a panel logit model with control variables. The dependent variable is a banking crises dummy based on the Laeven-Valencia banking crises data set. All explanatory variables are lagged 1 month. The sample includes all observations. Standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Panel B reports the change in the probability of a banking crisis resulting from a one standard deviation increase in each indicator. Here, the standard deviation is calculated for the estimation sample.

Table 6
Robustness checks: marginal effects without control variables in a reduced sample. (Sample: 1980M1-2016M10).

	(1)	(2)	(3)	(4)	(5)
Panel A: Marginal effects					
	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x
Liquid assets	−0.976***				−1.751***
	(0.257)				(0.444)
Foreign liabilities		0.032*			0.118*
		(0.0179)			(0.069)
Domestic financial liabilities			−4.842**		−3.331*
			(1.957)		(1.755)
Leverage				0.209	0.162
				(0.147)	(0.217)
Control variables	No	No	No	No	No
P-value	0.005	0.029	0.002	0.388	0.000
Observations	8091	21,253	5026	4389	4389
Panel B: Changes of probability due to increase with one S.D.					
	ΔP	ΔP	ΔP	ΔP	ΔP
Liquid assets	−0.139				−0.233
Foreign liabilities		0.085			0.037
Domestic financial liabilities			−0.445		−0.323
Leverage				0.041	0.032

Notes: Panel A shows the marginal effects of a panel logit model with country fixed effects. The dependent variable is a banking crises dummy based on the Laeven-Valencia banking crises data set. The sample only includes observations at the beginning of a banking crisis and excludes the following crisis observations. All explanatory variables are lagged 1 month. Standard errors in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Panel B reports the change in the probability of a banking crisis resulting from a one standard deviation increase in each indicator. Here, the standard deviation is calculated for the estimation sample.

Table A2.5 of Appendix 2 shows the results with the new control variables. They suggest that low liquid assets, low domestic financial liabilities, and high foreign liabilities increase the probability of a banking crisis. These findings are consistent with our earlier results. However, the results for leverage are more volatile.

4.4. Comparing the predictive performance for different lags

In this section, we investigate to what extent the predictive power of bank balance sheet variables changes if we use different lags of these indicators. Table 7 shows the changes in the probability of a banking crisis resulting from a one standard deviation increase in the indicators for different numbers of lags (based on the results shown in Table A2.4 in Appendix 2). The impact of a one standard deviation increase in the liquid assets of banks on the probability of a banking crisis decreases from −0.019 (for a 6-month lag) to −0.134 (for a 48-month lag). The liquid assets indicator with a 48-month lag has the strongest link to the probability of a banking crisis. Foreign liabilities have the largest impact on increasing the probability of a banking crisis when it is 24 months lagged. On the other hand, domestic financial liabilities have the largest impact on decreasing the probability when the indicators are 30 months lagged. Lastly, leverage has the largest impact on increasing the probability of a banking crisis when the indicator is 36 or 42 months lagged.

Following Bruno and Shin (2013), Table 8 presents the R-squared statistics of models in which we include the balance sheet indicators with the same (but increasing) number of lags for each indicator. The results in columns (1) to (4) are based on univariate models, while the model in column (5) includes all four bank balance sheet indicators. Row (1) shows the results when using predictors with a 1-month lag. The results presented in rows (2) to (9) refer to lags from 6 to 48 months, with a stepwise increase of 6 months.

Column (1) of Table 8 shows that the higher the number of lags, the higher the R-squared for liquid assets. When the liquid assets indicator is lagged 48 months, its explanatory is the highest. Column (2) shows that the R-squared for the model with the foreign-liabilities indicator exhibits a reversed U-shaped relationship; the indicator has the highest explanatory power when it is lagged by 36 months. Interestingly, the R-squared value of the model with domestic financial liabilities decreases when the number of lags increases. Domestic financial liabilities predict banking crises best when this indicator has a lag of 1 month. Column (4) shows that the R-squared value for leverage increases at first, but then decreases. The R-squared value reaches its peak when this indicator is 12 months lagged.

Next, we include the four indicators simultaneously. As column (5) of Table 8 shows, the R-squared value is highest when all indicators are lagged 24 months.

Finally, the R-squared value in the last row, labeled "Mixed", is for the model with a lag of 48 months for liquid assets, 36 months for foreign liabilities, 1 month for domestic financial liabilities, and 12 months for leverage. These numbers of lags correspond to the lag with the highest R^2 in the first 4 columns of Table 8. The R-squared of the mixed model is lower than that of the model in which the 24-months lags are used, suggesting that using all indicators with the same number of lags gives the best prediction of banking crises.

In all, these results suggest that the bank balance sheet structure variables are long-term indicators of banking crises, perhaps with the exception of domestic financial liabilities.

Table 7
Changes in the probability of a banking crisis due to a one standard deviation increase in indicators with variable lags (Sample: 1980M1-2016M10).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	6M	12M	18M	24M	30M	36M	42M	48M
Variables	ΔP	ΔP	ΔP	ΔP	ΔP	ΔP	ΔP	ΔP
Liquid assets	−0.019	−0.049	−0.080	−0.107	−0.121	−0.117	−0.108	**−0.134**
Foreign liabilities	0.002	0.026	0.057	**0.090**	0.078	0.054	0.045	0.032
Domestic financial liabilities	−0.060	−0.153	−0.202	−0.283	**−0.288**	−0.268	−0.234	−0.114
Leverage	0.021	0.031	0.043	0.053	0.063	**0.070**	**0.070**	0.069
Interest rate	0.025	0.048	0.035	0.019	0.012	0.018	0.030	0.066
Inflation	−0.002	−0.006	−0.004	−0.006	−0.005	−0.002	−0.002	−0.002
World GDP growth	−0.015	−0.031	−0.021	−0.011	−0.014	−0.026	−0.033	−0.051
Credit-to-GDP	0.058	0.101	0.094	0.082	0.068	0.062	0.056	0.073

Note: This table reports the change in probability of a banking crisis resulting from a one standard deviation increase in each indicator derived from the results in Table A2.4 in Appendix 2. The standard deviation is calculated using the estimation sample. The dependent variable is a banking crises dummy based on the Laeven-Valencia banking crises data base. Highest numbers are shown in bold.

Table 8
Predictive performance with different lags. Sample: 1980M1-2016M10.

	(1)		(2)		(3)		(4)		(5)	
Lagged	Liquid assets		Foreign liabilities		Domestic financial liabilities		Leverage		ALL	
periods	*R2*	*N*	*R2*	*N*	*R2*	*N*	*R2*	*N*	*R2*	*N*
1M	0.0038	22812	0.0003	47385	**0.0059**	14761	0.0138	13777	0.0540	13777
6M	0.0060	22795	0.0005	47307	0.0034	14761	0.0168	13777	0.0617	13777
12M	0.0100	22765	0.0009	47135	0.0016	14761	**0.0213**	13777	0.0742	13777
18M	0.0151	22735	0.001	46961	0.0009	14761	0.0203	13777	0.0801	13777
24M	0.0203	22705	0.0011	46784	0.0004	14761	0.0189	13777	**0.0854**	13777
30M	0.0249	22675	0.0012	46602	0.0001	14761	0.0168	13777	0.0814	13777
36M	0.0274	22633	**0.0013**	46404	0.0000	14749	0.0144	13765	0.0707	13765
42M	0.0303	22591	0.0012	46206	0.0000	14737	0.0130	13753	0.0642	13753
48M	**0.0330**	22535	0.0011	45991	0.0001	14725	0.0131	13741	0.0596	13741
Mixed									0.0624	10580

Note: This table shows the R-squared statistics for different numbers of lags for the bank balance sheet indicators. Columns (1) to (4) are based on univariate models while Column (5) includes all four indicators. Row (1) presents the results for using predictors with a 1-month lag, and the results presented in Rows (2) to (9) use predictors that are lagged from 6 to 48 months, with a step-wise increase of 6 months. The R-squared value in the final row (labeled Mixed) is for the model with liquid assets that are lagged 48 months, foreign liabilities that are lagged 36 months, domestic financial liabilities that are lagged 1 month, and leverage that is lagged 12 months.

5. Conclusions

After the Global Financial Crisis, there has been a renewed interest in the factors behind banking crises. This study investigates early warning indicators based on bank balance sheets for predicting banking crises. It turns out that these indicators give warnings so early that policymakers may have time to act.

We first investigate the pro-cyclicality of banks by extending the model of Hahm et al. (2013). Model simulations show that during a credit boom, banks prefer to hold fewer liquid assets, more non-core liabilities, and a higher leverage than is typically the case, while during an economic recession, banks react in the opposite way. This behavior is in line with the financial instability hypothesis of Minsky (1992).

Thereafter, we have investigated the relationship between bank balance sheet structure variables and banking crises in a case study of 147 developing countries using data taken from 1980 to 2016. The results suggest that low levels of bank liquid assets and domestic financial liabilities, and high levels of foreign liabilities and financial leverage increase the likelihood of a banking crisis. These results are robust when we use different dependent variables and control variables. We also find that there is no single optimal lag length for all the indicators. Combining all indicators together, we find that the indicators have the best predictive power with a lag of 42 months.

Thus, this paper has three key policy implications. First, our indicators have the best predictive power for banking crises about three years and a half ahead, suggesting that these indicators can serve as useful leading indicators in constructing an early warning system. Second, this paper supports the newest regulations proposed by Basel III for liquidity risk. Specifically, Basel III introduces the Liquidity Coverage Ratio (BCBS, 2013) requiring banks to hold additional reserves for potential liquidity needs. In addition, Basel III introduces the Net Stable Funding Ratio (BCBS, 2014) to limit banks' short-term borrowing to reduce their funding liquidity risk. Third, this paper supports the newest regulations for the leverage ratio.

CRediT authorship contribution statement

Jakob de Haan: Writing - review & editing. **Yi Fang:** Conceptualization, Methodology. **Zhongbo Jing:** Methodology, Formal analysis, Data curation, Writing - original draft.

Acknowledgement

We thank the National Natural Science Foundation of China (NSFC Grant Numbers: 71703182, 71973162, 71850008, and 71532013) and Central University of Finance and Economics (Grant number: QYP1906) for support. The views expressed do not necessarily reflect those of De Nederlandsche Bank.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iref.2020.03.013.

References

Abreu, J. F., Alves, M. G., & Gulamhussen, M. A. (2019). State interventions to rescue banks during the global financial crisis. *International Review of Economics & Finance, 62*, 213–229.

Adrian, T., & Shin, H. S. (2014). Procyclical leverage and value-at-risk. *Review of Financial Studies, 27*(2), 373–403.

Barrell, R., Davis, E. P., Karim, D., & Liadze, I. (2010). Bank regulation, property prices and early warning systems for banking crises in OECD countries. *Journal of Banking & Finance, 34*, 2255–2264.

Basel Committee on Banking Supervision. (2013). Basel III: The liquidity coverage ratio and liquidity risk monitoring tools. Available at: https://www.bis.org/publ/bcbs238.pdf.

Basel Committee on Banking Supervision. (2014). Basel III: The net stable funding ratio. Available at: https://www.bis.org/bcbs/publ/d295.pdf.

Betz, F., Oprică, S., Peltonen, T. A., et al. (2014). Predicting distress in European banks. *Journal of Banking & Finance, 45*, 225–241.

Blundell-Wignall, A., & Roulet, C. (2012). Business models of banks, leverage and the distance-to-default. *OECD Journal: Financial Market Trends, 2*, 7–34.

Boissay, F., Collard, F., & Smets, F. (2016). Booms and banking crises. *Journal of Political Economy, 124*(2), 489–538.

Borio, C. E. V., & Drehmann, M. (2009). *Assessing the risk of banking crises - revisited*. BIS Quarterly Review No. 147, Basel.

Borio, C. E. V., & Lowe, P. (2004). *Securing sustainable price stability: Should credit come back from the wilderness?*. BIS Working Paper 157, Basel.

Bruno, V., & Shin, H. S. (2013). *Capital flows, cross-border banking and global liquidity*. NBER Working Paper 19038, Cambridge.

Bussière, M., & Fratzscher, M. (2008). Low probability, high impact: Policy making and extreme events. *Journal of Policy Modeling, 30*(1), 111–121.

Caggiano, G., Calice, P., & Leonida, L. (2014). Early warning systems and systemic banking crises in low income countries: A multinomial logit approach. *Journal of Banking & Finance, 47*, 258–269.

Carmona, P., Climent, F., & Momparler, A. (2019). Predicting bank failure in the U.S. banking sector: An extreme gradient boosting approach. *International Review of Economics & Finance, 61*, 304–323.

Chaudron, R., & de Haan, J. (2014). Dating banking crises using incidence and size of bank failures: Four crises reconsidered. *Journal of Financial Stability, 15*, 63–75.

Chung, K., Lee, J. E., Loukoianova, E., Park, H., & Shin, H. S. (2015). Global liquidity through the lens of monetary aggregates. *Economic Policy, 30*(82), 231–290.

Claessens, S., Dell' Ariccia, G., Igan, D., & Laeven, L. (2010). Cross country experiences and policy implications from the Global Financial Crisis. *Economic Policy, 25*(62), 267–293.

Danielsson, J., Valenzuela, M., & Zer, I. (2018). Learning from history: Volatility and financial crises. *Review of Financial Studies, 31*(7), 2775–2805.

Davis, E. P., & Karim, D. (2008). Comparing early warning systems for banking crises. *Journal of Financial Stability, 4*, 89–120.

Davis, E. P., Karim, D., & Liadze, I. (2011). Should multivariate early warning systems for banking crises pool across regions? *Review of World Economics, 147*, 693–716.

Dell'Ariccia, G., Laeven, L., & Suarez, G. (2017). Bank leverage and monetary policy's risk-taking channel: Evidence from the United States. *The Journal of Finance, 72*(2), 613–654.

Demirgüç-Kunt, A., & Detragiache, E. (2000). Financial liberalization and financial fragility. In G. Caprio, P. Honohan, & J. E. Stiglitz (Eds.), *Financial Liberalization: How far, how Fast?* (pp. 96–122). Cambridge (UK): Cambridge University Press.

Drehmann, M., & Tsatsaronis, K. (2014). The credit-to-GDP gap and countercyclical capital buffers: Questions and answers. *BIS Quarterly Review*, 55–73. March.

Duarte, F., & Eisenbach, T. M. (2018). *Fire-sale spillovers and systemic risk*. FRB of New York Staff Report 645. Available at SSRN: https://ssrn.com/abstract=2340669.

Duffie, D., Gârleanu, N., & Pedersen, L. H. (2005). Over-the-Counter markets. *Econometrica, 73*, 1815–1847.

Eijffinger, S. C. W., & Karataş, B. (2019). Together or apart? The relationship between currency and banking crises. *Journal of Banking & Finance, In Press*.

Frankel, J. A., & Rose, A. K. (1996). Currency crashes in emerging markets: An empirical treatment. *Journal of International Economics, 41*(3–4), 351–366.

Gerhardt, M., & vander Vennet, R. (2017). Bank bailouts in Europe and bank performance. *Finance Research Letters, 22*, 74–80. https://doi.org/10.2139/ssrn.2895936.

Goldsmith-Pinkham, P., & Yorulmazer, T. (2010). Liquidity, bank runs, and bailouts: Spillover effects during the northern Rock episode. *Journal of Financial Services Research, 37*(2–3), 83–98.

Gourinchas, P. O., & Obstfeld, M. (2012). Stories of the twentieth century for the twenty-first. *American Economic Journal: Macroeconomics, 4*(1), 226–265.

Hahm, J. H., Shin, H. S., & Shin, K. (2013). Noncore bank liabilities and financial vulnerability. *Journal of Money, Credit, and Banking, 45*(S1), 3–36.

Jimenez, G., Ongena, S., Pedro, J.-L., & Saurina, J. (2014). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica, 82*(2), 463–505.

Jing, Z. (2015). On the relation between currency and banking crises in developing countries, 1980-2010. *The North American Journal of Economics and Finance, 34*, 267–291.

Klomp, J. (2010). Causes of banking crises revisited. *The North American Journal of Economics and Finance, 21*(1), 72–87.

König, P., Anand, K., & Heinemann, F. (2014). Guarantees, transparency and the interdependency between sovereign and bank default risk. *Journal of Banking & Finance, 45*, 321–337.

Laeven, L., & Valencia, F. (2013). Systemic banking crises database. *IMF Economic Review, 61*(2), 225–270.

Lee, S. J., Posenau, K. E., & Stebunovs, V. (2020). The anatomy of financial vulnerabilities and banking crises. *Journal of Banking & Finance, 112*. In this issue.

Manasse, P., Roubini, N., & Schimmelpfennig, A. (2003). *Predicting sovereign debt crises*. IMF Working Paper 221, Washington, DC.

Milesi-Ferretti, G.-M., & Tille, C. (2011). The great retrenchment: International capital flows during the global financial crisis. *Economic Policy, 26*(66), 285–342.

Minsky, H. P. (1992). *The financial instability hypothesis. The jerome levy economics institute of bard college working paper 74*.

Pedro, C. P., Ramalho, J. J. S., & Silva, J. V. D. (2018). The main determinants of banking crises in OECD countries. *Review of World Economics, 154*(4), 1–25.

Reinhart, C. M., & Rogoff, K. S. (2009). *This time is different: Eight centuries of financial folly*. Princeton (NJ): Princeton University Press.

Rocheteau, G., & Wright, R. (2013). Liquidity and asset-market dynamics. *Journal of Monetary Economics, 60*(2), 275–294.
Rose, A. K., & Spiegel, M. M. (2011). Cross-country causes and consequences of the crisis: An update. *European Economic Review, 55*(3), 309–324.
Rose, A. K., & Spiegel, M. M. (2012). Cross-country causes and consequences of the 2008 crisis: Early warning. *Japan and the World Economy, 24*(1), 1–16.
Roy, S., & Kemme, D. M. (2012). Causes of banking crises: Deregulation, credit booms and asset bubbles, then and now. *International Review of Economics & Finance, 24*, 270–294.
Schularick, M., & Taylor, A. M. (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *The American Economic Review, 102*(2), 1029–1061.
Shin, S. H. (2009). Reflections on northern Rock: The bank run that heralded the global financial crisis. *The Journal of Economic Perspectives, 23*(1), 101–119.
Shin, H. S., & Shin, K. (2011). *Procyclicality and monetary aggregates*. NBER Working Paper 16836. Cambridge (MA).
Tepper, A., & Borowiecki, K. A. (2014). *A leverage-based measure of financial instability*. FRB of New York Staff Report 688. Available at SSRN https://ssrn.com/abstract=2488155.
Tressel, T. (2010). *Financial contagion through bank deleveraging: Stylized facts and simulations applied to the financial crisis* (Vol. 236). Washington DC: IMF Working Paper.
Vasicek, O. A. (2002). The distribution of loan portfolio value. *Risk*. December http://www.moodyskmv.com/conf04/pdf/papers/dist_loan_port_val.pdf.
Wong, J., Wong, T. C., & Leung, P. (2010). Predicting banking distress in the EMEAP economies. *Journal of Financial Stability, 6*, 169–179.