Does More Finance Lead to More Crises?

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Abstract

Economists have argued that finance can facilitate growth and increase stability. There are, however, reasons that finance, especially the quantity of credit, can be a source of instability. While there is a vigorous debate on the benefits and costs of the financial sector, there is no direct evidence of whether more finance is related to a higher probability of future systemic banking crises. By using panel data for 150 countries from 1960 to 2009, I find that a larger quantity of finance measured by the ratio of private credit to GDP is associated with a higher probability of future systemic banking crises, a result that is robust to excluding the recent global financial crisis. This effect is stronger for countries whose quantity of private credit is relatively larger. An increase in the equity market capitalization relative to the outstanding credit is associated with a lower probability of a systemic banking crisis.

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1 Introduction

As Levine (2005) summarizes, economists have provided both theoretical arguments and empirical evidence for a positive impact of finance on economic growth. These theories also suggest that finance efficiently allocates risk to those in the best position to manage it and therefore increases stability. However, because of the global financial crisis in the late 2000s and the economic recession that followed, academics, regulators, and commentators have raised the issue of whether, in contrast to those theories, finance actually decreases stability by making the economy more prone to financial crises. Turner (2011), the chairman of the Financial Services Authority of the United Kingdom, concludes that the recent crisis is evidence that the growth of the financial sector does not increase financial stability but decreases it. Shleifer and Vishny (2010) build a model in which banks' investment in securities makes them unstable and crisis prone. Further, Stiglitz (2010a) concludes that the primary lesson of the recent crisis is that "the pursuit of self-interest, particularly within the financial sector, may not lead to societal well-being". Krugman and Wells (2011) state that the experience of the US in the last 40 years shows that finance did not improve America's productive capacity and was ultimately destructive.

However, so far, there is no systematic empirical investigation of the relation between the quantity of finance available in an economy and the probability of a financial crisis. In this paper, I fill this gap by examining whether more finance is related to a higher probability of banking crises, using a panel of 150 countries from 1960 to 2009. I study banking crises as a form of financial crisis for two reasons. First, as Reinhart and Rogoff (2009) show, banking crises are "an equal-opportunity menace": while the frequency of sovereign debt crises or crises related to high inflation is substantially lower in advanced economies than in emerging market economies, banking crises have impacted both advanced and emerging markets economies alike. Studying banking crises enables me to examine both types of countries. Second, compared to other kinds of financial crises, banking crises are very costly in terms of both the associated output losses (Reinhart and Rogoff (2009)) and their role in causing or deepening other types of crises (Kaminsky and Reinhart (1999)).

Of course, the financial system of a country consists of many components. Of particular importance in financial crises is the quantity of credit provided by the financial sector to the economy.

On the one hand, leverage in the economy increases with the quantity of credit. When the leverage of the economy is higher, firms are more likely to default (Merton (1974)) and cause trouble for the financial sector. On the other hand, the quantity of credit can also be a measure of excessive risk-taking and borrowing in the economy that can lead to financial instability (Minsky (1986)). Therefore, I first focus in my empirical analysis on the relation between the quantity of credit and the probability of a future banking crisis.

I measure the quantity of credit in the economy by using the ratio of private credit to GDP, *Private Credit/GDP*, and my primary methods of empirical analysis include panel logit regressions, panel linear probability regressions, and Cox proportional hazard models. After controlling for a number of variables used in the previous literature as determinants of banking crises[1], I find that the quantity of credit is positively related to the probability of a future banking crisis. A one standard deviation increase of the quantity of credit from its mean is associated with an around 80% increase of the probability of having a banking crisis in the future five years. This effect is robust to excluding the recent global financial crisis and robust to using all three estimation methods.

This paper then studies the effect of the quantity of credit relative to those of other components of the financial system on the probability of banking crises. First, I consider the ratio of outstanding credit to stock market capitalization as a measure of the leverage of the economy. I find that an increase in the ratio of outstanding credit to equity market capitalization is associated with a higher probability of a banking crisis, while the quantity of credit retains both the sign and significance level of its effect on the probability of a banking crisis. This result is consistent with a higher leverage being related to a higher probability of default, which in turn increases financial instability. Second, I consider the ratio of the quantity of market-based financing to the quantity of bank-based financing and the ratio of the quantity of market-based credit to the quantity of bank-based credit in explaining the occurrence of banking crises. I do not find a significant relation between any of these ratios and the probability of a banking crisis.

Because there are reasons that financial liberalization can induce excessive risk taking behavior (Dell'Ariccia and Marquez (2004) and Hellman, Murdock, and Stiglitz (2000)), I examine whether

[1]See Demirgüç-Kunt and Detragiache (1998, 2002), and Beck, Demirgüç-Kunt, and Levine (2006)

financial liberalization impacts the sensitivity of the probability of banking crises to the quantity of credit. The relation between the quantity of credit and the probability of a systemic banking crisis is stronger during large financial reforms than during reforms and reversals. Furthermore, for a country that liberalizes its equity market, a higher quantity of credit is more strongly related to the probability of a systemic banking crisis for the postliberalization period than for the preliberalization period. These results are consistent with the explanations that changes associated with financial liberalization can induce excessive risk taking, which can increase both the quantity of credit and the probability of financial instability.

The results on financial liberalization suggest that the way credit is extended in the recent past may affect the relation between the quantity of credit and the probability of banking crises. I find that the positive relation between *Private Credit/GDP* and the probability of banking crises exists primarily for countries that have experienced a positive growth of *Private Credit/GDP* in the past five years, and this relation is the strongest when the growth of *Private Credit/GDP* is above 10%. This result is consistent with the interpretation that when part of the credit is extended through relatively fast credit growth, it can be of poor quality and induce trouble for the financial sector.

I then study whether the strength of the relation between the quantity of credit and the probability of a banking crisis differs across different groups of countries that have different levels of quantity of credit. I find that the relation is stronger for countries whose quantity of credit is more than 1.5 cross-sectional standard deviations above the cross-sectional average and is the strongest when the quantity of credit is more than 2 standard deviations above the cross-sectional average. These results suggest that the relation between the quantity of credit and the probability of a banking crisis is nonlinear: this relation is stronger for countries with the largest quantity of credit than for other countries.

To ensure the robustness and refine the interpretation of the results, I also examine a number of alternative explanations of the positive relation between the quantity of credit and the probability of banking crises. First, although waves of capital flows are related to the occurrence of banking crises, they do not significantly affect the effect of the quantity of credit on the probability of banking crises. Second, the ratio of central government debt to GDP does not affect my results.

In addition, this ratio is not positively related to the probability of systemic banking crises after controlling for the quantity of credit. Third, the government ownership of banks does not drive out the effect of the quantity of private credit on the probability of systemic banking crises.

I organize this paper as follows. Section 2 reviews the theories and empirical evidence of the way finance affects growth and stability. Section 3 introduces the data. Section 4 studies the relation between the quantity of credit and the probability of a banking crisis. Section 5 examines the relation between the structure of the financial system and the probability of a banking crisis. Section 6 studies how financial liberalization affects the relation between the quantity of credit and the probability of systemic banking crises. Section 7 studies the nonlinearity in the relation between the quantity of credit and the probability of systemic banking crises. Section 8 focuses on the interaction between the quantity of credit and the growth of credit. Section 9 considers a number of alternative explanations of the primary findings. Section 10 concludes.

2 What Do We Know about the Way Finance Affects Growth and Stability?

2.1 Finance and Growth

Levine (2005) highlights five channels through which the development of financial systems positively influences growth: (1) financial systems produce information ex ante about possible investments and allocate capital; (2) financial systems monitor investment and exert corporate governance after providing finance; (3) financial systems facilitate the trading, diversification, and management of risk; (4) financial systems mobilize and pool savings; (5) financial systems ease the exchange of goods and services. There are theoretical arguments supporting each channel.

Using both cross-country panel data (King and Levine (1993); Levine, Loayza, and Beck (2000); Beck and Levine (2004)) and natural experiments (Rajan and Zingales (1998); Jayaratne and Strahan (1996)), researchers provide support for a positive role of finance on economic growth. However, a number of recent papers question this positive role. Favara (2009) argues that the cross-country relation between finance and growth is not robust because of econometric difficulties. Dabós and

Gantmann (2010) and Rousseau and Wachtel (2011) show that the previously documented positive relation disappears or becomes reversed in the recent periods. In addition, Arcand, Berks, and Panizza (2011) find a non-monotonic relationship between economic growth and the quantity of finance: finance starts to have a negative effect on output growth when the credit to the private sector reaches 110 percent of GDP. These recent papers, however, do not identify the channel through which the positive relation between finance and economic growth disappears or reverses. In particular, they do not address the issue of whether a larger financial sector or a larger quantity of finance decreases economic stability and is associated with a higher probability of crises.

My paper is related to the literature on finance and growth in two ways. First, while this literature studies the joint effect of the benefits and the costs of financial development, my paper focuses on the costs of finance in the forms of banking crises, which have not been well studied. Second, although the quantity of credit could also gauge financial development, it does not directly measure many aspects of financial development. For example, it does not measure how well the financial systems research firms, monitor managers, mobilize savings, pool risk, and ease transactions. Therefore, my results do not directly speak to the relation between these other aspects of financial development and the probability of banking crises.[2]

2.2 How Finance Can Increase Stability?

A number of theories suggest that finance can increase economic and financial stability. First, the development of financial intermediation and markets helps diversify risks and absorb shocks and efficiently mobilize savings (Greenwood and Jovanovic (1990); Bencivenga and Smith (1991); Greenwood and Smith (1997)). Second, the combination of capital market imperfection and unequal access to investment opportunities across individuals can induce endogenous and permanent economic fluctuations (Aghion, Banerjee, and Piketty (1999)); economies with more developed financial systems provide more equal access to investment opportunities and hence can reduce economic instability. In addition to above mechanisms related to cross-sectional risk diversification, Allen and Gale (1997) show that financial intermediation can help diversify intertemporally across

[2]In Section 5, I study the relation between the structure of financial systems and the probability of banking crises.

generations risks that are hard to diversify at a particular time. According to these theories, finance can efficiently allocate risks to those in the best position to manage them and therefore increase both economic and financial stability.

A few papers empirically examine the relation between finance and the volatility of economic growth. Denizer, Iyigun, and Owen (2002) find that countries with more developed financial sectors experience less fluctuations in real per capita output, consumption, and investment growth. Beck, Lundberg, and Majnoni (2006) show that well-developed financial intermediaries dampen the effect of real sector shocks and magnify the effect of monetary shocks. Raddatz (2006) finds that financial system development leads to a comparatively larger reduction in the volatility of output in industries that have higher liquidity needs. These papers, however, do not focus on the relation between the development of financial systems and financial stability.

In explaining why finance can reduce stability, these above papers also focus on the efficiency of risk allocation and diversification. On the one hand, the quantity of credit can be a proxy of the ability of financial intermediaries to allocate and diversify risks. On the other hand, the quantity of credit can also be a result of risk allocation and diversification or measures something different than risk allocation and diversification. Therefore, the positive relation between the quantity of credit and the probability of banking crises does not negate the positive impact of risk allocation and diversification on stability.

2.3 How Finance Can Lead to Instability and Financial Crises?

2.3.1 Theories

The previous literature has offered a number of reasons why more finance may decrease economic and financial stability and lead to more crises. These reasons can be summarized into two primary lines of reasoning. The first focuses on an array of macro forces and is named by Turner (2011) the "Macro-Minsky" school of thought. The second, which Turner (2011) dubs "Micro-structuralist" school of thought, is related to the structures of markets and incentives at a micro-economic level. I discuss the theories and arguments related to both schools of reasoning below starting with the "Macro-Minsky" view.

At a macro-economic level, when the average leverage of the economy, especially the leverage of the firms and the households in the real sector, is high, the average distance to default can be low. When a negative shock hits, it is more likely for the firms and households to default according to Merton (1974). Through the claims on the non-financial real sector by financial institutions, these defaults can cause trouble in the financial sector, which can feed back to the adverse performances of the firms because of the amplification of shocks through incentive compatibility or collateral channels (Bernanke and Blinder (1988), Bernanke and Gertler (1989, 1990), and Kiyotaki and Moore (1997)). If the quantity of credit is a reflection of the high leverage in the economy, this story implies a positive relation between the quantity of credit and the probability of crises.

Minsky (1986) suggests that periods of financial stability can lead to future crises because these periods encourage individuals to borrow more and take more risky and speculative positions. The speculative risk-taking and borrowing may reinforce each other when asset prices increase. But, when negative shocks hit and the asset prices fall, it turns out that people have taken too much risk and debt. As a result, they go into distress, the number of nonperforming loans increases, and the financial positions of financial institutions deteriorate, which can lead to financial crises and worsen the economic downturn. According to this explanation, speculative risk-taking and excessive borrowing lead to endogenous boom of credit and increase the probability of financial crises.[3]

Related to the argument of Minsky (1986), the changes in the financial sector during financial liberalization can also induce excessive financing through credit and lead to financial instability. These changes in the financial sector can ease legal barriers to entry and enlarge the scope of activities of banks and other financial intermediaries. Competition that comes with these changes may reduce the existing banks' franchise values (Keeley (1990) and Hellman, Murdock, and Stiglitz (2000)) and lead informed banks to allocate more credit to lenders that are relatively more opaque to their uninformed competitors (Dell'Ariccia and Marquez (2004)). As a result, banks lower the standards of lending and lend more to borrowers that have lower quality. In sum, these changes in the financial sector can lead to an increase in the quantity of credit and a higher probability of

[3]Other early works that examine the instability of financial and banking systems include Fisher (1933), Keynes (1936), and Tobin (1978, 1984). Minsky (1986) bases his Financial Instability Hypothesis on Keynes (1936).

banking crises.

Shleifer and Vishny (2010) propose a new explanation of the instability of banks. In their model, profit-maximizing banks cater to investor sentiment. When investor sentiment leads to high asset prices, banks use up their capital to buy securities. Although banks may know that a crisis is likely to come, because they realize that there is so much money to be made during the booms, they nonetheless fully extend themselves. Consequently, this behavior of banks exposes themselves to risks of asset liquidation and fire sales in bad times. A key point of Shleifer and Vishny (2010) is that rational behaviors of banks can actually increase the instability of the banking sector as a whole.

The "Micro-structuralist" school of thought emphasizes the role of opacity and perverse incentives in inducing financial crises. These issues emerge at both the organizational and the individual level (Stiglitz (2010b)). At the organizational level, banks can enjoy implicit public guarantees that essentially give them a put option: If they take extraordinary risks and win, they make profits; if they suffer losses as the result of the big bets, the tax payers will pay the bills. The incentives associated with the implicit public guarantees make banks grow too large by taking excessively risky investments. The experiences of the US before the recent crisis also suggests that in addition to bankers, traders in the shadow-banking systems also worked with this kind of incentives and took too many risks. McKinnon and Pill (1998) and Krugman (1998) also make similar arguments about explicit or implicit public guarantee and excessive risk-taking to understand the Asian financial crisis in 1990s.

At the individual level, agency problems and compensation structure can lead to herding and tail-risk taking. Rajan (2006) argues that compensation structure and performance evaluation methods give investment managers the incentives to herd with each other and take tail risks that can be concealed from investors. Adrian and Shin (2008) focus on a particular form of business practice of banks and argue that when banks finance their activities through collateralized borrowing, they adjust exposures so that the probability of default is kept at a constant – a level given by the Value-at-Risk threshold. This practice can induce procyclical leverage of banks and lead to a funding crisis when the permitted leverage of the financial intermediaries falls.

Table D.1 summarizes the theories of the way finance can lead to instability and financial crises.

2.3.2 Empirical Evidence

As Gorton and Winton (2003) point out, most of empirical studies of financial instability focus on the experiences of the US, especially those during the great depression, while relatively less work focuses on a broad cross section of countries. An exception is Demirgüç-Kunt and Detragiache (1998), who consider a wide range of possible determinants of banking crises and explain the relation between the probability of a banking crisis and the contemporaneous country characteristics. These authors, however, do not emphasize the relation between the quantity of finance and the probability of a future banking crisis. There is also evidence suggesting that explicit deposit insurance increases the probability of banking crises (Demirgüç-Kunt and Detragiache (2002)) and banking crises are less likely in economies with more concentrated banking systems (Beck, Demirgüç-Kunt, and Levine (2006)).

Gourinchas and Obstfeld (2011) is related to my paper. They focus on the effect of short-term time-series increases in leverage on the probability of three kinds of crises: currency crises, banking crises, and government default crises, and find that domestic credit expansion and real currency appreciation robustly predict the occurrence of future crises. While controlling for and discussing the time-series change in variables that may proxy for leverage, my paper stresses the quantity of finance as a risk factor of banking vulnerability. In sum, in the previous literature, whether more finance leads to more banking crises remains an open question.

Schularick and Taylor (2009) study the long-run dynamics of money, credit, and output in 14 developed countries from 1870 to 2008. One of their findings is that the lagged credit growth is a strong predictor of financial crises. This finding is in line with my finding that the quantity of credit plays an important role in explaining the occurrence of future banking crises. Jordà, Schularick, and Taylor (2011) find a positive relation between the rate of credit growth relative to GDP in the expansion phase of the business cycle and the severity of the subsequent recession. While these papers focus on the time-series behavior of credit within each country and do not examine the level of credit across countries, I examine the relation between the quantity of credit and the probability

of crises across a wide range of countries.

Economists have long studied the determinants of currency crises and their relation with the banking crises. The researchers at IMF have laid some early groundwork in this area, such as Kaminsky, Lizondo, and Reinhart (1998) and Berg and Pattillo (1999a). Kaminsky and Reinhart (1999) document a close relation between currency crises and banking crises, arguing that the currency crises often occur in immediate succession with banking crises and worsen the banking crises. They call this phenomenon "twin crises". These researchers use two kinds of approaches to develop an Early Warning System (EWS) of currency crises. One approach extracts signals from a number of indicators, i.e. a crisis signal flips up when an economic variable passes a threshold. Kaminsky and Reinhart (1999), Kaminsky, Lizondo, and Reinhart (1998), and Goldstein, Kaminsky, and Reinhart (2000) have used this approach. The other approach is logit or probit models, implemented by, for example, Eichengreen, Rose, and Wyplosz (1995), Frankel and Rose (1996), and Berg and Pattillo (1999b). Improving upon these approaches, Bussière and Fratzscher (2006) develop binomial and multinomial logistic regressions models to deal with a post-crisis bias faced by many previous models of EWS. This above literature provides useful tools for analyzing crisis events. My approach of panel logit regressions is similar to the binomial logistic regressions in Bussière and Fratzscher (2006).

3 Data

3.1 Measures of the Quantity of Credit

I consider several standard measures of the quantity of credit in the finance and growth literature. First, I use *Private Credit/GDP*, which is defined as the claims on the private sector by deposit money banks and other financial institutions normalized by GDP. This variable is the primary measure of the quantity of credit in my paper. This measure is related to an alternative but narrower measure: *Bank Credit/GDP*. The numerator of the latter is limited to claims on the private sector by only deposit money banks. I also consider a measure of the overall asset size of the financial sector, *Financial Assets/GDP*, which is the claims on the whole non-financial real

sector, including government, public enterprise, and the private sector, by deposit money banks and other financial institutions divided by GDP.

These variables measure the credit extended to the economy by deposit banks and other financial institutions. I focus on the credit in the economy both because theories suggest that credit can be an important driver of financial instability and because these measures of credit are available for a wide range of countries over a relatively long period. As Levine, Loayza, and Beck (2000) and Levine (2005) point out, there are many other important aspects of financial development that these variables do not measure, such as ability of the financial system to monitor and control managers or to conduct risk management and facilitate resource mobilization.

I obtain these measures from a database of country-level financial structure compiled by Beck and Demirgüç-Kunt (2009).[4] Because private credit, bank credit, or financial assets are stock variables measured at the end of a period and because GDP is a flow variable measured over the period, the change in inflation over the period can introduce biases unrelated to the quantity of credit normalized by GDP. Beck and Demirgüç-Kunt (2009) correct for these biases by calculating the ratios as

$$\frac{0.5 \times \left(F_t/P_t^e + F_{t-1}/P_{t-1}^e\right)}{GDP_t/P_t^a},$$

where F is private credit, bank credit, or financial assets, P^e and P^a are end-of-period and period-average CPI, and GDP is nominal GDP. Table B.1 has the details of all variables that I use.

3.2 Measures of the Structure of the Financial System

To study the relation between aspects of the financial system other than the quantity of credit and the probability of systemic banking crises, I consider three ratio variables that measure the structure of the financial system: *Credit/Stock Market Cap*, *Market/Bank*, and *Private Credit/Credit*. *Credit/Stock Market Cap* is the sum of private bond market capitalization and private credit divided by stock market capitalization. This variable measures the size of the credit market relative to the size of stock market. *Market/Bank* measures the relative importance of market-based financing and

[4] I use the April 2010 version of the database. Their raw data are from the electronic version of the IMF's International Financial Statistics.

bank financing. The numerator of this variable is the sum of stock market capitalization and private bond market capitalization, while the denominator is the claims on non-financial private sector by deposit banks.[5] Because the numerator of *Credit/Stock Market Cap* is the credit to non-financial real sector and the denominator is the equity of publicly traded companies, this variable could be interpreted as a measure of the leverage of whole economy.[6] *Private Credit/Credit* is the ratio of private credit to the sum of private credit and private bond market capitalization. This variable measures the importance of bank-based debt financing relative to that of the market-based debt financing.

3.3 The Sample of Countries

I start with all countries for which I can obtain information on *Private Credit/GDP* and real GDP per capita for the period from 1960 to 2009. I then select countries of which *Private Credit/GDP* is higher than the 20th percentile of the cross-country distribution of *Private Credit/GDP* in that year.[7] This sample selection method alleviates the concern that my results can be driven by the fact that a country that does not have a sufficiently developed financial sector cannot have meaningful banking crises. For example, in such a country, there can be only a small number of banks controlled by the government of the country. The mechanism behind the bank failure and subsequent government rescue in this kind of countries can be very different from that in other countries. This procedure results in a sample that includes 150 countries, of which 23 are advanced economies and 127 are emerging market economies.[8] The list of countries in my sample is in Table A.1.[9]

[5] I construct *Credit/Stock Market Cap* and *Market/Bank* so that their values lie between zero and one, i.e. $Market/Bank = \frac{Market}{Market+Bank}$ and $Credit/Stock\ Market\ Cap = \frac{Credit}{Credit+Stock\ Market\ Cap}$.

[6] This interpretation works well if the ratio of the size of public companies to the size of private companies and households is relatively the same across different countries.

[7] See Figure A.1 for the cross-country distribution of *Private Credit/GDP* over time before I select countries for my sample.

[8] I identify Advanced Economies and Emerging Market Economies (EME) according to the 1993 World Economic Outlook (IMF (1993)).

[9] In Figure A.2, I compare the mean and volatility of log real per capita GDP growth between countries in my sample and countries outside of my sample. This figure shows that countries that have relatively developed financial systems (my sample) have on average higher mean and lower volatility of log real per capita GDP growth than other countries.

3.4 Data on Banking Crises

The data of banking crises are from Laeven and Valencia (2010). This database covers the universe of systemic banking crises for the period 1970–2009 and also includes data on the resolution, fiscal, and economic costs of the banking crises. Laeven and Valencia (2010) build this database based on the earlier work by Caprio, Klingebiel, Laeven, and Noguera (2005), Laeven and Valencia (2008), and Reinhart and Rogoff (2008) but add the crisis ending dates and a broader coverage of crisis management policies.

Laeven and Valencia (2010) define a particular year as the first year of a systemic banking crisis if both the following two conditions are met:

1. Significant signs of financial distress in the banking system indicated by significant bank runs, losses in the banking system, and bank liquidations.

2. Significant banking policy intervention measures in response to significant losses in the banking system.

Laeven and Valencia (2010) use six "quantitative" criteria to identify significant banking policy intervention. If three or more of these six criteria are satisfied, the banking policy intervention is considered significant. Because the thresholds of their quantitative criteria are admittedly arbitrary, they also maintain an additional list of "borderline cases" that almost met their definition of systemic crisis.[10] The end of a crisis in the database of Laeven and Valencia (2010) is defined as the year before both real GDP growth and real credit growth are positive for two consecutive years. In all cases, they truncate the duration of a crisis at 5 years, including the first crisis year. In my sample, the number of countries that have experienced a systemic banking crisis or crises is 73, among which 18 are advanced economies and 55 are emerging market economies.

For two reasons, I base the primary analysis in this paper on a sample of crises that have large economic consequences.[11] First, these crises better enable me to examine the interaction between the financial sector and the real economy on the downside. Second, for the purpose of policy making, it is important to understand the determinants of the future occurrence of the crises with

[10] These borderline cases do not have significant potential output losses.

[11] My primary results are robust to using a sample that has all banking crises.

large economic consequences. I follow Allen, Gu, and Kowalewski (2011) to select banking crises that are associated with a potential output loss of more than 10%.[12] The potential output loss numbers are based on the computation in Laeven and Valencia (2010).[13] For a crisis that starts in year T, the potential output loss is the cumulative sum of the differences between actual and extrapolated real GDP over the period $[T, T+3]$ divided by the extrapolated real GDP in year T. To conduct the extrapolation of real GDP, Laeven and Valencia (2010) first apply a Hodrick-Prescott filter to the log real GDP series over the period $[T-20, T-1]$ to obtain the trend of log real GDP, requiring at least four observations. They then extrapolate the real GDP using the trend growth rate. In my sample, there are 58 country-crisis events with a potential output loss of more than 10% experienced by 49 countries, among which 16 are advanced economies and 33 are emerging market economies. Table A.2 lists all country-crisis events experienced by the countries in my sample. Table 1 shows the key features of my data.

I also collect a number of additional variables. I describe these variables when I discuss the results of my analysis. Table B.1 has the description and sources of these variables.

3.5 Comparing the Country Characteristics of Crisis Countries and Non-crisis Countries

Table 2 compares country characteristics of countries that have experienced at least a crisis with a potential output loss of greater than 10% and those of countries that have not experienced such crises. I refer to these two groups of countries as crisis countries and non-crisis countries. For each crisis country, the country characteristic is measured as the mean over a five-year window ending at the year before the first year of the crisis. For each non-crisis country, the country characteristic is measured as the average over the whole sample period. I test whether there is a significant difference in the country characteristic between the two groups of countries using the student's T-test and the Mann-Whitney test (equivalent to Wilcoxon rank sum test).

The difference in mean of *Private Credit/GDP* between crisis countries and non-crisis countries

[12] This procedure does not mean that banking crises cause output losses. A decline in economic performance may lead to a banking crisis, which in turn worsens the economic downturn.

[13] I also calculate potential output losses according to their procedure but with my data. I get numbers close to theirs.

is positive 26.9% and statistically significant at the 1% level, and the difference in mean of *Financial Assets/GDP* is positive 31.3% with a T-test p-value less than 1%. *Bank Credit/GDP* also shows the similar trend between crisis countries and non-crisis countries. These numbers show that crisis countries have on average larger quantities of credit than non-crisis countries.

The next two variables, *Growth of Private Credit/GDP* and *Growth of Financial Assets/GDP*, show that crisis countries also have slightly lower growth rates of *Private Credit/GDP* and *Financial Assets/GDP* than non-crisis countries. According to the T-test p-values, these differences, however, are not statistically significant at the conventional levels of confidence, such as 10%. The growth of *Bank Credit/GDP* also shows the similar pattern. These numbers show that the crisis countries and non-crisis countries have similar growth rates of credit normalized by the growth of GDP.

The next four variables are the measures of the structure of the financial system. Because information on the stock market and the private bond market is available after 1990 and for around 40 countries in my sample, the numbers of countries substantially reduce for both crisis countries and non-crisis countries. The Students' t and Wilcoxon test statistics for these four variables show that the crisis countries have on average higher *Credit/GDP* and *Credit/Stock Market Cap* and lower *Private Credit/Credit* than non-crisis countries. These differences imply that the economies of the crisis countries are on average more highly leveraged than those of the non-crisis countries, and that the quantity of bank-based debt financing is on average smaller than the quantity of outstanding market-based debt financing in the crisis countries compared with non-crises countries.

Crisis countries also have on average a higher level of economic development, measured by *Real GDP Per Capita*, and a lower rate of economic growth, measured by *Growth of Real GDP*, than non-crisis countries. These differences are statistically significant at 5% and 10% levels respectively. I also compare a number of macroeconomic variables, such as *Real Interest Rate*, *Inflation*, and *Depreciation*. The differences in these variables between the two groups of countries are not statistically significant. The last variable compared in Table 3 is *Political Risk*, of which higher values mean politically less risky. There is no statistically significant difference in *Political Risk* between crisis and non-crisis countries.

4 Is More Credit Related to a Higher Probability of A Banking Crisis?

In this section, I study whether more credit is related to a higher probability of a future banking crisis using three different methods: panel logit regressions, panel linear probability regressions, and Cox proportional hazard models.

4.1 Panel logit Regressions and Panel Linear Probability Regressions

I use a specification of panel logit regressions[14] as follows:

$$log\left(\frac{\pi(X_{i,t})}{1-\pi(X_{i,t})}\right) = (Quantity\ of\ Credit)_{i,t}\beta + C_{i,t}\gamma. \quad (1)$$

I include as explanatory variables the measure of the quantity of credit as well as a vector of other control variable, $C_{i,t}$. On the left-hand side of the regression equation, $X_{i,t}$ stands for a vector of the covariates including the measure of the quantity of credit, control variables, and a constant term. For country i and year t, the response variable of the logit regressions is one if there is a crisis in any year over the next five years and zero otherwise. For example, for the US at 2002, because the crisis of 2007 is within five years, the response variable is one. Similarly, the response variable for the US is also one for 2003, 2004, 2005, or 2006. But, for 2000 or 2001, since there is no crisis in any year over the next five years, the response variable is zero. Therefore, $\pi(X_{i,t})$ on the left-hand-side of this equation is the conditional probability that a banking crisis happens in any year over the next five years given the covariates.[15] In addition to panel logit regressions, I also conduct analysis by using panel linear probability regressions, which are ordinary least square regressions that use the same response variable above as the left-hand-side variable. One advantage of linear probability regressions is that the coefficients of these regressions can be directly interpreted as changes in

[14]This approach is related to prior studies studying financial crises. For example, Demirgüç-Kunt and Detragiache (1998) apply logit regressions to study the contemporaneous relation between country characteristics and the occurrences of banking crises, and Bussière and Fratzscher (2006) develop an Early Warning System (EWS) of currency crises by using models of binomial logistic regressions and multinomial logistic regressions. My approach is similar to the binomial logistic regressions models of Bussière and Fratzscher (2006).

[15]The left-hand-side of Equation 1 is also called *logit* or *log odds*.

probability when the corresponding covariate increases by one unit, while other covariates do not change.

As opposed to studying the exact timing of banking crises, which may be an ambitious goal (Berg and Pattillo (1999a)), I use the response variable described above to study the occurrence of a banking crisis within a fixed future time horizon. This design of the response variable is similar to the approach in Bussière and Fratzscher (2006) and is different from the method used by Demirgüç-Kunt and Detragiache (1998), who regress the crisis indicator, which is one if there is a banking crisis and zero otherwise for each country and year, on contemporaneous explanatory variables. Because the effects of a banking crisis can propagate quickly to the rest of the economy, compared to the contemporaneous variable timing, my variable timing is less subject to the concern that the explanatory variables are not exogenous.[16]

As pointed out by Bussière and Fratzscher (2006), including the observations during and after the crisis can lead to a "post-crisis" bias, which can affect the inferences from the logit models for two reasons.[17] First, to study whether the quantity of credit is related to the likelihood of a country experiencing a banking crisis, I want to compare the quantity of credit during the period prior to the crisis with that during a "safer" period in "safer" countries, rather than with that during or right after the crisis. Second, the financial and economic conditions of a country often become chaotic once a crisis happens and then undergo a volatile recovery after the crisis. Therefore, comparing their values during and after the crisis with those before the crisis can lead to incorrect inferences if after the crisis, the quantity of credit tends to decrease from the pre-crisis level. By comparing the quantity of credit before and after the crisis, I potentially conclude that a larger quantity of credit is associated with a higher probability of crisis when in fact I am documenting the post-crisis drop in the quantity of credit. Therefore, before estimating the logit models, I exclude the observations

[16]Of course, my approach does not eliminate the concern of endogeneity because there could be factors that drive both the quantity of credit and the probability of a banking crisis. For instance, poor institutional development can simultaneously drive a high risk of having a banking crisis and a large quantity of credit. (Acemoglu, Johnson, Robinson, and Thaicharoen (2003)). This factor is unlikely an omitted factor because my results show that the relation between the quantity of credit and the probability of crises is stronger in more developed countries, which have relatively stronger institutions. I address some of other possible omitted factors in Section 9.

[17]Several other researchers also realize this potential bias and make effort to correct for it. For example, see Demirgüç-Kunt and Detragiache (1998), Demirgüç-Kunt and Detragiache (2002), and Beck, Demirgüç-Kunt, and Levine (2006).

in a five-year window starting at the first year of the crisis. This five-year window for identifying a crisis/post-crisis period coincides with the definition of crisis periods in Laeven and Valencia (2010), who use a five-year cutoff to define the end of a banking crisis. My approach of correcting for the bias is also similar to that of Bussière and Fratzscher (2006).[18]

4.2 Cox Proportional Hazard Models

Another method of analysis that I use is Cox proportional hazard models:

$$h_i(t|X_{i,t}) = h_0(t)e^{(\textit{Quantity of Credit})_{i,t}\beta + C_{i,t}\gamma}. \tag{2}$$

In the above equation, $h_i(t|X_{i,t})$ is the hazard function[19] of a systemic banking crisis for country i at year t; $X_{i,t}$ is a vector of time dependent explanatory variables, including *Quantity of Credit* and a set of controlling variables, $C_{i,t}$; $h_0(t)$ is the baseline hazard at time t. $h_0(t)$ has no particular parameterization: the model makes no assumption about the shape of $h_0(t)$ over time. Furthermore, $h_0(t)$ is the same for every country. One country's hazard is a multiplicative replica of another's. Comparing country j to country k, the model implies that

$$\frac{h(t|X_{j,t})}{h(t|X_{k,t})} = \frac{e^{(\textit{Quantity of Credit})_{j,t}\beta + C_{j,t}\gamma}}{e^{(\textit{Quantity of Credit})_{k,t}\beta + C_{k,t}\gamma}}. \tag{3}$$

This equation shows that the relative difference in hazard between countries are determined by the covariates.

The variable of interest in a Cox proportional hazard model is the analysis time, the time during which the subject is at risk. For each country-crisis event, I calculate the analysis time as the time from the beginning of the first year when the data is available to end of the last year before a systemic banking crisis. If a country has experienced multiple crises, this definition of analysis time means that multiple crises in a country have different analysis times. Under the assumption that

[18] Removing the observations after the crisis may remove useful information on the recovery of the crisis. In order to use this information, Bussière and Fratzscher (2006) propose a multinomial logistic regression approach, which sets the outcome variable to three different values: 0 for a tranquil period, 1 for a pre-crisis period, and 2 for a post-crisis period.

[19] Section C of the appendix introduces a number of important functions usually used in survival analysis.

every crisis is of the same type[20], this definition of analysis time is valid because two same banking crises cannot happen to one country at the same time.[21]

Multiple crises within one country also mean that the analysis times of different crises can be correlated within a country, violating the independence of analysis times assumption required in traditional estimation of survival analysis. To deal with this issue, I follow Cleves (1999) to adopt an approach of treating multiple crises in a country as ordered events of the same type and hence, use the definition of analysis time described above. I then follow Cleves (1999) to adjust for the dependence of analysis times by clustering standard errors within a country.

4.3 Variables Used in the Analysis

Table 3 shows the summary statistics of the variables used in the panel logit regressions and linear probability regressions. The first panel shows the mean, standard deviation, minimum, and maximum of these variables, and the second panel shows the pooled Spearman correlation coefficients in percentage. *Private Credit/GDP* has a wide variation, ranging from 7.7% to 269.8%. The pooled standard deviation of *Private Credit/GDP* is 35.3%. The between and within standard deviations of *Private Credit/GDP* show that although both cross-sectional variation and time-series variation contribute to the overall variation of this variable, the cross-sectional standard deviation, 0.257, is higher than the time-series standard deviation, 0.220. *Financial Assets/GDP* has a similar wide difference between maximum and minimum values, and its between-country standard deviation is also higher than its within-country standard deviation. In order to reduce the possible influence of outliers of these measures of the quantity of credit, especially those of high values, I transform these measures into log scale: $log\,(1 + Private\ Credit/GDP)$ and $log\,(1 + Financial\ Assets/GDP)$. *Growth of Private Credit/GDP* (*Growth of Financial Assets/GDP*) is the log of annual growth rate of *Private Credit/GDP* (*Financial Assets/GDP*), which measures how fast the private credit (financial asset) grows relative to GDP growth.

[20] Andersen and Gill (1982) develop methods to analyze multiple failure-time data under this assumption.

[21] An alternative definition of the analysis time of a crisis is the period from the beginning of the sixth year after the last crisis starts to the end of last year before the current crisis. This definition implies that two crises in a country can have the same analysis time. The underlying assumption of this definition is that different crises in a country have different types: the second crisis is of a different nature than the first one, the third one is different from the second one, and so on.

Crisis Year is an indicator variable that is one if a country-year is in a banking crisis and zero otherwise. *Crisis* is an indicator variable that is one if a country-year is the first year of a banking crisis and zero otherwise. The means of these two variables show that 6.3% of country-years in my sample are in a banking crisis and the unconditional probability that a country has a banking crisis is 2.3%.[22] *Crisis Year*$_{Loss\geq 10\%}$ is an indicator variable that is one if a country-year is in a banking crisis associated with a potential output loss of more than 10% and zero otherwise, and *Crisis*$_{Loss\geq 10\%}$ is an indicator variable that is one if a country-year is the first year of such a banking crisis and zero otherwise. The means of these two variables show that the unconditional probability of a country having a banking crisis with a potential output loss of more than 10% is 1.5%, and 4.1% of country-years are in such crises. $Crisis5_{Loss\geq 10\%}$ is the response variable used for my primary logit regressions. It is an indicator variable that is one for a country-year if there is a banking crisis associated with a potential output loss of greater than 10% in any year over the next five years and zero otherwise. The mean of this variable indicates that the unconditional probability of having such a crisis over the next five years is 6.8%.

I report the summary statistics for a number of other variables as well.[23] *Real GDP Per Capita* measures the level of economic development. To alleviate the influence of outliers, I use the log of this variable in the regressions. *Growth of Real GDP* measures the shocks to the overall economy that can make the country more or less vulnerable to banking crises. This variable is also useful for addressing a concern that high past economic growth tends to reverse and result in crises. *Nominal Interest Rate* measures the short-term borrowing costs of financial institutions. A sudden increase in *Nominal Interest Rate* can adversely affect the balance sheets of financial institutions if they cannot increase their lending rates or adjust their investment positions quickly enough. *Inflation* reflects shocks that may affect the financial sector and the real sector through many channels. *Depreciation* is the rate of change of the exchange rate. This variable measures the foreign exchange risk exposure

[22] In un-reported results, I split the sample into two periods: 1960–1989 and 1990–2009. In the former period, 3.9% of country-years are in crisis, and the unconditional probability of a country having a banking crisis is 1.5%. In the latter period, 7.8% of country-years are in crisis, and the unconditional probability of a country having a banking crisis is 2.9%. These results show that there are more crises in the latter sample period than in the former sample period.

[23] These variables are used by Demirgüç-Kunt and Detragiache (1998), Demirgüç-Kunt and Detragiache (2002), and Beck, Demirgüç-Kunt, and Levine (2006) in their primary specifications of analysis.

faced by the financial sector and/or the real sector. To alleviate the influence of outliers in the explanatory variables, I winsorize all the explanatory variables used in the logit regressions at levels of 0.5% and 99.5%, except for the indicator variables.

4.4 Results

Table 4 shows the results from the panel logit regressions, panel linear probability regressions, and Cox proportional hazard models that study the relation between the quantity of private credit and the probability of a banking crisis with a potential output loss of more than 10% over the next five years. Panel A reports results of the logit regressions, and Panel B reports results from the linear probability regressions. Panel C reports results of the Cox proportional hazard models.

The response variable for both logit and linear probability regressions in this table is an indicator variable that is one if the country has a banking crisis associated with a potential output loss of greater than 10% in any year over the next five years and zero otherwise. Because of this definition of the response variable, the response variable could be correlated over time within a country. The explanatory variables can also be correlated over time within a country. In addition to the correlation over time, countries in the same region tend to have banking crises around the same time, which introduces correlation across countries at a given year in the response variable. To alleviate the concerns that the observations are potentially correlated across countries and over time, I use two-way clustered standard errors by country and year (Cameron, Gelbach, and Miller (2006) and Petersen (2009)).[24]

I interpret estimated coefficients from the logit regressions as the change in odds when the corresponding covariate increases by one unit, controlling for other covariates. This interpretation helps us understand the economic magnitude of the estimated coefficients for two reasons. First, the exponential of the estimated coefficient is the odds ratio, $\frac{\pi(X+\Delta X)}{1-\pi(X+\Delta X)} / \frac{\pi(X)}{1-\pi(X)}$. Because the odds, $\frac{\pi(X)}{1-\pi(X)}$, is a positive monotone transformation of the probability, $\pi(X)$, itself, we can directly gauge the direction of the change in probability by checking whether the odds ratio increases, which is equivalent to checking whether the estimated coefficient is positive. Second, the odds ratio is close

[24]The Stata routine for two-way clustered standard errors is available from Mitchell A. Petersen's webpage.

in value to the relative risk $\frac{\pi(X+\Delta X)}{\pi(X)}$ if $\frac{(1-\pi(X))}{(1-\pi(X+\Delta X))} \approx 1$, which is the case when both $\pi(X+\Delta X)$ and $\pi(X)$ are small. Because banking crises are rare[25], this approximation is likely to hold for the odds ratios. Hence, the magnitude of an increase in odds is a close approximation of the magnitude of the corresponding increase in probability.[26]

Model (1) in Panel A of Table 4 explains the probability of future crises using *log(1+Private Credit/GDP)* while controlling for economic development, log(*Real GDP Per Capita*). The estimated coefficient on $log(1 + $ *Private Credit/GDP*) is positive, which means that after controlling for economic development, an increase in the quantity of private credit is related to an increase in the probability of banking crises in the next five years. The estimated coefficient is also statistically significant. The coefficient of 2.838 suggests that a one standard deviation increase in *log(1+Private Credit/GDP)*, 0.211 as in Table 3, is associated with an odds ratio of $exp(2.838 \times 0.211) = 1.82$. This odds ratio means a 82% increase in odds of having a banking crisis in the next five years.

Model (2) of Panel A adds to the explanatory variables *Growth of Private Credit/GDP*. In order to control for the differences in average probability of banking crises between advanced economies and emerging market economies, this model also adds a dummy variable that is one if the country is an advanced economy and zero otherwise. Model (3) controls for *Real Interest Rate* and *Depreciation*, and Model (4) controls for *Inflation*. The estimated coefficients on $log(1+$*Private Credit/GDP*) are still positive and statistically significant in Models (2), (3), and (4), and the economic magnitude is similar to that of Model (1). These results show that the quantity of private credit normalized by GDP is a determinant of banking crises that is robust to controlling for the growth of private credit as well as other variables. All these results confirm a positive relation between the quantity of private credit and the probability of a banking crisis over the next five years.

Model (2), (3), and (4) show that the effect of *Growth of Private Credit/GDP* on the probability of banking crises is also positive. I use the estimated coefficient on *Growth of Private Credit/GDP* in Model (2), 2.232, to interpret the economic magnitude of this effect. This coefficient means

[25]Table 3 shows that the unconditional probability of a banking crisis starting is 2.3%, and the unconditional probability of a banking crisis associated with a potential output loss greater than 10% starting over the future 5 years is 6.6%.

[26]The estimated coefficients from the linear probability model can be directly interpreted as the change in probability when the corresponding covariate increases by one unit, while holding other covariates constant.

that a one standard deviation in *Growth of Private Credit/GDP* is associated with an odds ratio of $exp(2.232 \times 0.109) = 1.275$, which means that a one standard deviation increase in *Growth of Private Credit/GDP* is associated with a 27.5% increase in the odds or the probability of a banking crisis over the next five years. This result shows that the growth of private credit relative to GDP growth is a strong predictor of a banking crisis in addition to the quantity of private credit. Because *Growth of Private Credit/GDP* is the growth of real private credit normalized by real economic growth (the growth of real GDP), when this variable has a high value, private credit may be growing too fast, which is a sign of excessive risk taking. Therefore, this result also supports excessive risk-taking as a mechanism of the occurrence of banking crises.[27]

In Models (5) and (6), I conduct analysis similar to those in Model (3) and (4) but exclude the recent global financial crisis by including only observations before 2002. These regressions study the relation between the quantity of private credit and the probability of future banking crises before the recent crisis. The estimated coefficients on $log(1 + Private\ Credit/GDP)$ are still positive and statistically significant in both Models (5) and (6). To interpret the economic magnitude, I recompute the standard deviation of *log(1+Private Credit/GDP)* because the sample size substantially changes when excluding the recent crisis. For Model (5), the standard deviation is 0.199, and for Model (6), the standard deviation is 0.203. These standard deviation numbers are slightly smaller than that for the full sample, which is 0.211. The odds ratios associated with a one standard deviation change in *log(1+Private Credit/GDP)* are 1.952 and 2.02 for Model (5) and (6), respectively. These numbers imply that in the period before the recent crisis, a one standard deviation increase in the quantity of private credit is still associated with a substantial increase in the odds or probability of a banking crisis in the next five years.[28] The coefficients on the *Growth of Private Credit/GDP* is also positive, but have smaller magnitude and lower statistically significance than those from the whole sample period.

In Panel B of Table 4, I estimate panel linear probability regressions rather than panel logit regressions. The panel linear probability regressions are linear ordinary least square regressions

[27] This result is consistent with the evidence in Schularick and Taylor (2009) that the growth of credit significantly predicts the occurrence of future financial crises.

[28] In unreported panel logit regressions, I replace *log(1+Private Credit/GDP)* with $log(1 + Financial\ Assets/GDP)$. I find similar results for the whole sample period.

that use the same response variable and the same explanatory variables as in the logit regressions of Panel A. The results show that the coefficient on *log(1+Private Credit/GDP)* retains the sign and statistical significance level as those in Panel A of this table.

The coefficients from linear probability regressions can be directly interpreted as changes in probability when the corresponding covariate increases by one unit, while the other covariates stay the same. Multiplied by the standard deviation of *log(1+Private Credit/GDP)*, the estimated coefficient on *log(1+Private Credit/GDP)* in model (1), 0.237, means that a one standard deviation increase in *log(1+Private Credit/GDP)* is associated with an increase of 5% in the probability of a banking crisis over the next five years. Relative to the sample probability of a banking crisis over the next five years, 6.8%, 5% represents a 73.5% increase.

Other models in Panel B of this table show that the effect of *log(1+Private Credit/GDP)* on the probability of a banking crisis is robust to different sets of explanatory variables when using linear probability regressions. The estimated coefficients on other explanatory variables also have similar signs and statistical significance levels as those in Panel A of this table. These results suggest that the effect of the quantity of private credit on the probability of a banking crisis is robust to using the linear probability models.

Panel C of this table shows the results of Cox proportional hazard models. The specifications of covariates are similar to those in the previous two panels. The estimated coefficients on *log(1+Private Credit/GDP)* show that the effect of the quantity of private credit is still positive and statistically significant. The coefficient on *log(1+Private Credit/GDP)* is also economically significant. According to the value of the coefficient in Model (3), 2.921, when *log(1+Private Credit/GDP)* increases by one standard deviation, the hazard of a systemic banking crisis increases by $exp(2.921 \times 0.211) - 1 = 0.85$, or 85%.

The coefficients on *Growth of Private Credit/GDP* are also positive, but their statistically significance is lower than that in the previous two panels. Only the coefficient in Model (4) is significantly different from zero. Because Cox proportional hazard models non-parametrically control for time-specific common factors, this result could mean that the time-specific common factors are closely related to the relation between the growth of private credit and the occurrence of systemic banking

crises.

To further understand the economic significance of the result from Cox model estimation, I calculate the cumulative probability of a systemic banking crisis as a function of time and plot this function. In Figure 1, the solid line is the cumulative probability of a systemic banking crisis when *log(1+Private Credit/GDP)* is one standard deviation above its sample mean, while other covariates are at their sample means. The dashed line is the cumulative probability when all covariates are at their sample means. The calculation of these cumulative probability functions are based on Model (3) of Panel C. The solid line is increasing faster with time than the dashed line, suggesting that the risk of a systemic banking crisis is accumulating at a faster rate for a country that has a higher quantity of private credit than for a country that is otherwise comparable but has a lower quantity of private credit. At 5 years, the value of the solid line is 0.0623, while the value at the dashed line is 0.0344. These numbers indicate that the probability of a systemic banking crisis over the next 5 years increases by 81% when *log(1+Private Credit/GDP)* increases by one standard deviation from the mean. This magnitude is consistent with that from the panel logit regressions.

5 The Structure of the Financial System and the Probability of Banking Crises

So far, I have focused on the quantity of credit and the growth of private credit to explain the probability of banking crises. However, the financial system consists of many components, each of which can have a unique effect on financial instability. In this section, I consider three primary components of a financial system: equity market, private bond market, and banks and other financial institutions. I examine the importance of the quantity of private credit relative to these other components of the financial system in explaining the probability of banking crises.

In Table 5, I examine how the other measures of the structure of the financial system are related to the probability of banking crises, after controlling for the quantity of private credit and other variables. The response variable and the controlling variables in the panel logit regressions are the same as those in Panel A of Table 4. Because *Inflation* is highly correlated with either *Nominal*

Interest Rate or *Depreciation*, I estimate two regressions for each measure of the structure of the financial system. One regression includes *Inflation*, and the other does not.

In Models (1) and (2), I consider *Credit/Stock Market Cap*, the ratio of the total credit outstanding relative to the capitalization of the equity market. To the extend that the proportion of public firms to other sectors is relatively constant across countries and to the extent that equity market can efficiently value the public firms, this ratio can be considered as a measure of the leverage of the economy. The results show that *Credit/Stock Market Cap* is positively related to the probability of future crises. A one standard deviation increase in *Credit/Stock Market Cap* is associated with an increase of $exp(3.941 \times 0.161) - 1 = 88.6\%$ in the probability of a banking crisis. This result implies that an increase in the equity market capitalization relative to the outstanding credit is related to a lower probability of a banking crisis. This implication is consistent with *Credit/Stock Market Cap* being a proxy for the leverage of the economy and higher leverage being related to a higher probability of defaults and the worsening of the claim quality of financial institutions.

In both Models (1) and (2), the coefficient on *log(1+Private Credit/GDP)* is still significantly positive. Because according to the second panel of Table 3, the correlation coefficient between *Credit/Stock Market Cap* and *log(1+Private Credit/GDP)*, 16.4%, is low, these two variables measure risk factors that are orthogonal to each other. These results mean that the *log(1+Private Credit/GDP)* could be measuring a risk factor of banking crises that is different from the leverage of the economy.

Models (3) and (4) consider a measure of the relative importance between market-based financing and bank-based financing: *Market/Bank*. I find that *Market/Bank* is negatively related to the probability of a banking crisis with a potential output loss of greater than 10%. This effect, however, is not statistically significantly different from zero. This result suggests that the relative importance of market-based financing and bank-based financing does not have a strong association with the occurrence of banking crises.

In Models (5) and (6), I compare bank-based credit with market-based credit by including both *log(1+Private Credit/GDP)* and *Private Bond/GDP* as covariates of the panel logit regressions. The coefficients on *Private Bond/GDP* are significantly positive, when *log(1+Private Credit/GDP)*

also has positive coefficients. This result means that both the quantity of bank-based credit (the quantity of private credit) and the quantity of market-based credit (the quantity of private bond) are significantly positively related to the probability of a systemic banking crisis.

These regressions do not tell us directly about the relative importance of bank-based credit and market-based credit. In Models (7) and (8), I directly consider this relative importance by using the ratio of quantity of private credit to the sum of private credit and bond market capitalization, *Private Credit/Credit*, as an explanatory variables while controlling for *log(1+Private Credit/GDP)*. *Private Credit/Credit* measures the size of the bank-based credit financing relative to that of the market-based credit financing. The coefficient on *Private Credit/Credit* is negative but not statistically significant different from zero. This results suggests that the relative quantity between the outstanding bank-based credit and the market-based credit is not associated with the risk of having a banking crisis.

In sum, the results in the section point out that an increase in the ratio of total credit outstanding to equity market capitalization is related to an increase in the probability of a systemic banking crisis. To the extent that this variable measures the leverage of the whole economy, the results suggest that when the leverage of the economy is positively related to the probability of a systemic banking crisis.

6 Financial Liberalization

There is a large literature on the effect of financial liberalization on growth and financial markets. Many papers in this literature examine the relation between financial liberalization and financial crises. A number of papers have tried to model the link between financial liberalization and financial fragility. Hellman, Murdock, and Stiglitz (2000) argue that when financial liberalization increases competition in the financial sector, banks' expected future profits decrease, and their franchise values (i.e. the capitalized value of expected future profits) also decrease. As a result, banks have lower incentives to make loans with good quality. At the same time, banks are given greater freedom to allocate assets. As a consequence, financial liberalization may encourage the gambling of banks and increase both the quantity of private credit and financial fragility. Dell'Ariccia and Marquez (2004)

also argue that when facing increased competition, informed banks may reduce lending to a greater extent in less captive sectors and allocate proportionally larger market shares in the more captive but more profitable sectors because the more captive sectors have less information asymmetry with them than with the relatively uninformed competitors. This behavior can potentially lower the quality of the informed banks' overall loan portfolio because there tends to be a negative correlation between borrower quality and the degree of information asymmetry. Empirically, Kaminsky and Reinhart (1999) find that banking crises are much more likely following the deregulation of the domestic banking sector. Based on the above arguments and evidence, it is important to examine whether financial liberalization drives the relation between the quantity of private credit and the occurrence of systemic banking crises. In addition, examining the process of financial liberalization may shed light on the mechanism underlying the relation between the quantity of private credit and the probability of systemic banking crises.

To empirically study the impact of financial liberalization, I consider two alternative sources of data on financial liberalization around the world. The first source is the dating of equity market liberalization in Bekaert, Harvey, and Lundblad (2005). They use a variety of data sources to date the liberalization of access by foreigners to the domestic equity market, which is an important element of financial liberalization. Their data covers the period of 1980 to 2004 and 95 countries, including 42 countries that liberalized between 1980 and 2004. By assuming that the liberalization status of these countries does not change after 2004, I extend the time coverage of their data to 2009. According to this data, I divide the country-year observations into four groups indicating whether a country was *always liberalized*, *never liberalized*, the periods before liberalization for liberalizing countries (*preliberalization*), and the periods after liberalization (*postliberalization*) for liberalizing countries.

Because equity market liberalization is only one aspect of the financial liberalization process, I consider an alternative data source of financial liberalization: a database of financial reforms constructed by Abiad, Detragiache, and Tressel (2010). This database covers seven aspects of financial sector policy[29] and provides a graded score for each of these aspects. In this database, the

[29]These seven aspects are credit controls and excessively high reserve requirements, interest rate controls, entry barriers, state ownership in the banking sector, financial account restrictions, prudential regulations and supervision

sum of the scores for the seven aspects is the *index of financial reform*, the values of which ranges from 0 to 21, indicating from the most repressed to fully liberalized financial sector. I measure the pace at which financial reforms progress in a country by using the average annual changes in the index of financial reform over the last five years. Then, I divide the annual observations into four groups: *large reforms*, *reforms*, *status quo*, and *reversal*, corresponding to the five-year average of annual changes in the index of financial reforms being less than 0, equal to 0, greater than 0 and less than or equal to 0.5, and greater than 0.5, respectively.

Table 6 shows the results of linear probability regressions that study the occurrence of systemic banking crises and equity market liberalization. Because the liberalization of equity market tends not to reverse its course, postliberalization periods are usually after the preliberalization periods, which raises the concern that the difference between different periods of equity market liberalization may be due to systemic banking crises becoming more frequent over time. To address this concern, I use year fixed effects in the regressions of Table 6.

In Panel A of this table, I include the indicators of equity market liberalization as covariates. This panel shows after controlling for these indicator variables, the relation between the quantity of private credit and the occurrence of systemic banking crises is still significantly positive, and the magnitudes of the coefficients are close to those before controlling for financial liberalization indicator variables. This result shows that the relation between the quantity of private credit and the probability of banking crises is not simply due to equity market liberalization simultaneously increasing both the quantity of private credit and the probability of banking crises.

In Panel B of Table 6, I add as covariates the interaction terms between *log(1+Private Credit/GDP)* and the indicators of equity market liberalization. In this panel, the coefficients on the interaction between *log(1+Private Credit/GDP)* and the indicator of post-liberalization periods are positive and significantly different from zero, while the coefficients on the interaction between *log(1+Private Credit/GDP)* and the indicator of pre-liberalization periods are statistically indistinguishable from zero. This result means that for liberalizing countries, a higher quantity of private credit is more strongly associated with the occurrence of systemic banking crises after equity market liberalization

of the banking sector, and securities market policy.

than before the liberalization.

Although equity market liberalization can occur simultaneously with reforms in other parts of the financial system, it is useful to directly measure the reforms in the financial sector. The database of financial reforms constructed by Abiad, Detragiache, and Tressel (2010) provides such measures. Table 7 studies how financial reforms affect the relation between the quantity of private credit and the probability of systemic banking crises. Specifically, this table considers the interaction terms between the quantity of private credit and the indicators of financial reforms as covariates. The relation between quantity of private credit and the probability of systemic banking crises is stronger for large reforms than for reforms and reversals.

This result and the result in Panel B of Table are consistent with the stories that financial liberalization can lead to excessive risk taking, which can increase the probability of systemic banking crises and lead to a large quantity of private credit. Relative to the previous literature that suggests an increased probability of systemic banking crises after financial liberalization, these results also point out the critical role of credit in understanding the relation between banking crises and financial liberalization.

These findings are not inconsistent with the findings in Bekaert, Harvey, and Lundblad (2005) that equity market liberalization leads to a higher economic growth. First, financial liberalization could increase the likelihood of crises only in the short-run, while over the long run, the markets tend to stabilize if the liberalization persists (Kaminsky and Schmukler (2008)). Second, Tornell, Westermann, and Martinez (2003), Rancière, Tornell, and Westermann (2006), and Rancière, Tornell, and Westermann (2008) argue that credit risk taking can drive both high economic growth and high likelihood of crises.

7 Nonlinearity in the Effect of Quantity of Credit on the Probability of Banking Crises

The previous sections focus on a positive relation between the quantity of private credit and the probability of a banking crisis. In this section, I examine whether the strength of this relation

changes as a country's quantity of private credit moves away from the cross-country mean. When a country's *Private Credit/GDP* is above the cross-country mean, the quantity of private credit relative to the size of its economy is higher than the world-wide average. When *Private Credit/GDP* moves further away from the world-wide average, the sensitivity of the probability of a systemic banking crisis to the quantity of private credit may change. This possible nonlinearity is the focus of this section.

To measure how far away a country's *Private Credit/GDP* is relative to the cross-country average, for each year, I calculate the deviation of *log(1+Private Credit/GDP)* from its cross-sectional mean and normalize this deviation by the cross-sectional standard deviation. I label this normalized cross-sectional deviation *CD(log(1+Private Credit/GDP))*. I then construct indicator variables that indicate whether a country's *CD(log(1+Private Credit/GDP))* is in one of the four ranges, $CD <= 0$, $0 < CD <= 1$, $1 < CD <= 2$, and $2 < CD$. Finally, I construct interaction terms between *log(1+Private Credit/GDP)* and these indicator variables and include the interaction terms as covariates in the regressions. The coefficient on each one of these interaction terms measures by how much the probability of banking crises changes when $log(1 + Private\ Credit/GDP)$ increases by one unit within the corresponding range of *log(1+Private Credit/GDP)*. By comparing these coefficients, I can show whether the strength of the relation between the probability of systemic banking crises and quantity of private credit changes as *log(1+Private Credit/GDP)* moves away from the cross-country mean.

I also implement another method of analysis by considering indicators variables indicating eight ranges: $CD <= -1$, $-1 < CD <= -0.5$, $-0.5 < CD <= 0$, $0 < CD <= 0.5$, $0.5 < CD <= 1$, $1 < CD <= 1.5$, $1.5 < CD <= 2$, and $2 < CD$, and consider only these indicator variables as covariates in the regressions. The coefficient on each one of these indicator variables measures the average probability of systemic banking crises in the corresponding range. By examining whether these coefficients differ across different ranges, I can also show whether the relation between the probability of systemic banking crises and quantity of private credit changes as *log(1+Private Credit/GDP)* moves away from the cross-country mean.

I estimate linear probability regressions for both the above two methods and report the results

in Table 8. Panel A of this table shows the analysis using the first method, and Panel B shows the analysis using the second method. In Panel A, across all alternative model specifications, the coefficients on the interaction between *log(1 + Private Credit/GDP)* and *I(2 < CD)* or *I(1<CD<=2)* is positive and statistically significant, while the coefficients on other interaction terms are not statistically different from zero. In addition, the coefficients on *log(1 + Private Credit/GDP) × I(2 < CD)* is larger than that on *log(1 + Private Credit/GDP) × I(1 < CD <= 2)*. This result shows that the relation between the quantity of credit and the probability of banking crises is stronger when the quantity of private credit is higher and further away from the cross-sectional mean and is the strongest when it is two standard deviations away from the cross-country mean.

In Panel B, the coefficients for the top two ranges, *1.5 < CD <= 2* and *2 < CD*, are larger than the coefficients for other ranges. Furthermore, when we move from lower ranges to higher ranges, the magnitude of coefficients is very similar in the first three ranges, *-1 < CD <= -0.5*, *-0.5 < CD <= 0*, and *0 < CD <= 0.5*, but increases quickly when moving to *0 < CD <= 0.5* and *0.5 < CD <= 1* and increases even more sharply when moving to the last two ranges. This pattern is consistent with the result in the previous panel that the relation between the quantity of private credit and probability of banking crises is nonlinear.

Overall, the results in this section suggest that a higher quantity of private credit is more dangerous in terms of its association with banking crises when the quantity of private credit is higher than the world-wide average than when it is lower than the world-wide average. Furthermore, the quantity of private credit becomes increasingly dangerous when it is above and further away from the world-wide average. The range above two standard deviation from the world-wide average seems to be a region in which the quantity of private credit is most risky.

8 The Interaction between the Quantity of Private Credit and the Growth of Private Credit

In the previous sections, I have used the quantity of private credit and the growth of private credit as separate variables. There are, however, reasons that there may be strong interaction between

these two variables.

First, if a part of a large quantity of private credit is extended because of excessive risk taking, then it can cause trouble to the financial sector. Therefore, when examining the relation between the quantity of private credit and systemic banking crises, it is important to check how the existing quantity of private credit is realized. I use *Growth of Private Credit/GDP* to gauge the way private credit is extended. Because this variable is the growth of real quantity of private credit scaled by the growth of real GDP, when its value is high, it may suggest that the quantity of private credit is growing too fast. Given a fast growth rate of private credit in the recent past, a higher quantity of private credit can be more risky because part of the private credit can be the result of excessive risk taking and of low quality.

I examine this intuition by considering eight different ranges of the average growth rate of private credit over the past 5 years, $Average(Growth\ of\ Private\ Credit/GDP)_{t-4,t}$ or AG. These eight ranges are $AG <$ *-10%*, *-10%* $<= AG <$ *-5%*, *-5%* $<= AG <$ *-2.5%*, *-2.5%* $<= AG <$ *0*, *0* $<= AG <$ *2.5%*, *2.5%* $<= AG <$ *5%*, *5%* $<= AG <$ *10%*, and *10%* $<= AG$. I then interact *log(1+Private Credit/GDP)* with these indicators and estimate linear probability regressions that use these interaction terms as covariates. The coefficient on each one of these interaction terms shows the sensitivity of systemic banking crises to the quantity of private credit for countries that have experienced the corresponding growth rate of *Private Credit/GDP* in the past five years. By comparing these coefficients, I can examine whether this sensitivity differs depending on how fast the private credit has grown in the recent past.

Panel A of Table 9 shows the results of these linear probability regressions. When the average growth of private credit in the past five years is above zero, the coefficients on the interaction terms show that there is a positive relation between the quantity of private credit and the probability of systemic banking crises. For ranges *0* $<= AG <$ *2.5%*, *2.5%* $<= AG <$ *5%*, and *5%* $<= AG <$*10%*, the magnitudes of the coefficients on the interaction terms are similar. When private credit has experienced the highest rates of growth in the past 5 years, i.e. $Average(Growth\ of\ Private\ Credit/GDP)_{t-4,t}$ is greater than or equal to 10%, the probability of systemic banking crises are highly sensitive to the quantity of private credit. The coefficient from Model (3), 0.628, shows that

a one standard deviation increase in *log(1+Private Credit/GDP)* is associated with an increase of 13% in the probability of a systemic banking crisis in the future five years. On the other hand, when the average growth of private credit is less than -2.5%, the coefficients on the interaction terms are not significantly different from zero. These results suggest that when there is recent fast growth of private credit, quantity of private credit is more strongly related to the occurrence of systemic banking crises.

Another aspect of the interaction between the quantity of private credit and the growth of private credit is whether a higher growth rate of private credit is more dangerous for countries that already have a high quantity of private credit. I examine this issue by considering the interaction between the average growth rate of private credit over the past 5 years and the indicators based on the cross-sectional deviation of private credit 5 years ago. Specifically, I consider eight different ranges of the cross-sectional deviation: $CD < -1$, $-1 < CD <= -0.5$, $-0.5 < CD <= 0$, $0 < CD <= 0.5$, $0.5 < CD <= 1$, $1 < CD <= 1.5$, $1.5 < CD <= 2$, and $2 < CD$. The coefficient on an interaction term between $Average(Growth\ of\ Private\ Credit/GDP)_{t-4,t}$ and one of these indicator variables measures the relation between the probability of banking crises and the average growth of private credit when the country's quantity of private credit is in the corresponding range. Based on these coefficients, I can examine how the strength of this relation changes across these ranges.

Panel B of Table 9 shows the results of the linear probability regressions that use these interaction terms as covariates. The coefficients on the interaction terms are positive for most ranges except for $CD < -1$ and $-1 < CD <= -0.5$, when a country's quantity of private credit is far below the cross-sectional average. A higher growth rate of private credit does not increase the probability of systemic banking crises for countries in these two ranges. When the quantity of private credit is higher than 0.5 standard deviation below the cross-sectional mean, the growth of private credit positively affects the probability of systemic banking crises. For the highest range of the quantity of private credit, $2<CD$, the effect of private credit growth on the probability of banking crises is also significantly positive. The probability of systemic banking crises is most sensitive to the growth of private credit when a country is in the range of $1< CD <=1.5$ five years ago. There does not, however, seem to be an obvious trend in the coefficients on the interaction term when moving from

low ranges to high ranges.

In sum, when the growth of private credit in the recent past is higher, the relation between the probability of systemic banking crises and the quantity of private credit is stronger. Because high credit growth likely indicates excessive risk-taking, this result supports the view that when excessive risk-taking is severe in the recent past, part of a large quantity of private credit can be of poor quality and cause trouble for the banking sector.

9 Alternative Explanations and Robustness of the Results

In this section, I consider a number of alternative explanations for and check the robustness of the positive relation between quantity of private credit and the occurrence of systemic banking crises.

9.1 Four Waves of Capital Flows

The existing literature shows that capital flow volatility can have important economic consequences. For example, Calvo (1998) argues that sudden stops in international capital flows may lead to financial and balance of payments crises. Reinhart and Reinhart (2009) show that capital inflow surges or bonanzas are associated with a higher likelihood of economic crises, especially for emerging market economies.

While many papers examine the net capital flows, the more recent literature studies gross capital flows, which differentiate between the foreign and domestic investors' behavior. To investigate whether episodes of extreme gross capital flows are associated with the occurrence of systemic banking crises, I consider four waves of gross capital flows: surges, stops, flight, and retrenchment, which are defined as follows:

- "Surges": a sharp increase in gross capital inflows;
- "Stops": a sharp decrease in gross capital inflows;
- "Flight": a sharp increase in gross capital outflows; and
- "Retrenchment": a sharp decrease in gross capital outflows.

In the above definition, gross inflows is the net of foreign purchases of domestic securities and foreign sales of domestic securities, while gross outflows is the net of domestic residents' purchases. Surges and stops are driven by foreigners, while flight and retrenchment are driven by domestic investors. I use the quarterly indicator variables that Forbes and Warnock (2011) construct to identify these four waves of capital flows. Specifically, for 58 countries from 1980 to 2009, they define surges as a period in which gross inflows is at least one standard deviation above its five-year rolling average, given that it is at least two standard deviations above the rolling mean for at least one quarter. Stops is similarly defined as a period in which gross outflows is at least one standard deviation below its five-year rolling average and two standard deviations below for at least one quarter. Episodes of flight and retrenchment are defined similarly but using gross capital inflows rather than gross outflows.

I construct indicators of the four waves of capital flows at annual frequency based on the quarterly indicator variables of Forbes and Warnock (2011). More specifically, for each year, I set the annual indicator to one for one of the four waves if there is a corresponding wave in any quarter during the year according to the quarterly indicators and to zero otherwise. I then include the annual indicator variables as covariates in the panel logit regressions.

Table 10 has the results of these regressions. Models (1) to (4) show that when the annual indicator variable for only one type of flow wave is included as covariates, surges and flight are related to a higher probability of systemic banking crises, while stops and retrenchment are associated with a lower probability. When indicators of all four types of waves are included as covariates in Model (5), only stops are significantly negatively related to the occurrence of systemic banking crises.

In Models (6) and (7), I add the quantity of private credit as well as other variables, and in model (8) and (9), I exclude the recent global financial crisis. The relation between quantity of private credit and the occurrence of systemic banking crises is still positive and statistically significant when either excluding or including the recent global financial crisis. Therefore, this positive relation is unlikely due to episodes of extreme capital flows.

The relation between *growth of private credit/GDP* and the occurrence of systemic banking crises is significantly positive when including the recent global financial crisis but is not statistically

significantly when excluding the recent global financial crisis. The magnitude of the coefficient on *growth of private credit/GDP* is also lower when excluding the recent global financial crisis than when including it. This result suggests that the episodes of extreme capital flows may be related to periods of extreme credit growth for periods before the recent global financial crisis.

The results in this section show that although there is some evidence that the episodes of capital flows are related to the occurrence of systemic banking crises, these episodes do not drive away the explanatory power of the quantity of private credit on the probability of systemic banking crises.

9.2 Central Government Debt

The current European sovereign debt crises draw people's attention to government debt. The political debates in the US also often focus on the role of large government debt on the economic recovery after the recent financial crisis and economic recession and on long-run economic growth. Although many of these issues about government debt are directly related to what has happened after the start of the recent global financial crises, people have asked whether large central government debt is associated with the occurrence of future banking crises.

In this section, I examine this question by considering the ratio of central government debt to GDP from the World Economic Outlook database of the IMF. The numerator of this ratio consists of all liabilities of the central government that require payment or payments of interest and/or principal by the debtor to the creditor in the future. The data cover the period from 1980 to 2009. I use this ratio as a covariate in panel logit regressions in addition to the quantity of private credit as well as other controlling variables. This approach examines whether central government debt is associated with the occurrence of banking crises and whether it affects the relation between the quantity of private credit and the occurrence of systemic banking crises.

I report the results of these regressions in Table 11. The relation between the quantity of private credit and the probability of a systemic banking crisis is still positive and statistically significant. This result is consistent with the conjecture that the economic effect of *Central Government Debt/GDP* is independent of the effect of the quantity of private credit on the occurrence of systemic banking crises. Furthermore, *Central Government Debt/GDP* is not positively related

to the occurrence of systemic banking crises: the relation is negative when the recent global financial crisis is excluded and is not significantly different from zero for the overall sample. These results suggest that a high level of central government debt relative to GDP is not related to a high probability of systemic banking crises in the future.

9.3 Government Ownership of Banks

Another aspect of financial systems that may affect both the quantity of private credit and the occurrence of systemic banking crises is government ownership of banks. La Porta, Lopez-de Silanes, and Shleifer (2002) show that such ownership is pervasive around the world, and has significant consequences for economic and financial development. La Porta, Lopez-de Silanes, and Shleifer (2002) also focus on two views of the government's ownership of banks. The first view, an optimistic, "development" view is that in countries that the banking system is not developed enough to attract sufficient funds to finance large scale industrialization, government can step in and jump start both financial and economic development (Gerschenkron (1962)). The alternative "political" view emphasizes that the government acquires control of enterprises and banks in order to provide employment, subsidies, and other benefits to supporters, who return the favor in the form of votes, political contributions, and bribes. According to the first view, government ownership of banks enables the government both to collect savings and to direct them toward strategic long-term projects, and hence generate aggregate demand and foster growth. According to the second view, through ownership of banks, the government is able to finance inefficient but politically desirable projects. The first view suggests that the projects are efficient and socially desirable. The second view suggests that the projects are not efficient or socially desirable.

These two theories may also have implications for the relation between the quantity of private credit and the probability of systemic banking crises. On the one hand, the financing of projects by banks owned by government can lead to a large quantity of private credit. On the other hand, the financing of these projects may increase or decrease the probability of systemic banking crises. The "development" theory could imply an efficient allocation of risks to those at best position to

manage them, and therefore reduce the probability of systemic banking crises.[30] The "political" theory implies that the inefficient projects financed by government-owned banks may cause trouble to the financial sector in the future and lead to a higher probability of systemic banking crises. Furthermore, the government may be more inclined to bail out the banks when its ownership of banks is large. It is ultimately an empirical question what the overall outcome of all these alternative effects is.

To examine whether government ownership of banks is related to the probability of systemic banking crises and whether it affects the relation between the quantity of private credit and the probability of systemic banking crises, I use the variable *Government Ownership of Banks* from La Porta, Lopez-de Silanes, and Shleifer (2002). This variable measures the share of the assets of top 10 banks in a given country that is owned by the government at 1970 for 92 countries. In Table 12, I add *Government Ownership of Banks* as a covariate in addition to the quantity of private credit and other variables. The results show that after including *Government Ownership of Banks* as a covariate, the relation between the quantity of private credit and the probability of systemic banking crises is still positive and statistically significant. The results also show that there is a positive relation between *Government Ownership of Banks* and the probability of systemic banking crises in the overall sample. This positive relation is not statistically significant when the recent global financial crisis is excluded.

9.4 Comparing Economies with Different Economic Development

In the previous sections, using all available data in my sample, I document a positive relation between the quantity of credit and the probability of a banking crisis. In this subsection, I focus on the comparison between advanced economies and emerging market economies. I choose this focus for two reasons. First, because the advanced economies in general have more developed financial systems than emerging market economies, the effects of quantity of credit on the probability of banking crises can differ between these two groups of countries. Second, because advanced economies

[30]The "development" theory may also imply a higher probability of systemic banking crises because the projects financed by government owned banks may not only increase systemic risks in the short run but also foster long-run economic growth.

and emerging market economies differ in many other aspects, such as economic development and political systems, examining each of these two groups countries separately control for these factors.

The results of this comparison is in Table 13. Panel A of this table reports the analysis using interaction terms between $log(1+$ *Private Credit/GDP*) and *Advanced Economy* with available data for both advanced and emerging market economies, and Panel B of this table shows the analysis using separate samples for advanced economies and emerging market economies. For both panels, the method of analysis is panel logit regressions with the same response variable as in the previous section. Model (1) of Panel A shows that the interaction between *log(1+Private Credit/GDP)* and *Advanced Economy* is positive and statistically significant, while the coefficient on *log(1+Private Credit/GDP)* itself is not significantly different from zero. This result shows that the effect of the quantity of credit on the probability of banking crises is stronger among advanced economies than among emerging market economies. Model (2) considers the interaction between *Growth of Private Credit/GDP* and *Advanced Economy*. This interaction term is positive, which suggests that the effect of *Growth of Private Credit/GDP* on the probability of a banking crisis is also stronger among advanced economies than among emerging market economies but the difference in the effect is small.

In Model (3) to (6), I consider a number of alternative model specifications. In all these specifications, the estimated coefficient on the interaction between $log(1 +$ *Private Credit/GDP*) and *Advanced Economy* is always positive and statistically significant, which confirms that the effect of the quantity of credit on the probability of a banking crisis is stronger among advanced economies than among emerging market economies. The interaction between *Growth of Private Credit/GDP* and *Advanced Economy* is positive and significant for Model (4) and (6) but not statistically significant for Model (3) and (5). These results confirm that the effect of *Growth of Private Credit/GDP* on the probability of a banking crisis is also stronger for advanced economies than for emerging market economies, but the difference in the effect is small.

In Panel B of Table 13, I study the difference in the effect of the quantity of credit on the probability of banking crises between advanced economies and emerging market economies by using separate samples for these two groups of countries. I consider both the whole sample period (in

Models (1) to (4)) and the period before the recent global financial crisis (in Models (5) to (8)). For the whole sample period, the coefficients on $log(1+Private\ Credit/GDP)$ for the advanced economy sample (in Models (1) and (2)) are positive and significantly different from zero, while those for the emerging market economy sample (in Models (3) and (4)) are not significantly different from zero. These results are consistent with the finding in Panel A that the effect is stronger among advanced economies than among emerging market economies. When comparing the coefficient on *log(1+Private Credit/GDP)* in Models (5) and (6) with those in Models (7) and (8), I find that this pattern also exists for the period before the recent global financial crisis.

In Panel B, when comparing the coefficients on *Growth of Private Credit/GDP* between the advanced economy sample and the emerging market economy sample, I find that the effect of the growth of *Growth of Private Credit/GDP* on the probability of banking crises is also stronger for advanced economies than for emerging market economies, and this pattern persists after excluding the recent global financial crisis.

10 Conclusion

Economists have argued that finance can facilitate growth and increase stability. However, the recent global financial crisis has led some to argue that finance can decrease stability and lead to more crises. So far, there is no direct examination of whether more finance leads to a higher probability of a banking crisis.

I fill this gap using panel data for 150 countries from 1960 to 2009. I find that a larger quantity of private credit normalized by GDP is related to a higher probability of future banking crises with a potential output loss of more than 10%. A one standard deviation increase in *log(1+Private Credit/GDP)* from its mean is associated with a doubling of the probability of having a banking crisis with a potential output loss of more than 10% over the next five years. This effect is robust to excluding the recent global financial crisis. I also find that this effect is nonlinear: it becomes stronger when the quantity of private credit becomes larger. This effect is also stronger for periods of large financial reforms and for countries that have experienced high growth of *Private Credit/GDP* in the recent past.

There could be, however, other factors that can simultaneously drive both a country's risk of having a banking crisis and the quantity of credit in its economy. I examine whether waves of capital flows, central government debt normalized by GDP, and government ownership of banks affect the relation between quantity of private credit and the occurrence of banking crises. None of these factors can drive out the relation between the quantity of private credit and the probability of systemic banking crises. Nevertheless, the concern of endogeneity is an issue that future research should further address.

The positive relation between the quantity of credit and the probability of a banking crisis does not necessarily imply that more credit has an adverse effect on economic growth. It could be that countries that have higher risks of systemic crises have, on average, higher long-run economic growth (Rancière, Tornell, and Westermann (2008)). This paper focuses only on the downside of having a large quantity of finance. To improve the understanding of the overall effect of a large quantity of finance, future research should consider the trade off between the benefits and the costs of having a large quantity of finance in the economy.

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Table 1: Key Features of the Data

	Advanced Economies (AE)	Emerging Market Economies (EME)	Total
Overall Sample (1960–2009)			
Number of countries	23	127	150
Number of country-years	1100	3229	4329
All Banking Crises (1970–2009)			
Number of crisis countries	18	55	73
Number of banking crises	21	69	90
Number of country-years in banking crisis	39	204	243
Banking Crises with Potential Output Losses of More Than 10% (1970–2009)			
Number of crisis countries	16	33	49
Number of banking crises	18	40	58
Number of country-years in banking crises	34	124	158

This table shows the key features of the data used in my paper. I start with all countries that I can find information on real GDP and *Private Credit/GDP*. For each year, I select countries for which *Private Credit/GDP* is above the 20th percentile of the cross-country distribution of *Private Credit/GDP* in that year. I identify Advanced Economies and Emerging Market Economies (EME) according to the 1993 World Economic Outlook (IMF (1993)). The list of countries in my sample is in Table A.1. The data on banking crises around the world from 1970 to 2009 are from Laeven and Valencia (2010). The crises experienced by countries in my sample are described in the panel titled "All Banking Crises (1970-2009)". These crises are listed in Table A.2. In the primary analysis in my paper, I consider a sample of banking crises associated with a more than 10% potential output loss based on the calculation of Laeven and Valencia (2010). For a crisis starting at year T, the potential output loss is the cumulative sum of the differences between actual and extrapolated real GDP over the period $[T, T+3]$, expressed as a percentage of the extrapolated real GDP at year T. When necessary, Laeven and Valencia (2010) use the GDP forecasts from the April 2010 version of WEO as estimates of future real GDP. To extrapolate the real GDP, they first apply an Hodrick-Prescott filter with $\lambda = 100$ to the log of real GDP over the period $[T-20, T-1]$ to obtain the trend log real GDP, while requiring at least four pre-crisis observations. The log of real GDP is extrapolated using the growth rate of the trend over the same period. Finally, Laeven and Valencia (2010) take the exponential of the extrapolated log real GDP to obtain the extrapolated real GDP.

Table 2: Summary Statistics: Comparing Crisis Countries and Non-crisis Countries

	Crisis Country Obs	Non-crisis Country Obs	Crisis Country Mean	Non-crisis Country Mean	Difference in Mean	T-test P-value	Crisis Country Median	Non-crisis Country Median	Wilcoxon P-value
Private Credit/GDP	47	94	0.631	0.362	0.269	0.001	0.472	0.286	0.002
Financial Assets/GDP	47	94	0.762	0.449	0.313	0.001	0.607	0.363	0.003
Bank Credit/GDP	47	94	0.572	0.340	0.232	0.001	0.469	0.275	0.003
Growth of Private Credit/GDP	46	92	0.041	0.056	−0.015	0.249	0.037	0.035	0.977
Growth of Financial Assets/GDP	46	92	0.043	0.051	−0.008	0.491	0.033	0.033	0.894
Growth of Bank Credit/GDP	46	92	0.041	0.058	−0.017	0.224	0.035	0.034	0.713
Market/Bank	18	11	0.510	0.571	−0.061	0.216	0.465	0.583	0.204
Credit/GDP	18	11	1.491	1.070	0.421	0.065	1.477	1.144	0.049
Credit/Stock Market Cap	18	11	0.699	0.555	0.144	0.010	0.721	0.556	0.009
Private Credit/Credit	18	11	0.756	0.843	−0.087	0.079	0.746	0.867	0.102
Real GDP Per Capita	46	92	14735.451	9082.283	5653.168	0.018	7983.777	5632.061	0.034
Growth of Real GDP	46	91	0.036	0.044	−0.008	0.110	0.033	0.040	0.056
Nominal Interest Rate	42	93	0.107	0.110	−0.003	0.910	0.080	0.076	0.586
Inflation	47	93	0.108	0.107	0.000	0.984	0.065	0.073	0.240
Depreciation	47	89	−0.032	−0.031	−0.001	0.965	0.000	−0.017	0.142
Political Risk	34	61	70.935	66.654	4.281	0.192	76.650	65.542	0.042

This table compares country-level characteristics of countries that have experienced banking crises with a potential output loss of greater than 10% and those of countries that have not had such crises. For each crisis country, the country-level characteristic is measured as the mean in a five-year window ending at the year before the first year of the banking crisis. If a country experiences multiple crises in my sample, I use only the first crisis to calculate the mean of the country characteristic. For each non-crisis country, the country-level characteristic is measured as the mean over the whole sample period. As a result, for the tests in this table, there is one observation per country for each variable. The T-test P-value is the p-value of a two-sided Student's T-test against the null hypothesis that the difference in mean is zero between the two groups of countries. The Wilcoxon P-value is the p-value of a two-sided Wilcoxon rank-sum test against the null hypothesis that the distributions of crisis countries and non-crisis countries have relatively the same location. Detailed definitions of variables are in Table B.1.

Table 3: Summary Statistics of the Variables Used in the Logit Regressions

Variable		Mean	Std. Dev.	Min	Max	Obervations
Private Credit/GDP	overall	0.462	0.353	0.077	2.698	4329
	between		0.257			150
	within		0.220			28.9
Financial Assets/GDP	overall	0.577	0.419	0.087	2.716	4311
	between		0.308			150
	within		0.257			28.7
$log\,(1 + Private\ Credit/GDP)$	overall	0.355	0.211	0.090	1.059	4329
	between		0.162			150
	within		0.125			28.9
$log\,(1 + Financial\ Assets/GDP)$	overall	0.425	0.235	0.104	1.162	4311
	between		0.183			150
	within		0.137			28.7
Growth of Private Credit/GDP	overall	0.035	0.109	−0.357	0.418	4204
	between		0.067			148
	within		0.103			28.4
Growth of Financial Assets/GDP	overall	0.033	0.105	−0.364	0.460	4188
	between		0.061			148
	within		0.100			28.3
Crisis Year	overall	0.063	0.243	0.000	1.000	3843
	between		0.126			150
	within		0.228			25.6
Crisis	overall	0.023	0.151	0.000	1.000	3843
	between		0.042			150
	within		0.148			25.6
$Crisis\ Year_{Loss\geq 10\%}$	overall	0.041	0.199	0.000	1.000	3843
	between		0.088			150
	within		0.186			25.6
$Crisis_{Loss\geq 10\%}$	overall	0.015	0.122	0.000	1.000	3843
	between		0.035			150
	within		0.120			25.6

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$Crisis5_{Loss\geq 10\%}$	overall	0.068	0.252	0.000	1.000	4003
	between		0.093			150
	within		0.236			26.7
Real GDP Per Capita	overall	11350.279	10659.450	405.941	51483.318	4252
	between		10160.593			148
	within		4615.104			28.7
log (*Real GDP Per Capita*)	overall	8.808	1.138	6.006	10.849	4252
	between		1.188			148
	within		0.311			28.7
Growth of Real GDP	overall	0.040	0.051	−0.137	0.246	4242
	between		0.019			147
	within		0.049			28.9
Nominal Interest Rate	overall	0.104	0.142	0.001	1.451	3822
	between		0.145			149
	within		0.106			25.7
Inflation	overall	0.091	0.138	−0.092	1.155	4135
	between		0.122			149
	within		0.116			27.8
Depreciation	overall	−0.032	0.114	−0.619	0.289	4241
	between		0.061			145
	within		0.102			29.2
Market/Bank	overall	0.551	0.152	0.120	0.853	719
	between		0.122			40
	within		0.090			18.0
Credit/GDP	overall	1.112	0.663	0.119	3.407	737
	between		0.601			40
	within		0.318			18.4
Credit/Stock Market Cap	overall	0.610	0.161	0.176	0.938	721
	between		0.127			40
	within		0.100			18.0
Private Credit/Credit	overall	0.795	0.151	0.229	0.998	737
	between		0.143			40
	within		0.056			18.4

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Correlations		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
log (1 + *Private Credit/GDP*)	(1)	100.0												
log (1 + *Financial Assets/GDP*)	(2)	94.4	100.0											
Growth of Private Credit/GDP	(3)	1.5	0.2	100.0										
Growth of Financial Assets/GDP	(4)	1.0	-0.5	86.8	100.0									
log (*Real GDP Per Capita*)	(5)	65.0	67.6	-0.9	-4.3	100.0								
Growth of Real GDP	(6)	-11.8	-13.1	-0.8	-6.1	-10.2	100.0							
Nominal Interest Rate	(7)	-34.9	-33.4	-3.0	-1.2	-28.0	-10.0	100.0						
Inflation	(8)	-27.5	-26.9	-11.8	-12.7	-18.3	1.7	51.7	100.0					
Depreciation	(9)	20.0	18.8	8.1	5.9	20.5	12.2	-42.8	-31.6	100.0				
Market/Bank	(10)	6.0	11.4	-2.1	-1.4	14.4	14.5	-24.4	-11.5	9.2	100.0			
Credit/GDP	(11)	92.7	92.4	3.2	6.1	67.5	-22.4	-61.3	-55.7	27.5	17.6	100.0		
Credit/Stock Market Cap	(12)	16.4	20.0	-4.9	-1.9	23.3	-29.9	3.2	-13.8	6.4	-62.7	27.4	100.0	
Private Credit/Credit	(13)	-28.8	-36.5	8.9	4.1	-53.7	24.5	39.3	42.3	-23.0	-36.1	-53.7	-33.9	100.0

This table shows the summary statistics of variables used in the panel logit regressions that study the relation between the probability of future banking crises and the quantity of finance. The first panel shows the mean, standard deviation, minimum, and maximum of each variable. The second panel shows the pooled Spearman correlation coefficients in percentage. In the first panel, for each variable, I separately present numbers for the overall panel data set, for the variations between countries, and for the variation within a country. In the rows labeled "between", the standard deviation is the between-country standard deviation of the within-country means, and the number of observations is the number of countries. In the rows labeled "within", the standard deviation is the cross-country mean of within-country standard deviations, and the number of observations is the cross-country mean of numbers of observations within a country. The detailed variable definitions are in Table B.1.

Table 4: The Quantity of Private Credit and the Probability of A Systemic Banking Crisis with A Potential Output Loss of More than 10%

Panel A: Logit models

					Excluding the Recent Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
log (1 + *Private Credit/GDP*)	2.838***	2.785***	3.147***	3.535***	3.120**	3.362**
	(3.22)	(3.26)	(3.58)	(4.17)	(2.15)	(2.37)
log (*Real GDP Per Capita*)	−0.188	−0.237	−0.319	−0.297	−0.470**	−0.453**
	(−0.94)	(−1.24)	(−1.56)	(−1.48)	(−1.97)	(−2.00)
Growth of Private Credit/GDP		2.232**	2.446**	3.009***	1.263	2.414**
		(2.09)	(2.12)	(2.95)	(1.09)	(2.14)
Growth of Real GDP			1.346	1.323	1.776	1.797
			(0.86)	(0.88)	(1.24)	(1.26)
Nominal Interest Rate			2.524***		2.672***	
			(3.56)		(3.25)	
Depreciation			0.039		0.599	
			(0.03)		(0.38)	
Inflation				3.294***		3.315***
				(4.20)		(4.18)
Advanced Economy		0.263	0.269	0.334	−1.056*	−1.095*
		(0.58)	(0.58)	(0.76)	(−1.84)	(−1.93)
Intercept	−1.939	−1.652	−1.432	−1.853	0.144	−0.213
	(−1.17)	(−1.08)	(−0.89)	(−1.13)	(0.09)	(−0.13)
Model χ^2	61.90***	67.81***	84.05***	121.65***	80.38***	98.35***
No. of Obs.	3297	3238	2906	3167	2183	2382
AIC	1762	1724	1519	1664	1051	1125
BIC	1780	1754	1566	1706	1097	1166

Panel B: Linear probability models

					Excluding the Recent Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
log (1 + *Private Credit/GDP*)	0.237***	0.231***	0.252***	0.296***	0.190**	0.197**
	(2.70)	(2.73)	(3.20)	(3.46)	(2.11)	(2.22)
log (*Real GDP Per Capita*)	−0.014	−0.017	−0.021*	−0.021*	−0.028**	−0.025*
	(−1.16)	(−1.52)	(−1.85)	(−1.92)	(−2.02)	(−1.78)
Growth of Private Credit/GDP		0.136*	0.152*	0.212***	0.090	0.177**
		(1.92)	(1.88)	(2.70)	(1.10)	(2.09)
Growth of Real GDP			0.101	0.099	0.137	0.124
			(1.05)	(1.06)	(1.32)	(1.20)
Nominal Interest Rate			0.300***		0.331***	
			(2.79)		(2.89)	
Depreciation			0.022		0.064	
			(0.27)		(0.75)	
Inflation				0.302***		0.314***
				(3.35)		(3.47)
Advanced Economy		0.019	0.015	0.023	−0.045	−0.048*
		(0.51)	(0.43)	(0.61)	(−1.64)	(−1.85)
Intercept	0.115	0.136	0.128	0.117	0.223*	0.193*
	(1.12)	(1.51)	(1.35)	(1.28)	(1.95)	(1.71)
Adj. R^2	0.02	0.03	0.03	0.04	0.04	0.04
No. of Obs.	3297	3238	2906	3167	2183	2382

Panel C: Cox proportional hazard models

					Excluding the Recent Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
log (1 + *Private Credit/GDP*)	2.770***	2.683***	2.921***	3.016***	3.299***	2.886***
	(3.63)	(3.60)	(3.30)	(3.90)	(2.88)	(2.66)
log (*Real GDP Per Capita*)	−0.353**	−0.409**	−0.495***	−0.412**	−0.547**	−0.486**
	(−2.34)	(−2.21)	(−2.66)	(−2.30)	(−2.48)	(−2.23)
Growth of Private Credit/GDP		1.600	1.318	2.255**	0.794	1.661
		(1.22)	(1.02)	(2.00)	(0.55)	(1.25)
Growth of Real GDP			−6.877**	−6.595**	−5.236*	−5.545*
			(−2.19)	(−2.24)	(−1.73)	(−1.93)
Nominal Interest Rate			2.485***		2.455***	
			(4.98)		(4.60)	
Depreciation			0.628		1.320	
			(0.43)		(0.84)	
Inflation				2.060***		1.679***
				(3.34)		(2.72)
Advanced Economy		0.271	0.247	0.142	−1.077*	−1.081*
		(0.75)	(0.60)	(0.40)	(−1.85)	(−1.90)
Model χ^2	13.42	15.34	57.50	37.09	57.15	43.83
No. of Subjects	148	145	141	144	132	134
No. of Obs.	3464	3397	3063	3326	2328	2529

This table studies the relation between the quantity of credit and the probability of a country having a banking crisis with a potential output loss of greater than 10%. Panel A shows the results from the panel logit regressions, Panel B shows the results from the panel linear probability regressions, and Panel C shows the results from Cox proportional hazard models. For both the panel logit and panel linear probability regressions, the response variable is one for a country-year if there is a banking crisis associated with a potential output loss greater than 10% in any year over the next five years and zero otherwise. For the Cox proportional hazard model, the event time is the number of years from the first year when the data is available to the last year before a systemic banking crisis with a potential output loss of more than 10%. To deal with the influence of repeated crises, I cluster the standard errors within a country by following Cleves (1999) and Andersen and Gill (1982). In these panels, the first column shows the explanatory variables and names of statistics, each one of the other columns shows the corresponding estimated coefficients and values of the statistics for a model. In order to correct for a post-crisis bias, before estimating the logit and the linear probability regressions, I exclude the observations in a five-year window starting at the first year of the crisis. In Panels A and B, the numbers between parentheses are the z-statistics based on two-way clustered standard errors by country and year. (Cameron, Gelbach, and Miller (2006) and Petersen (2009)). *, **, and *** mean the estimated coefficients are statistically significant at 10%, 5%, and 1% levels, respectively.

Table 5: Structure of the Financial System and the Probability of A Systemic Banking Crisis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit/Stock Market Cap	2.989*	3.402**						
	(1.94)	(2.22)						
Market/Bank			−1.784	−2.072				
			(−0.91)	(−0.99)				
Private Bond/GDP					1.710***	1.704***		
					(2.99)	(2.99)		
Private Credit/Credit							−1.547	−1.744
							(−1.03)	(−1.19)
log (1 + *Private Credit/GDP*)	2.918**	3.038**	2.965**	3.071**	2.604**	2.610**	3.191**	3.232**
	(2.19)	(2.34)	(1.96)	(2.02)	(2.22)	(2.26)	(2.41)	(2.52)
Growth of Private Credit/GDP	8.118***	9.209***	8.050***	9.198***	6.659**	7.862***	6.860***	8.103***
	(2.82)	(3.24)	(3.11)	(3.68)	(2.47)	(3.07)	(2.59)	(3.20)
log (*Real GDP Per Capita*)	0.040	−0.020	0.072	0.022	−0.242	−0.314	−0.176	−0.272
	(0.07)	(−0.03)	(0.13)	(0.04)	(−0.42)	(−0.52)	(−0.29)	(−0.42)
Growth of Real GDP	9.151*	8.548	8.071	7.323	8.961*	8.477	8.925*	8.482
	(1.66)	(1.58)	(1.55)	(1.42)	(1.66)	(1.59)	(1.66)	(1.60)
Nominal Interest Rate	6.149*		6.460**		6.824**		7.106**	
	(1.92)		(2.09)		(2.31)		(2.26)	
Inflation		5.132***		4.990***		5.180***		5.483***
		(4.68)		(4.33)		(5.20)		(4.79)
Advanced Economy	−0.042	−0.000	0.251	0.293	0.344	0.450	0.466	0.573
	(−0.06)	(−0.00)	(0.32)	(0.36)	(0.46)	(0.60)	(0.62)	(0.76)
Depreciation	2.158		2.541		2.213		2.255	
	(0.80)		(0.97)		(0.88)		(0.88)	
Intercept	−6.651	−6.282	−4.317	−3.588	−2.600	−1.776	−1.969	−0.778
	(−1.46)	(−1.28)	(−0.92)	(−0.72)	(−0.54)	(−0.35)	(−0.35)	(−0.13)
Model χ^2	57.06***	56.79***	51.16***	48.77***	55.35***	57.72***	49.97***	49.60***
No. of Obs.	549	549	547	547	562	562	562	562
AIC	477	467	483	474	483	475	493	484
BIC	516	501	521	509	522	509	532	519

This table studies the relation between the structure of financial systems and the probability of a banking crisis with a potential output loss of greater than 10%. The response variable of the logit regressions in this table is an indicator variable that is one if there is a banking crisis associated with a potential output loss of more than 10% in any year over the next five years and zero otherwise. Among the independent variables that measure the structure of the financial system, *Credit/Stock Market Cap* is the ratio of the sum of private credit and private bond market capitalization to the stock market capitalization; *Market/Bank* is the ratio of sum of stock market capitalization and private bond market capitalization to bank credit, which is the credit to domestic non-financial private sector by deposit money banks; and *Private Credit/Credit* is the ratio of private credit to the sum of private credit and private bond market capitalization. I construct *Market/Bank* and *Credit/Stock Market Cap* in such a way that the value of it is between zero and one, i.e. $\textit{Market/Bank} = \frac{Market}{Market+Bank}$ and $\textit{Credit/Stock Market Cap} = \frac{Credit}{Credit+Stock\ Market\ Cap}$.

In the data used for this table, there are 21 advanced countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France,

Germany, Greece, Iceland, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States. and 19 emerging market countries: Argentina, Brazil, Chile, Colombia, Czech Republic, Hong Kong, Hungary, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Singapore, South Africa, South Korea, Thailand, Turkey, Venezuela. Data for the regressions in this table covers the period from 1990 to 2009.

To deal with the post-crisis bias, I exclude the observations in a five-year window starting at the first year of the crisis. I also cluster standard errors by country and by year.

Table 6: Systemic Banking Crises, Quantity of Private Credit, and Equity Market Liberalization

Panel A: Controlling for only the indicators of equity market liberalization

					Excluding Recent Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
Postliberalization	0.030	0.007	0.015	0.005	0.090	0.084
	(0.77)	(0.16)	(0.37)	(0.12)	(1.63)	(1.59)
Preliberalization	0.048	0.035	0.042	0.034	0.010	0.006
	(0.89)	(0.63)	(0.69)	(0.61)	(0.16)	(0.10)
Always liberalized	0.062	−0.008	0.012	0.001	0.010	0.016
	(0.99)	(−0.16)	(0.23)	(0.02)	(0.19)	(0.29)
log (1 + *Private Credit/GDP*)		0.311***	0.331***	0.365***	0.237**	0.237**
		(2.90)	(3.07)	(3.31)	(2.08)	(2.09)
log (*Real GDP Per Capita*)		−0.038**	−0.038**	−0.043**	−0.035	−0.038*
		(−2.16)	(−2.32)	(−2.52)	(−1.64)	(−1.71)
Growth of Private Credit/GDP		0.298**	0.314**	0.369***	0.227*	0.322**
		(2.45)	(2.32)	(2.76)	(1.68)	(2.31)
Growth of Real GDP			0.054	0.041	0.089	0.154
			(0.26)	(0.20)	(0.38)	(0.70)
Inflation				0.294**		0.226*
				(2.08)		(1.78)
Nominal Interest Rate			0.249**		0.239**	
			(1.99)		(2.03)	
Depreciation			−0.027		0.118	
			(−0.19)		(0.82)	
Advanced Economy		0.044	0.029	0.052	−0.094*	−0.080
		(0.70)	(0.47)	(0.87)	(−1.84)	(−1.64)
Intercept	0.082***	0.306**	0.270**	0.283**	0.347**	0.345*
	(2.84)	(2.35)	(2.05)	(2.08)	(2.00)	(1.93)
Adj. R^2	0.03	0.06	0.06	0.08	0.08	0.07
No. of Obs.	1808	1780	1664	1772	1219	1292
Year Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Panel B: Interaction between quantity of private credit and indicators of equity market liberalization

					Excluding Recent Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
log(1+Private Credit/GDP)×postliberalization	0.347***	0.380***	0.408***	0.449***	0.458**	0.463**
	(2.72)	(2.63)	(2.70)	(3.07)	(2.02)	(2.07)
log(1+Private Credit/GDP)×preliberalization	−0.226	−0.208	−0.129	−0.143	−0.057	−0.055
	(−1.29)	(−1.07)	(−0.65)	(−0.70)	(−0.29)	(−0.27)
log(1+Private Credit/GDP)×always liberalized	0.403*	0.419*	0.383*	0.428**	0.067	0.058
	(1.85)	(1.91)	(1.90)	(1.96)	(1.06)	(0.97)
log(1+Private Credit/GDP)×never liberalized	0.036	0.148	0.278	0.255	0.540**	0.552**
	(0.20)	(0.60)	(1.15)	(1.03)	(2.13)	(2.28)
Postliberalization	−0.094	−0.067	−0.032	−0.061	0.082	0.075
	(−1.24)	(−0.81)	(−0.41)	(−0.77)	(0.88)	(0.82)
Preliberalization	0.126	0.169	0.185	0.180	0.197	0.195*
	(1.25)	(1.53)	(1.61)	(1.62)	(1.61)	(1.66)
Always liberalized	−0.176	−0.130	−0.040	−0.075	0.217**	0.232**
	(−1.38)	(−0.78)	(−0.26)	(−0.45)	(2.00)	(2.30)
log (Real GDP Per Capita)		−0.028	−0.034*	−0.036*	−0.045*	−0.048**
		(−1.49)	(−1.85)	(−1.94)	(−1.95)	(−2.05)
Growth of Private Credit/GDP		0.325***	0.333**	0.390***	0.227	0.330**
		(2.58)	(2.42)	(2.84)	(1.62)	(2.28)
Growth of Real GDP			0.048	0.039	0.078	0.142
			(0.24)	(0.20)	(0.35)	(0.69)
Inflation				0.287**		0.262**
				(2.02)		(1.98)
Nominal Interest Rate			0.252**		0.260**	
			(1.98)		(2.09)	
Depreciation			−0.010		0.119	
			(−0.07)		(0.82)	
Advanced Economy		0.038	0.024	0.044	−0.107**	−0.095*
		(0.56)	(0.38)	(0.69)	(−2.03)	(−1.91)
Intercept	0.090**	0.264**	0.242*	0.245*	0.335**	0.328*
	(2.05)	(2.04)	(1.86)	(1.82)	(2.00)	(1.89)
Adj. R^2	0.06	0.07	0.07	0.09	0.09	0.09
No. of Obs.	1808	1780	1664	1772	1219	1292
Year Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

This table studies the relation between the occurrence of systemic banking crises and equity market liberalization. The estimation method is panel linear probability regressions with year fixed effects. The response variable of these regressions is an indicator variable that is one if there is a systemic banking crisis with a potential output loss of greater than 10% in any year over the next five years and zero otherwise. The numbers between parentheses are the z-statistics based on two-way clustered standard errors by country and year (Cameron, Gelbach, and Miller (2006) and Petersen (2009)). *, **, and *** mean the estimated coefficients are statistically significant at 10%, 5%, and 1% levels, respectively. Table B.1 has the detailed variables definitions.

Table 7: Systemic Banking Crises, Quantity of Private Credit, and Financial Reforms

			Excluding Recent Crisis	
	(1)	(2)	(3)	(4)
log(1+Private Credit/GDP)×Large Reform	0.344**	0.353**	0.382**	0.395**
	(2.02)	(2.03)	(2.00)	(2.07)
log(1+Private Credit/GDP)×Reform	0.092	0.092	−0.043	−0.041
	(0.90)	(0.90)	(−0.40)	(−0.40)
log(1+Private Credit/GDP)×Status quo	0.369**	0.354**	0.057	0.042
	(2.06)	(1.96)	(0.47)	(0.35)
log(1+Private Credit/GDP)×Reversal	−0.121	−0.114	−0.101	−0.104
	(−0.33)	(−0.31)	(−0.25)	(−0.26)
Large Reform	−0.214	−0.212	−0.228	−0.232
	(−1.29)	(−1.26)	(−1.31)	(−1.30)
Reform	−0.077	−0.072	−0.016	−0.017
	(−0.48)	(−0.44)	(−0.09)	(−0.09)
Status quo	−0.167	−0.155	−0.068	−0.061
	(−0.96)	(−0.87)	(−0.39)	(−0.34)
log (Real GDP Per Capita)	−0.004	−0.003	0.006	0.008
	(−0.17)	(−0.11)	(0.22)	(0.29)
Growth of Private Credit/GDP	0.410***	0.466***	0.347**	0.429***
	(2.66)	(3.03)	(2.27)	(2.73)
Growth of Real GDP	−0.212	−0.212	−0.029	0.015
	(−0.71)	(−0.67)	(−0.09)	(0.04)
Inflation		0.268*		0.197
		(1.87)		(1.45)
Nominal Interest Rate	0.221*		0.213*	
	(1.88)		(1.81)	
Depreciation	−0.015		0.106	
	(−0.10)		(0.68)	
Advanced Economy	−0.095	−0.093	−0.179**	−0.175**
	(−1.30)	(−1.28)	(−2.54)	(−2.48)
Intercept	0.229	0.205	0.166	0.141
	(1.02)	(0.89)	(0.64)	(0.54)
Adj. R^2	0.06	0.06	0.09	0.09
No. of Obs.	1353	1353	1101	1101
Year Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*

This table studies how financial reforms affect the relation between the quantity of credit and the occurrence of systemic banking crises. The estimation method is panel linear probability regressions with year fixed effects. The response variable of these regressions is an indicator variable that is one if there is a systemic banking crisis with a potential output loss of greater than 10% over the next five years and zero otherwise. The numbers between parentheses are the z-statistics based on two-way clustered standard errors by country and year (Cameron, Gelbach, and Miller (2006) and Petersen (2009)). *, **, and *** mean the estimated coefficients are statistically significant at 10%, 5%, and 1% levels, respectively. Table B.1 has detailed variables definitions.

Table 8: Nonlinearity in the Effect of Quantity of Private Credit on the Probability of Systemic Banking Crises

Panel A: analysis using interaction terms	(1)	(2)	(3)	(4)	(5)
log (1 + *Private Credit/GDP*) ×*I(2 < CD)*	1.476***	1.468***	1.398***	1.528***	1.424***
	(3.14)	(3.15)	(3.01)	(3.26)	(3.08)
log (1 + *Private Credit/GDP*) ×*I(1 < CD <= 2)*	0.925***	0.955***	0.804***	1.023***	0.836***
	(2.94)	(3.00)	(2.82)	(3.15)	(2.90)
log (1 + *Private Credit/GDP*) ×*I(0 < CD <= 1)*	0.202	0.188	0.338	0.289	0.377
	(0.79)	(0.71)	(1.29)	(1.07)	(1.39)
log (1 + *Private Credit/GDP*) ×*I(CD <= 0)*	0.126	0.123	0.250	0.258	0.284
	(0.70)	(0.68)	(1.40)	(1.50)	(1.57)
I(2 < CD(log(1 + Private Credit/GDP)))	−1.119***	−1.113***	−1.011***	−1.105***	−1.018***
	(−3.12)	(−3.12)	(−2.81)	(−3.04)	(−2.85)
I(1 < CD(log(1 + Private Credit/GDP)) <= 2)	−0.513***	−0.534***	−0.400**	−0.522***	−0.406**
	(−2.76)	(−2.85)	(−2.44)	(−2.76)	(−2.48)
I(0 < CD(log(1 + Private Credit/GDP)) <= 1)	−0.048	−0.042	−0.069	−0.039	−0.074
	(−0.39)	(−0.33)	(−0.54)	(−0.30)	(−0.56)
Growth of Private Credit/GDP		0.126*	0.139*	0.196***	0.168**
		(1.85)	(1.77)	(2.61)	(2.00)
Advanced Economy	0.037	0.038	0.037	0.045	0.038
	(0.91)	(0.91)	(0.96)	(1.13)	(1.00)
log (*Real GDP Per Capita*)	−0.013	−0.013	−0.020	−0.019	−0.022*
	(−1.09)	(−1.04)	(−1.60)	(−1.57)	(−1.78)
Growth of Real GDP			0.105	0.105	0.104
			(1.19)	(1.25)	(1.15)
Nominal Interest Rate			0.299***		0.214**
			(2.79)		(2.13)
Depreciation			0.034		0.083
			(0.42)		(1.10)
Inflation				0.300***	0.195**
				(3.41)	(2.32)
Intercept	0.140	0.133	0.125	0.114	0.129
	(1.54)	(1.44)	(1.33)	(1.22)	(1.33)
Adj. R^2	0.05	0.05	0.05	0.07	0.06
No. of Obs.	3297	3238	2906	3167	2868

Panel B: Analysis using only indicators					
	(1)	(2)	(3)	(4)	(5)
I(2 < CD(log(1 + Private Credit/GDP)))	0.129*	0.129*	0.157**	0.167**	0.165**
	(1.87)	(1.89)	(2.37)	(2.44)	(2.47)
I(1.5 < CD(log(1 + Private Credit/GDP)) <= 2)	0.100*	0.101*	0.131**	0.132**	0.138**
	(1.83)	(1.86)	(2.17)	(2.35)	(2.23)
I(1 < CD(log(1 + Private Credit/GDP)) <= 1.5)	0.050	0.050	0.073	0.084**	0.081*
	(1.27)	(1.26)	(1.63)	(2.04)	(1.75)
I(0.5 < CD(log(1 + Private Credit/GDP)) <= 1)	0.040	0.039	0.083**	0.070*	0.090**
	(0.97)	(0.94)	(1.97)	(1.70)	(2.10)
I(0 < CD(log(1 + Private Credit/GDP)) <= 0.5)	0.015	0.017	0.039	0.041	0.044
	(0.44)	(0.49)	(1.15)	(1.20)	(1.26)
I(-0.5 < CD(log(1 + Private Credit/GDP)) <= 0)	0.024	0.025	0.052*	0.045	0.057*
	(0.78)	(0.83)	(1.69)	(1.53)	(1.80)
I(-1 < CD(log(1 + Private Credit/GDP)) <= -0.5)	0.012	0.012	0.034	0.024	0.037
	(0.58)	(0.58)	(1.50)	(1.14)	(1.57)
Growth of Private Credit/GDP		0.141**	0.155*	0.204***	0.176**
		(1.97)	(1.93)	(2.64)	(2.07)
Advanced Economy	0.015	0.015	0.010	0.017	0.009
	(0.40)	(0.39)	(0.28)	(0.46)	(0.26)
log (Real GDP Per Capita)	−0.004	−0.004	−0.010	−0.007	−0.011
	(−0.36)	(−0.32)	(−0.79)	(−0.58)	(−0.87)
Growth of Real GDP			0.074	0.060	0.065
			(0.76)	(0.62)	(0.66)
Inflation				0.248***	0.136
				(2.74)	(1.58)
Nominal Interest Rate			0.269***		0.211**
			(2.59)		(2.20)
Depreciation			0.019		0.054
			(0.23)		(0.66)
Intercept	0.084	0.076	0.077	0.060	0.078
	(0.86)	(0.75)	(0.74)	(0.58)	(0.74)
Adj. R^2	0.01	0.02	0.02	0.03	0.03
No. of Obs.	3297	3238	2906	3167	2868

This table studies the nonlinearity in the effect of the quantity of private credit on the probability of a banking crisis. Panel A shows analysis that uses interaction terms between the quantity of private credit and indicators based on the cross-sectional deviation of quantity of private credit, and Panel B shows analysis that uses only the indicators based on the cross-sectional deviation of quantity of private credit. In both panels, the method of estimation is linear probability regressions with the dependent variable that is one for a country-year observation if there is a banking crisis associated with a potential output loss greater than 10% in any year over the next five years and zero otherwise. In both panels, the first column shows the explanatory variables and the names of statistics. Each one of the other columns shows the corresponding estimated coefficients and the values of the statistics for a model. In order to correct for a post-crisis bias, before estimating the logit regressions, I exclude the observations in a five-year window starting at the first year of the crisis. The numbers between parentheses are the z-statistics based on two-way

clustered standard errors by country and year. (Cameron, Gelbach, and Miller (2006) and Petersen (2009)). *, **, and *** mean the estimated coefficients are statistically significant at 10%, 5%, and 1% levels, respectively.

Table 9: Interaction between the Quantity of Private Credit and the Growth of Private Credit

Panel A: Interaction between quantity of private credit and indicators based on the values of average growth of private credit over the past 5 years	(1)	(2)	(3)	(4)
$log\,(1 + Private\ Credit/GDP) \times I(10\% <= AG)$	0.559***	0.553***	0.626***	0.599***
	(2.93)	(2.93)	(3.18)	(3.17)
$log\,(1 + Private\ Credit/GDP) \times I(5\% <= AG < 10\%)$	0.261*	0.257*	0.242*	0.301**
	(1.91)	(1.94)	(1.91)	(2.33)
$log\,(1 + Private\ Credit/GDP) \times I(2.5\% <= AG < 5\%)$	0.223*	0.218*	0.245**	0.267**
	(1.95)	(1.93)	(2.23)	(2.42)
$log\,(1 + Private\ Credit/GDP) \times I(0 <= AG < 2.5\%)$	0.216*	0.208*	0.165	0.245**
	(1.80)	(1.79)	(1.47)	(2.12)
$log\,(1 + Private\ Credit/GDP) \times I(-2.5\% <= AG < 0)$	0.159	0.157	0.209*	0.212*
	(1.28)	(1.26)	(1.65)	(1.72)
$log\,(1 + Private\ Credit/GDP) \times I(-5\% <= AG < -2.5\%)$	−0.037	−0.034	0.027	0.028
	(−0.57)	(−0.53)	(0.36)	(0.38)
$log\,(1 + Private\ Credit/GDP) \times I(-10\% <= AG < -5\%)$	−0.119	−0.122	−0.043	−0.033
	(−1.39)	(−1.42)	(−0.48)	(−0.38)
$log\,(1 + Private\ Credit/GDP) \times I(AG < -10\%)$	0.089	0.079	0.193	0.146
	(0.92)	(0.72)	(1.57)	(1.28)
$I(10\% <= Average(Growth\ of\ Private\ Credit/GDP)_{t-4,t})$	−0.062	−0.064	−0.028	−0.052
	(−1.12)	(−1.13)	(−0.44)	(−0.90)
$I(5\% <= Average(Growth\ of\ Private\ Credit/GDP)_{t-4,t} < 10\%)$	0.019	0.016	0.079	0.028
	(0.36)	(0.30)	(1.22)	(0.50)
$I(2.5\% <= Average(Growth\ of\ Private\ Credit/GDP)_{t-4,t} < 5\%)$	0.007	0.004	0.043	0.012
	(0.15)	(0.08)	(0.77)	(0.23)
$I(0 <= Average(Growth\ of\ Private\ Credit/GDP)_{t-4,t} < 2.5\%)$	−0.004	−0.006	0.068	0.011
	(−0.07)	(−0.11)	(1.03)	(0.18)
$I(-2.5\% <= Average(Growth\ of\ Private\ Credit/GDP)_{t-4,t} < 0)$	0.010	0.007	0.044	0.008
	(0.29)	(0.17)	(0.93)	(0.21)
$I(-5\% <= Average(Growth\ of\ Private\ Credit/GDP)_{t-4,t} < -2.5\%)$	0.057**	0.052	0.080**	0.050
	(2.00)	(1.59)	(2.11)	(1.54)
$I(-10\% <= Average(Growth\ of\ Private\ Credit/GDP)_{t-4,t} < -5\%)$	0.078**	0.076*	0.101**	0.060
	(1.97)	(1.83)	(2.04)	(1.61)
$log\,(Real\ GDP\ Per\ Capita)$	−0.010	−0.013	−0.018	−0.016
	(−0.78)	(−1.15)	(−1.54)	(−1.43)
Growth of Real GDP			0.107	0.096
			(1.13)	(1.03)
Nominal Interest Rate			0.279**	
			(2.41)	
Depreciation			0.037	
			(0.46)	
Inflation				0.246***
				(2.64)
Advanced Economy		0.018	0.015	0.020
		(0.50)	(0.47)	(0.56)
Intercept	0.077	0.108	0.060	0.084
	(0.80)	(1.19)	(0.61)	(0.93)
Adj. R^2	0.04	0.04	0.05	0.05
No. of Obs.	3126	3126	2827	3064

Panel B: interaction between average growth of private credit over the past 5 years and indicators based on the cross-sectional deviation of the quantity of private credit 5 years ago

	(1)	(2)	(3)	(4)
Average(Growth of Private Credit/GDP)$_{t-4,t}$× *I(2 < CD)*	0.959**	0.960**	0.973**	0.972**
	(2.31)	(2.30)	(2.26)	(2.33)
Average(Growth of Private Credit/GDP)$_{t-4,t}$× *I(1.5 < CD <= 2)*	1.180	1.183	0.808	1.277
	(1.34)	(1.35)	(0.89)	(1.37)
Average(Growth of Private Credit/GDP)$_{t-4,t}$× *I(1 < CD <= 1.5)*	2.657***	2.660***	2.609***	2.724***
	(2.92)	(2.93)	(2.59)	(3.02)
Average(Growth of Private Credit/GDP)$_{t-4,t}$× *I(0.5 < CD <= 1)*	0.747	0.750	1.171**	0.903*
	(1.60)	(1.58)	(2.23)	(1.70)
Average(Growth of Private Credit/GDP)$_{t-4,t}$× *I(0 < CD <= 0.5)*	0.583**	0.584**	0.816***	0.702**
	(2.08)	(2.06)	(2.66)	(2.33)
Average(Growth of Private Credit/GDP)$_{t-4,t}$× *I(-0.5 < CD <= 0)*	0.521*	0.521*	0.554*	0.605**
	(1.70)	(1.69)	(1.79)	(2.00)
Average(Growth of Private Credit/GDP)$_{t-4,t}$× *I(-1< CD <= -0.5)*	0.418	0.417	0.540*	0.483
	(1.35)	(1.35)	(1.65)	(1.54)
Average(Growth of Private Credit/GDP)$_{t-4,t}$× *I(CD <= -1)*	−0.172	−0.174	−0.116	−0.094
	(−0.54)	(−0.55)	(−0.38)	(−0.30)
$I(2 < CD(log(1 + \text{Private Credit/GDP}))_{t-5})$	−0.036	−0.036	−0.002	−0.011
	(−0.57)	(−0.57)	(−0.04)	(−0.17)
$I(1.5 < CD(log(1 + \text{Private Credit/GDP}))_{t-5} < 2)$	−0.005	−0.005	0.004	0.012
	(−0.08)	(−0.08)	(0.07)	(0.22)
$I(1 < CD(log(1 + \text{Private Credit/GDP}))_{t-5} < 1.5)$	0.001	0.001	0.000	0.021
	(0.01)	(0.02)	(0.00)	(0.36)
$I(0.5 < CD(log(1 + \text{Private Credit/GDP}))_{t-5} < 1)$	−0.041	−0.041	−0.032	−0.024
	(−0.71)	(−0.71)	(−0.59)	(−0.44)
$I(0 < CD(log(1 + \text{Private Credit/GDP}))_{t-5} < 0.5)$	−0.060	−0.061	−0.046	−0.048
	(−1.08)	(−1.07)	(−0.89)	(−0.93)
$I(-0.5 < CD(log(1 + \text{Private Credit/GDP}))_{t-5} < 0)$	−0.039	−0.039	−0.029	−0.025
	(−0.77)	(−0.77)	(−0.60)	(−0.55)
$I(-1 < CD(log(1 + \text{Private Credit/GDP}))_{t-5} < -0.5)$	−0.048	−0.048	−0.032	−0.037
	(−1.11)	(−1.11)	(−0.79)	(−0.93)
log (Real GDP Per Capita)	0.003	0.004	−0.002	0.002
	(0.21)	(0.24)	(−0.14)	(0.12)
Growth of Real GDP			0.176	0.202*
			(1.49)	(1.67)
Nominal Interest Rate			0.217**	
			(2.12)	
Depreciation			0.053	
			(0.63)	
Inflation				0.150
				(1.55)
Advanced Economy		−0.001	0.001	0.002
		(−0.04)	(0.04)	(0.06)
Intercept	0.071	0.068	0.079	0.049
	(0.51)	(0.54)	(0.61)	(0.38)
Adj. R^2	0.03	0.03	0.03	0.04
No. of Obs.	2797	2797	2545	2754

This table studies the interaction between the quantity of private credit and the growth of private credit. Panel A shows the interaction between the quantity of private credit and the indicators based on the values of the average growth of private credit over the past 5 years. Panel B shows the interaction between the average growth of private credit over the past 5 years and the indicators based on the cross-sectional deviation of quantity of private credit 5 years ago. In both panels, the method of estimation is linear probability regressions of which the dependent variable is one for a country-year observation if there is a banking crisis associated with a potential output loss greater than 10% in any year over the next five years and zero otherwise. In order to correct for a post-crisis bias, before estimating the logit regressions, I exclude the observations in a five-year window starting at the first year of the crisis. The numbers between parentheses are the z-statistics based

on two-way clustered standard errors by country and year. (Cameron, Gelbach, and Miller (2006) and Petersen (2009)). *, **, and *** mean the estimated coefficients are statistically significant at 10%, 5%, and 1% levels, respectively.

Table 10: Four Waves of Financial Liberalization and the Occurrence of Banking Crises

								Excluding Recent Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Surges	0.438*				0.250	−0.004	0.109	0.119	0.218
	(1.79)				(0.95)	(−0.01)	(0.39)	(0.27)	(0.52)
Stops		−0.803***			−0.584*	−0.742**	−0.646*	−0.402	−0.434
		(−2.64)			(−1.88)	(−2.03)	(−1.87)	(−0.99)	(−1.01)
Flight			0.394**		0.202	0.057	0.113	0.636	0.658
			(1.97)		(0.95)	(0.21)	(0.45)	(1.21)	(1.23)
Retrenchment				−0.621*	−0.332	−0.523	−0.407	0.064	0.063
				(−1.87)	(−0.95)	(−1.17)	(−1.05)	(0.11)	(0.11)
log (1 + *Private Credit/GDP*)						3.444***	3.963***	3.326*	3.823*
						(3.22)	(3.75)	(1.66)	(1.85)
log (*Real GDP Per Capita*)						−0.026	−0.039	−0.456	−0.601
						(−0.06)	(−0.08)	(−1.02)	(−1.28)
Growth of Private Credit/GDP						5.533**	5.550***	0.922	1.707
						(2.57)	(2.85)	(0.32)	(0.59)
Growth of Real GDP						−0.783	−0.446	1.774	3.438
						(−0.13)	(−0.07)	(0.22)	(0.41)
Nominal Interest Rate						1.424		3.248**	
						(0.76)		(2.52)	
Depreciation						1.190		3.673	
						(0.54)		(1.21)	
Inflation							2.468		2.626*
							(1.28)		(1.80)
Advanced Economy						−0.207	−0.057	−1.593*	−1.081
						(−0.34)	(−0.09)	(−1.80)	(−1.09)
Intercept	−1.951***	−1.640***	−1.939***	−1.677***	−1.760***	−3.510	−3.849	0.453	1.168
	(−7.27)	(−6.53)	(−6.89)	(−6.52)	(−5.87)	(−0.89)	(−0.92)	(0.12)	(0.30)
Model χ^2	4.89**	9.89***	3.97**	6.33**	16.13***	66.27***	85.08***	78.76***	69.13***
No. of Obs.	933	933	933	933	933	902	925	584	587
AIC	756	749	757	754	750	643	676	303	300
BIC	765	759	766	763	774	701	729	356	349

This table studies the relation between four waves of capital flows and the occurrence of systemic banking crises. The estimation method is panel logit regressions. The response variable of these regressions is an indicator variable that is one if there is a systemic banking crisis with a potential output loss of greater than 10% in any year over the next five years and zero otherwise. The numbers between parentheses are the z-statistics based on two-way clustered standard errors by country and year (Cameron, Gelbach, and Miller (2006) and Petersen (2009)). *, **, and *** mean the estimated coefficients are statistically significant at 10%, 5%, and 1% levels, respectively. Detailed definitions of variables are in Table B.1.

Table 11: Central Government Debt

			Excluding Recent Crisis	
	(1)	(2)	(3)	(4)
log (1 + *Private Credit/GDP*)	3.445**	3.471***	8.245***	7.365***
	(2.28)	(2.65)	(3.33)	(3.19)
Central Government Debt/GDP	−0.010	−0.010	−0.047**	−0.045***
	(−1.28)	(−1.30)	(−2.23)	(−2.63)
Growth of Private Credit/GDP	6.027***	6.290***	3.788	6.364*
	(3.05)	(3.55)	(1.10)	(1.72)
log (*Real GDP Per Capita*)	0.300	0.305	−1.315**	−1.246**
	(0.73)	(0.70)	(−2.56)	(−2.56)
Growth of Real GDP	1.073	0.755	1.962	1.784
	(0.21)	(0.15)	(0.28)	(0.27)
Nominal Interest Rate	1.727		12.783***	
	(0.25)		(2.77)	
Depreciation	2.130		4.660*	
	(0.95)		(1.89)	
Inflation		1.286		7.241***
		(0.40)		(3.25)
Advanced Economy	0.623	0.636	−0.557	−0.275
	(1.09)	(1.21)	(−0.53)	(−0.29)
Intercept	−7.542**	−7.549*	5.941	6.163
	(−2.14)	(−1.96)	(1.23)	(1.45)
Model χ^2	110.01***	115.97***	50.85***	52.36***
No. of Obs.	1365	1365	709	709
AIC	613	613	200	210
BIC	660	655	241	246

This table studies whether the ratio of central government debt to GDP is related to the occurrence of systemic banking crises and whether this ratio affects the relation between the quantity of credit and the occurrence of systemic banking crises. The estimation method is panel logit regressions. The response variable of these regressions is an indicator variable that is one if there is a systemic banking crisis with a potential output loss of greater than 10% in any year over the next five years and zero otherwise. The numbers between parentheses are the z-statistics based on two-way clustered standard errors by country and year (Cameron, Gelbach, and Miller (2006) and Petersen (2009)). *, **, and *** mean the estimated coefficients are statistically significant at 10%, 5%, and 1% levels, respectively. Detailed definitions of variables are in Table B.1.

Table 12: Government Ownership of Banks

			Excluding Recent Crisis	
	(1)	(2)	(3)	(4)
Government Ownership of Banks	0.868*	0.944**	0.938	0.734
	(1.70)	(2.08)	(1.35)	(1.10)
log (1 + Private Credit/GDP)	3.850***	4.105***	3.922**	3.883**
	(3.66)	(4.21)	(2.32)	(2.38)
log (Real GDP Per Capita)	−0.433	−0.334	−0.609**	−0.513*
	(−1.64)	(−1.32)	(−1.96)	(−1.77)
Growth of Private Credit/GDP	3.333***	3.947***	2.482*	3.607***
	(2.82)	(3.47)	(1.93)	(2.80)
Growth of Real GDP	−0.420	−0.809	1.064	0.965
	(−0.17)	(−0.33)	(0.46)	(0.41)
Nominal Interest Rate	2.355***		2.547***	
	(3.60)		(3.44)	
Depreciation	0.764		1.472	
	(0.54)		(0.85)	
Inflation		2.668***		2.827***
		(2.77)		(2.95)
Advanced Economy	0.064	0.009	−1.275**	−1.345**
	(0.13)	(0.02)	(−2.02)	(−2.16)
Intercept	−0.790	−1.837	0.919	0.087
	(−0.36)	(−0.84)	(0.39)	(0.04)
Model χ^2	89.60***	110.05***	100.55***	95.60***
No. of Obs.	1946	2115	1495	1623
AIC	1207	1312	799	863
BIC	1257	1357	847	906

This table studies whether the government ownership of banks is related to the occurrence of systemic banking crises and whether this ratio affects the relation between the quantity of credit and the occurrence of systemic banking crises. The estimation method is panel logit regressions. The response variable of these regressions is an indicator variable that is one if there is a systemic banking crisis with a potential output loss of greater than 10% in any year over the next five years and zero otherwise. The numbers between parentheses are the z-statistics based on two-way clustered standard errors by country and year (Cameron, Gelbach, and Miller (2006) and Petersen (2009)). *, **, and *** mean the estimated coefficients are statistically significant at 10%, 5%, and 1% levels, respectively. Detailed definitions of variables are in Table B.1.

Table 13: Advanced Economies versus Emerging Market Economies

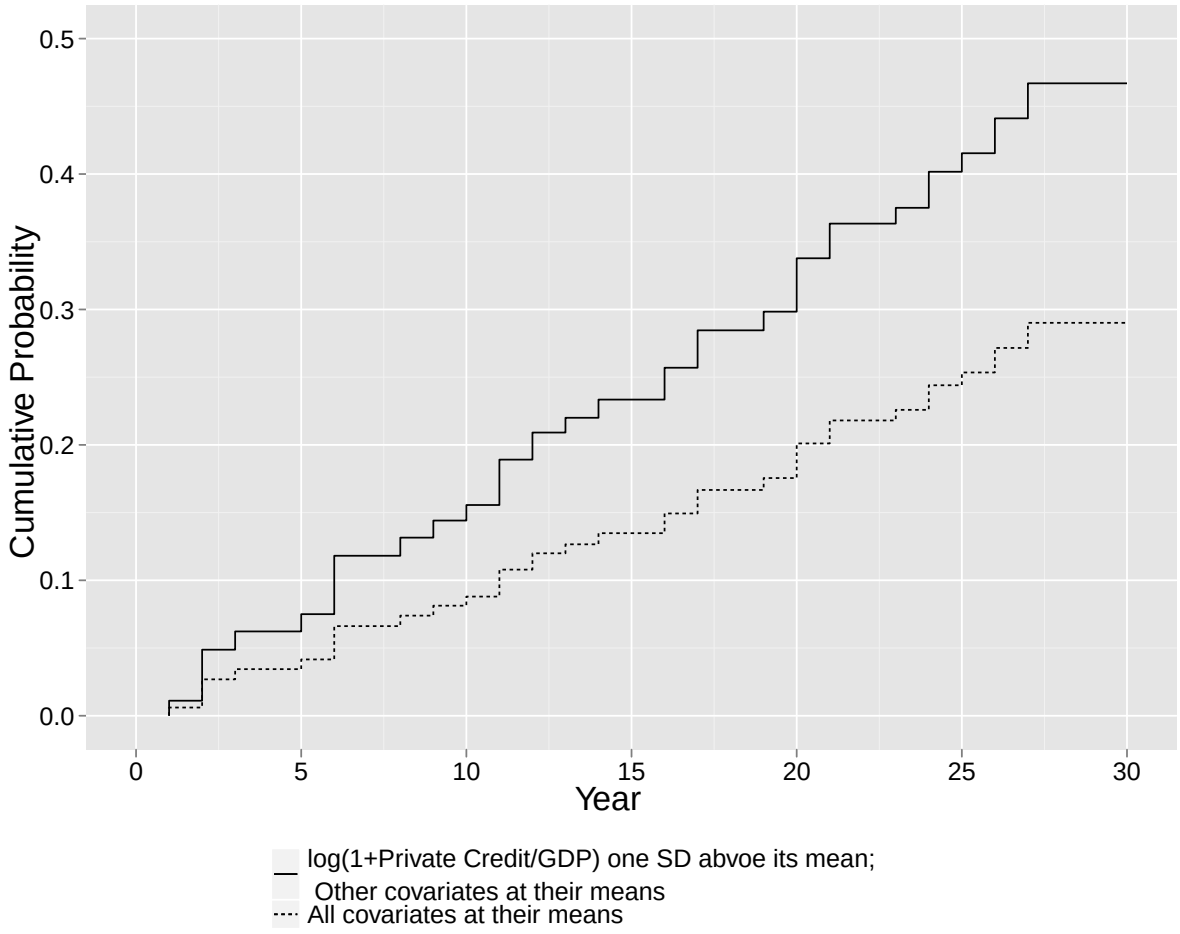
Panel A: Analysis using interaction terms						
	(1)	(2)	(3)	(4)	(5)	(6)
log (1 + *Private Credit/GDP*)	0.434		0.434	0.721	1.363	1.455
	(0.33)		(0.33)	(0.54)	(1.04)	(1.08)
×*Advanced Economy*	5.395***		5.352***	4.717***	4.805***	4.308***
	(3.04)		(3.13)	(2.87)	(2.87)	(2.64)
Growth of Private Credit/GDP		1.373	1.382	1.530	2.265**	1.914
		(1.33)	(1.34)	(1.35)	(2.11)	(1.64)
×*Advanced Economy*		3.865	3.822	5.111**	2.912	4.385*
		(1.63)	(1.58)	(2.29)	(1.22)	(1.94)
Advanced Economy	−2.943***	0.264	−3.085***	−2.874***	−2.681**	−2.520**
	(−2.63)	(0.61)	(−2.83)	(−2.64)	(−2.52)	(−2.37)
log (*Real GDP Per Capita*)	−0.048	0.087	−0.042	−0.061	−0.117	−0.176
	(−0.24)	(0.52)	(−0.20)	(−0.29)	(−0.54)	(−0.82)
Growth of Real GDP				0.911	1.059	1.060
				(0.60)	(0.70)	(0.68)
Real Interest Rate				0.740		1.534**
				(0.73)		(2.02)
Depreciation				−1.788		0.657
				(−1.37)		(0.58)
Inflation					2.813***	3.331***
					(3.85)	(3.22)
Intercept	−2.348	−3.412**	−2.460	−2.454	−2.515	−2.032
	(−1.56)	(−2.25)	(−1.59)	(−1.59)	(−1.55)	(−1.26)
Model χ^2	136.20***	37.35***	161.88***	115.60***	196.07***	142.09***
No. of Obs.	3297	3238	3238	2868	3167	2868
AIC	1715	1771	1676	1504	1627	1478
BIC	1746	1802	1719	1564	1681	1543

Panel B: Analysis using separate samples

					Excluding the recent crisis			
	AE		EME		AE		EME	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log (1 + *Private Credit/GDP*)	3.417*	3.400*	1.170	1.767	5.908**	6.788**	1.832	2.639
	(1.94)	(1.80)	(0.89)	(1.33)	(2.51)	(2.56)	(1.14)	(1.61)
log (*Real GDP Per Capita*)	2.920**	2.321*	−0.131	−0.251	−1.123	−0.898	−0.257	−0.399
	(2.22)	(1.77)	(−0.63)	(−1.21)	(−1.08)	(−0.80)	(−1.07)	(−1.64)
Growth of Private Credit/GDP	8.125***	6.800***	1.798	2.295**	5.791***	6.232***	1.256	2.212*
	(4.25)	(3.47)	(1.55)	(2.09)	(2.95)	(3.21)	(1.04)	(1.90)
Growth of Real GDP	−3.657	−1.453	1.692	1.560	−9.853	−6.118	2.295	2.550*
	(−0.57)	(−0.22)	(1.04)	(0.96)	(−1.15)	(−0.67)	(1.54)	(1.72)
Inflation		−2.104		3.015***		5.988		3.048***
		(−0.27)		(4.02)		(1.21)		(3.92)
Real Interest Rate	−14.342***		1.060		−7.418		0.938	
	(−3.33)		(1.39)		(−0.75)		(1.17)	
Depreciation	4.456**		−3.116**		5.353***		−2.550**	
	(2.40)		(−2.54)		(3.04)		(−2.00)	
Intercept	−34.356***	−28.179**	−2.147	−1.531	4.087	0.827	−1.040	−0.367
	(−2.73)	(−2.28)	(−1.38)	(−1.00)	(0.42)	(0.08)	(−0.61)	(−0.22)
Model χ^2	132.50***	96.13***	30.23***	51.06***	40.44***	25.54***	26.53***	50.41***
No. of Obs.	772	772	2096	2096	657	657	1494	1494
AIC	381	401	1078	1061	150	153	912	889
BIC	414	429	1117	1095	181	180	949	921

This table compares the effect of the quantity of private credit on the probability of a banking crisis between advanced economies and emerging market economies. Panel A shows analysis that uses interaction terms and Panel B shows analysis that uses separate samples. In both panels, the response variable of the logit regressions is one for a country-year if there is a banking crisis associated with a potential output loss greater than 10% in any year over the next five years and zero otherwise. In both panels, the first column shows the explanatory variables and the names of statistics. Each one of the other columns shows the corresponding estimated coefficients and the values of the statistics for a model. In order to correct for a post-crisis bias, before estimating the logit regressions, I exclude the observations in a five-year window starting at the first year of the crisis. The numbers between parentheses are the z-statistics based on two-way clustered standard errors by country and year. (Cameron, Gelbach, and Miller (2006) and Petersen (2009)). *, **, and *** mean the estimated coefficients are statistically significant at 10%, 5%, and 1% levels, respectively.

Figure 1: Cumulative Probability of A Systemic Banking Crisis as A Function of Time

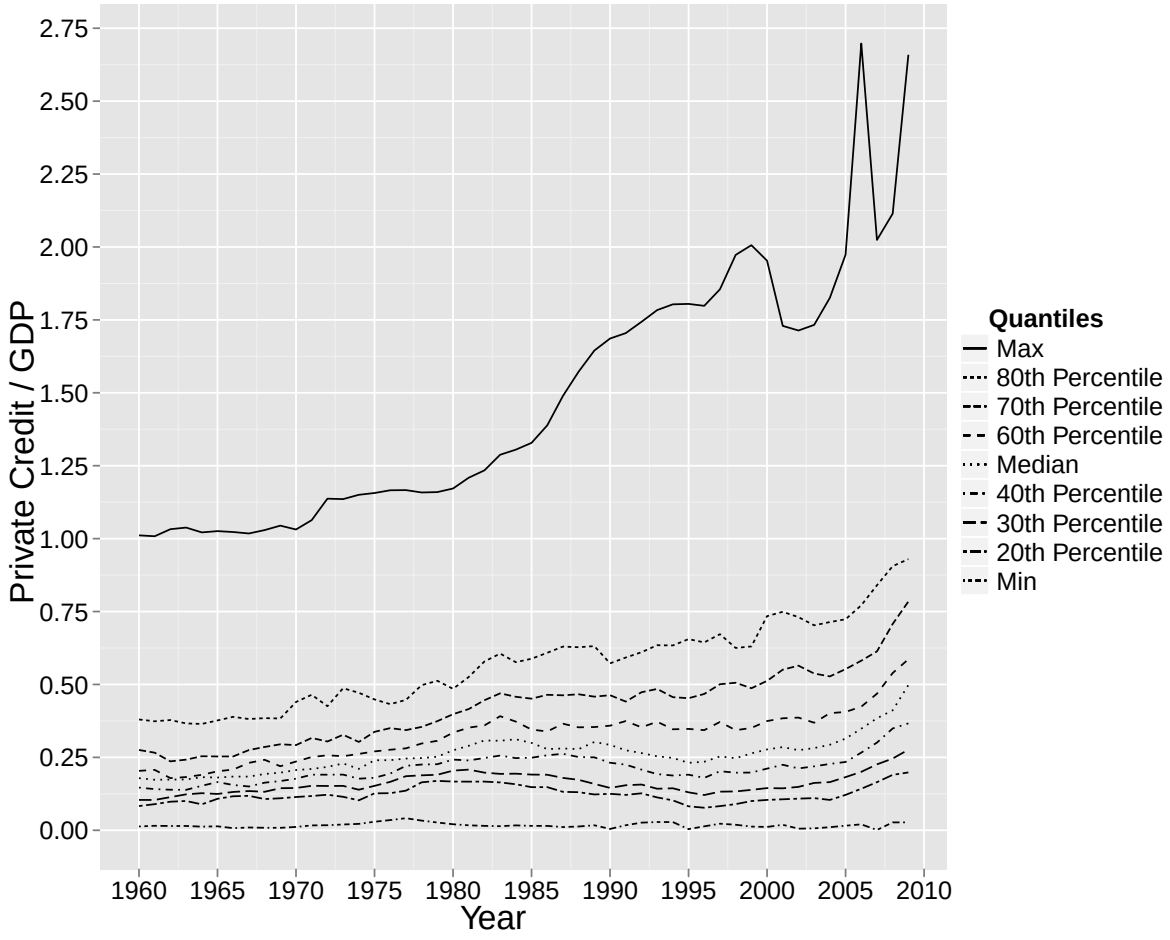


This figure shows the cumulative probability of a systemic banking crisis as a function of time. All calculation is based on Model (3) in Panel C of Table 4. The dashed line is the cumulative probability when all covariates are at their sample means, and the solid line is the cumulative probability when *log(1+Private Credit/GDP)* is one standard deviation above its sample mean, while other covariates are at their sample means.

Appendices

A Sample Description

Figure A.1: Cross-Country Distribution of Private Credit to GDP Over Time

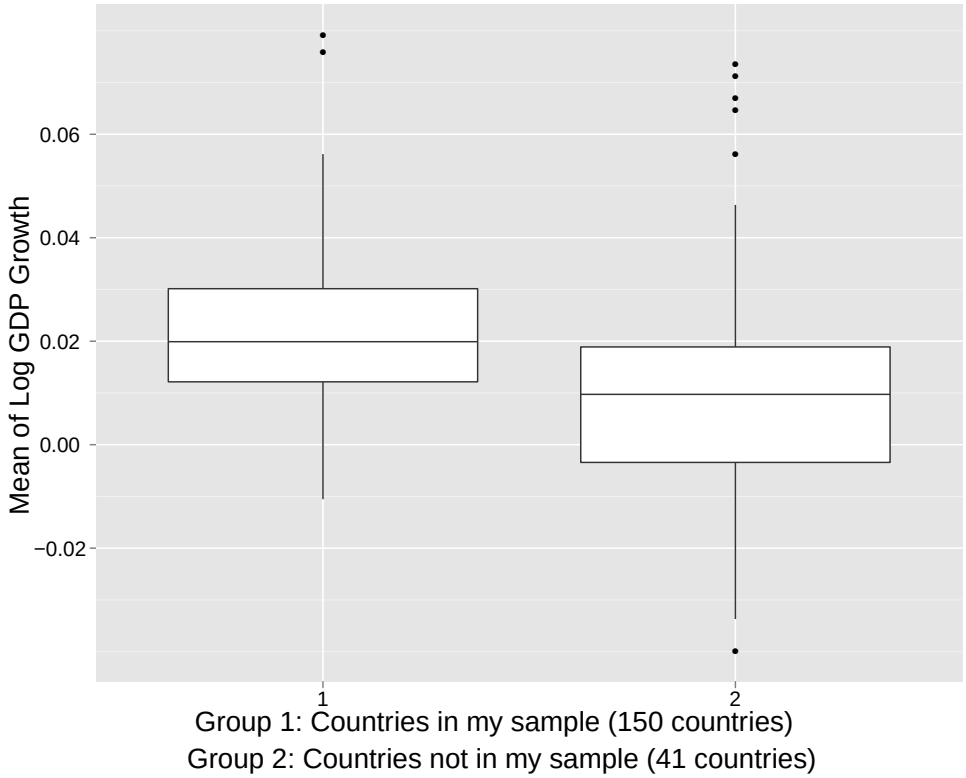


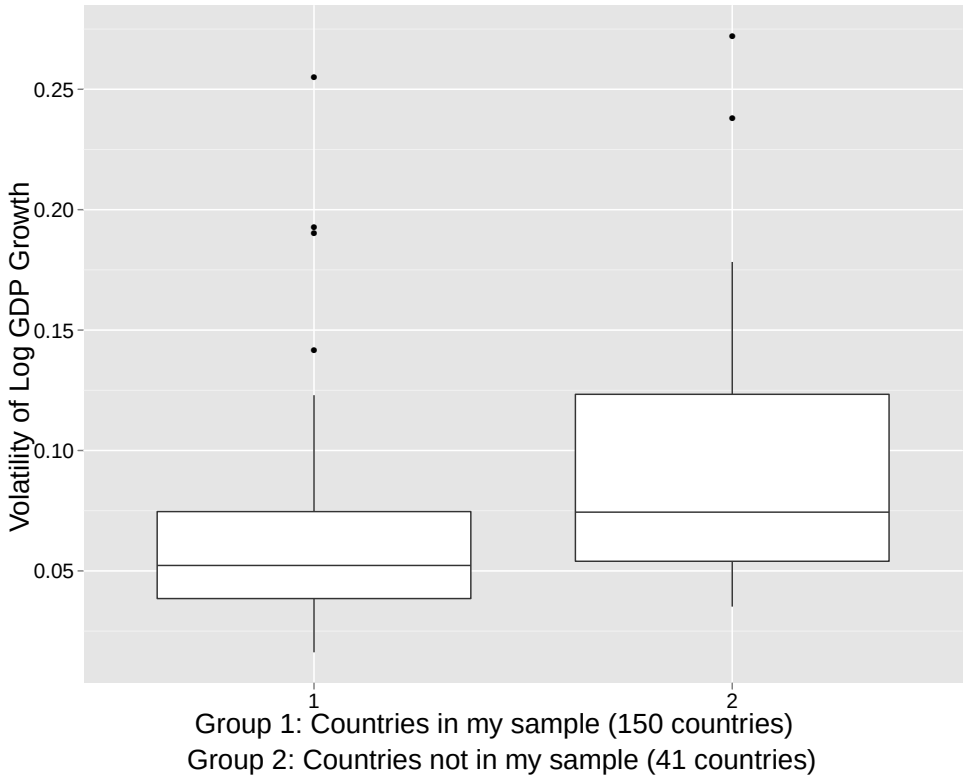
This figure shows the cross-country distribution of *Private Credit/GDP* among all the countries for which the data are available.

Table A.1: List of Countries

Regions	Countries
Emerging Market Economies	
East Asia and Pacific	Brunei Darussalam; Cambodia; Fiji; Hong Kong; Indonesia; Lao PDR; Macao, China; Malaysia; Mongolia; Papua New Guinea; Philippines; Samoa; Singapore; Solomon Islands; South Korea; Thailand; Timor-Leste; Tonga; Vanuatu; Vietnam
East Europe and Central Asia	Albania; Armenia; Bulgaria; Croatia; Czech Republic; Estonia; Georgia; Hungary; Kazakhstan; Kyrgyz Republic; Latvia; Lithuania; Macedonia, FYR; Moldova; Poland; Romania; Russia; Serbia; Slovakia; Slovenia; Turkey
Latin America and Caribbean	Argentina; Aruba; Bahamas; Barbados; Belize; Bolivia; Brazil; Chile; Colombia; Costa Rica; Dominica; Dominican Republic; Ecuador; El Salvador; Grenada; Guatemala; Guyana; Haiti; Honduras; Jamaica; Mexico; Netherlands Antilles; Panama; Paraguay; Peru; St. Kitts and Nevis; St. Lucia; St. Vincent and the Grenadines; Suriname; Trinidad and Tobago; Uruguay; Venezuela
Middle East and North Africa	Algeria; Bahrain; Egypt; Iran, Islamic Rep.; Iraq; Israel; Jordan; Kuwait; Libya; Malta; Morocco; Oman; Qatar; Saudi Arabia; Syrian Arab Republic; Tunisia
South Asia	Bangladesh; Bhutan; India; Nepal; Pakistan; Sri Lanka
Sub Saharan Africa	Benin; Botswana; Burkina Faso; Burundi; Cameroon; Cape Verde; Chad; Congo, Rep.; Cote d'Ivoire; Equatorial Guinea; Ethiopia; Gabon; Gambia; Ghana; Kenya; Lesotho; Madagascar; Malawi; Mali; Mauritania; Mauritius; Mozambique; Niger; Nigeria; Rwanda; Senegal; Seychelles; South Africa; Swaziland; Tanzania; Togo
West Europe	Cyprus
Advanced Economies	
East Asia and Pacific	Australia; Japan; New Zealand
Middle East and North Africa	Greece; Portugal
North America	Canada; United States
Western Europe	Austria; Belgium; Denmark; Finland; France; Germany; Iceland; Ireland; Italy; Luxembourg; Netherlands; Norway; Spain; Sweden; Switzerland; United Kingdom

Figure A.2: Mean and Volatility of Log Real Per Capita GDP Growth: My Sample and Other Countries





This figure uses the box plots to compare the distribution of mean and volatility of log real GDP growth between countries in my sample and other countries. Group 1 countries are countries in my sample, and Group 2 countries are countries outside of my sample. The first graph shows that Group 1 countries have on average higher mean of log real GDP growth than Group 2 countries. The second graph shows that Group 1 countries have lower volatility of log real per capita GDP growth than Group 2 countries.

Table A.2: List of Banking Crises

Country	Start	End	Potential Output Loss	Borderline	Transition Economy
Advanced Economies					
Austria	2008		17.00		
Belgium	2008		23.00		
Denmark	2008		36.00		
Finland	1991	1995	69.59		
France	2008		21.00	Yes	
Germany	2008		19.00		
Greece	2008		29.00	Yes	
Ireland	2008		110.00		
Japan	1997	2001	45.00		
Luxembourg	2008		47.00		
Netherlands	2008		25.00		
Norway	1991	1993	5.15		
Portugal	2008		37.00	Yes	
Spain	1977	1981	58.50		
Spain	2008		39.00	Yes	
Sweden	1991	1995	32.90		
Sweden	2008		31.00	Yes	
Switzerland	2008		0.00	Yes	
United Kingdom	2007		24.00		
United States	1988	1988	0.00	Yes	
United States	2007		25.00		
Emerging Market Economies					
Algeria	1990	1994	41.39		
Argentina	1989	1991	12.63		
Argentina	1995	1995	0.00	Yes	
Argentina	2001	2003	70.97		
Bolivia	1994	1994	0.00		
Brazil	1994	1998	0.00		
Bulgaria	1996	1997	59.51		
Burkina Faso	1990	1994			
Burundi	1994	1998	121.19		
Cameroon	1987	1991	105.53		
Cape Verde	1993	1993	0.00		
Chile	1981	1985	8.61		
Colombia	1982	1982	46.96		

Continued on next page

Country	Start	End	Potential Output Loss	Borderline	Transition Economy
Colombia	1998	2000	43.40		
Congo, Rep.	1992	1994	47.36		
Costa Rica	1987	1991	0.00		
Costa Rica	1994	1995	0.00		
Cote d'Ivoire	1988	1992	45.00		
Croatia	1998	1999			Yes
Czech Republic	1996	2000		Yes	Yes
Dominican Republic	2003	2004			
Ecuador	1982	1986	98.19		
Ecuador	1998	2002	25.35		
El Salvador	1989	1990	0.00		
Haiti	1994	1998	37.55		
Hungary	1991	1995			Yes
Hungary	2008		42.00	Yes	
India	1993	1993	0.00		
Indonesia	1997	2001	69.02		
Israel	1977	1977	76.01		
Jamaica	1996	1998	37.79		
Jordan	1989	1991	106.37		
Kazakhstan	2008		0.00	Yes	
Kenya	1985	1985	23.69		
Kenya	1992	1994	50.29		
South Korea	1997	1998	57.59		
Kuwait	1982	1985	143.43		
Latvia	1995	1996			Yes
Latvia	2008		116.00		
Lithuania	1995	1996			Yes
Madagascar	1988	1988	0.00		
Malaysia	1997	1999	31.45		
Mexico	1981	1985	26.58		
Mexico	1994	1996	13.66		
Mongolia	2008		0.00		
Morocco	1980	1984	21.92		
Niger	1983	1985	97.21		
Panama	1988	1989	85.04		
Paraguay	1995	1995	15.33		
Philippines	1983	1986	91.67		
Philippines	1997	2001	0.00	Yes	

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Country	Start	End	Potential Output Loss	Borderline	Transition Economy
Poland	1992	1994	0.00		Yes
Russia	1998	1998			Yes
Russia	2008		0.00	Yes	
Senegal	1988	1991	5.57		
Slovakia	1998	2002	0.00		Yes
Slovenia	1992	1992			Yes
Slovenia	2008		37.00	Yes	
Sri Lanka	1989	1991	19.58		
Swaziland	1995	1999	45.69		
Thailand	1983	1983	24.79		
Thailand	1997	2000	109.32		
Togo	1993	1994	38.81		
Tunisia	1991	1991	1.27		
Turkey	2000	2001	37.04		
Uruguay	1981	1985	38.11		
Uruguay	2002	2005	27.37		
Venezuela	1994	1998	1.16		
Vietnam	1997	1997	0.00		

This table list the country-crisis events experienced by the countries in my sample. The information on these country-crisis events is from Laeven and Valencia (2010). Column "Start" and "End" are the starting and ending years of the crisis. Laeven and Valencia (2010) truncate the duration of a crisis at 5 years when their methodology results in a crisis duration over 5 years or when they cannot apply their method due to unavailable data. For a crisis starting at year T, the potential output loss is the cumulative sum of the difference between actual and extrapolated real GDP over the period $[T, T+3]$, expressed as a percentage of the extrapolated real GDP at year T. When necessary, they use the GDP forecasts from the April 2010 version of WEO as estimates of future real GDP. To extrapolate the real GDP, they first apply an Hodrick-Prescott filter with $\lambda = 100$ to the log of real GDP over the period $[T-20, T-1]$ to obtain the trend log real GDP, while requiring at least four pre-crisis observations. The log of real GDP is extrapolated using the growth rate of the trend over the same period. Finally, they take the exponential of the extrapolated log real GDP to get extrapolated real GDP. Column "Borderline" indicates the list of borderline crises that almost meet their definition of a systemic crisis. Column "Transition Economy" indicates whether the country is in a transition to market economy when the crisis happens. For the transition economies, the potential output losses are not reported.

B Variable Definitions

Table B.1: Data Description

Variable	Description
Private Credit/GDP	Claims on the private sector by deposit money banks and other financial institutions divided by GDP. The data source is Beck and Demirgüç-Kunt (2009)
Growth of Private Credit/GDP	The difference in log of *Private Credit/GDP* between the current year and last year.
Bank Credit/GDP	Claims on the private sector by deposit money banks divided by GDP. The data source is Beck and Demirgüç-Kunt (2009)
Growth of Bank Credit/GDP	The difference in log of *Bank Credit/GDP* between the current year and last year.
Financial Assets/GDP	Claims on the whole non-financial real sector, including government, public enterprise, and the private sector, by deposit money banks and other financial institutions divided by GDP.
Growth of Financial Assets/GDP	The difference in log of *Financial Assets/GDP* between the current year and last year.
Market/Bank	The ratio of the sum of stock market capitalization and private bond market capitalization to the credit to domestic non-financial private sector by deposit money banks. I construct this variable so that its value lies between zero and one, i.e. $Market/Bank = \frac{Market}{Market+Bank}$. The data source is Beck and Demirgüç-Kunt (2009)
Credit/GDP	The ratio of sum of the private bond market capitalization and the credit to domestic non-financial private sector by deposit money banks and other financial institutions to GDP. The data source is Beck and Demirgüç-Kunt (2009).
Credit/Stock Market Cap	The ratio of the sum of private bond market capitalization and the credit to domestic non-financial private sector by deposit money banks and other financial institutions to the stock market capitalization. I construct this variable so that its value lies between zero and one, i.e. $Credit/Stock\ Market\ Cap = \frac{Credit}{Credit+Stock\ Market\ Cap}$. The data source is Beck and Demirgüç-Kunt (2009).
Private Credit/Credit	The ratio of private credit to the sum of private credit and private bond market capitalization. Private credit is the credit to domestic non-financial private sector by deposit money banks and other financial institutions. The data source is Beck and Demirgüç-Kunt (2009).
Private Bond/GDP	Private domestic debt securities issued by financial institutions and corporations as a share of GDP. The data source is Beck and Demirgüç-Kunt (2009).
Stock Market Turnover	The ratio of the real value of total shares traded to average real market capitalization. The source is Beck and Demirgüç-Kunt (2009).
Real GDP Per Capita	PPP converted GDP per capita (2005 constant price). The source is Penn World Table 7.0. (Heston, Summers, and Aten (2011))
Growth of Real GDP	The annual growth rate of real GDP. (Heston, Summers, and Aten (2011))
Advanced Economy	An indicator variable that is one if the country is an advanced economy and zero if the country is an emerging market economy. The data source is the 1993 World Economic Outlook (IMF (1993)).
Crisis Year	An indicator variable that is one if a country-year is in a banking crisis and zero otherwise. The definition and timing of a banking crisis is from Laeven and Valencia (2010).
Crisis	An indicator variable that is one if a country-year is the first year of a banking crisis and zero otherwise.

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Variable	Description
Real Interest Rate	The real interest rate is the nominal interest rate minus the contemporaneous rate of inflation. The nominal interest rate is the nominal rate on government bill if data are available. Otherwise, it is a rate charged by the central bank to domestic banks, such as the discount rate. If this variable is also not available, it is the commercial bank deposit interest rate. The rate of inflation is the rate of change of the GDP deflator. The nominal interest rate is constructed using variables from the IMF's International Financial Statistics, and the GDP deflator is from the World Development Indicators of the World Bank.
Nominal Interest Rate	The nominal interest rate is the nominal rate on government bill if data are available. Otherwise, it is a rate charged by the central bank to domestic banks, such as the discount rate. If this variable is also not available, it is the commercial bank deposit interest rate. The nominal interest rate is constructed using variables from the IMF's International Financial Statistics.
Inflation	The inflation calculated by using the GDP deflator. The data are from the World Development Indicators of the World Bank.
Depreciation	The rate of change of the exchange rate. The exchange rate is the period average of the US dollar value per national currency. If this variable is not available, the exchange rate is the nominal effective exchange rate. For the US, nominal effective exchange rate is used. The data for all these variables are from IMF's International Financial Statistics.
Political Risk	This is the Political Risk Index in the International Country Risk Guide (ICRG) from the Political Risk Services (PRS) Group. This index is constructed based on 12 components covering both political and social attributes. As a country's political risk rating changes from very high risk to very low risk, the value of this index moves from 0 to 100.
Surges, *Stops*, *Flight*, *Retrench*,	Indicators of four waves of capital flows. Surges is a sharp increase in gross capital flows; Stops is a sharp decrease in gross capital inflows; Flight is a sharp increase in gross capital outflows; and Retrenchment is a sharp decrease in gross capital outflows. I use the quarterly indicator variables that Forbes and Warnock (2011) construct to identify these four waves of capital flows. For each year, I construct indicators of these four waves at annual frequency by setting the annual indicator to one for one of the four waves if there is a corresponding wave in any quarter during the year according to the quarterly indicators and to zero otherwise.
Postliberalization, *Preliberalization*, *Always liberalized*, *Never liberalized*	Indicator variables indicating the equity market liberalization status of a country based on the dating of equity market liberalization of Bekaert, Harvey, and Lundblad (2005). *Always liberalized* is one if a country is always liberalized and zero otherwise. *Never liberalized* is one if a country is never liberalized and zero otherwise. *Postliberalization* is one if a year is after the liberalization for a liberalizing country and zero otherwise. *Preliberalization* is one if a year is before the liberalization for a liberalizing country and zero otherwise.
Large Reform, *Reform*, *Status Quo*, and *Reversal*	Indicators variables indicating the status of financial reforms in the country over the last five years. These indicator variables are based on the index of financial reform in Abiad, Detragiache, and Tressel (2010). To construct these indicator variables, I first calculate the average of annual changes of the financial reform index over the last five years. Then, *Large Reform* is a year when the average of annual changes is greater than 0.5, *Reform* is a year when the average of annual changes is greater than zero and less than 0.5, *Status Quo* is a year when the average of annual changes equals zero, and *Reversal* is a year when the average of annual changes is less than zero.

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Variable	Description
CD(log(1+Private Credit/GDP))	Cross-sectional deviation of *log(1+Private Credit/GDP)*. For each year, I calculate this variable as the deviation of *log(1+Private Credit/GDP)* from its cross-sectional mean normalized by the cross-sectional standard deviation.
Central Government Debt/GDP	The central government gross debt as a percentage of GDP. Data are from the IMF's World Economic Outlook database. Gross debt consists of all liabilities that require payment or payments of interest and/or principal by the debtor to the creditor at a date or dates in the future. This definition includes debt liabilities in the form of SDRs, currency and deposits, debt securities, loans, insurance, pensions and standardized guarantee schemes, and other accounts payable.
Government Ownership of Banks	The government ownership variable is the *GB70* from La Porta, Lopez-de Silanes, and Shleifer (2002). This variable is defined as $GB70_k = \frac{\sum_{i=1}^{10} GB70_{ik} a_{ik}}{\sum_{i=1}^{10} a_{ik}}$, where $GB70_{ik}$ is the government's share in bank i in country k and a_{ik} is the bank's total assets. The summation in this definition is over the top 10 banks in a country at 1970. Thus, $GB70_k$ is the share of the assets of top 10 banks in country k that is owned by the government at 1970.

This table reports the name, description, and data source of the variables used in this paper.

C A Brief Introduction to Survivor and Hazard Functions

Suppose T is a non-negative random variable of the time to a failure event. Rather than discussing the cumulative distribution function, $F(t) \equiv Pr(T \leq t)$, or, the density function of T, $f(t) \equiv \frac{dF(t)}{dt}$, survival analysis usually focuses on the survivor function, $S(t)$, or the hazard function, $h(t)$.

The survivor function, is the reverse of the cumulative distribution function:

$$S(t) \equiv Pr(T > t) = 1 - F(t). \tag{4}$$

It is a monotone, non-increasing function measuring the probability that there is no event prior to t.

The hazard function, $h(t)$, is the instantaneous rate of failure at time t:

$$h(t) \equiv \lim_{\Delta t \to 0} \frac{Pr(t + \Delta t > T > t | T > t)}{\Delta t} = \frac{f(t)}{S(t)} \tag{5}$$

The value of a hazard function can range from zero to positive infinity. When it takes the value of zero, the instantaneous rate of failure is zero. If the risk of an event is constant over time, then hazard function is a constant. If the risk is rising (falling) over time, then hazard function is increasing (decreasing) with time.

The four functions above, $f(t)$, $F(t)$, $h(t)$, and $S(t)$, all describes the same underlying distribution of T. In fact, given any one of them, the other three are determined. To see their relation with each other, it is helpful to define the cumulative hazard function,

$$\begin{aligned} H(t) &\equiv \int_0^t h(u)du \\ &= \int_0^t \frac{f(u)}{S(u)}du \\ &= -\int_0^t \frac{1}{S(u)} \left\{ \frac{d}{du} S(u) \right\} du \\ &= -ln\{S(t)\}. \end{aligned} \tag{6}$$

The cumulative hazard function measures the total amount of risk accumulated. As Equation 6 shows, it is negatively related to the probability of survival. Now, we use three equations to describe the relation between $f(t)$, $F(t)$, $h(t)$, and $S(t)$ as follows,

$$\begin{aligned} S(t) &= exp\{-H(t)\} \\ F(t) &= 1 - exp\{-H(t)\} \\ f(t) &= h(t)exp\{-H(t)\}. \end{aligned} \tag{7}$$

D Theories of the Way Finance Can Lead to Instability and Financial Crises

Table D.1: Theories

Theory	References	Implications	Possible Tests
Leverage: The size of financial sector can be proxying for the leverage of the economy. When the leverage of the economy, especially that of the firms in the real sector, is higher, the probability of default is also higher. When a negative real shock hits, the default of firms causes problems to banks' balance sheet, which feed back to the real sector through the mechanism of "financial accelerator".	Merton (1974), Bernanke and Blinder (1988), Kiyotaki and Moore (1997)	• The leverage of the economy is positively related to the probability of a banking crisis. • When the leverage of the economy is higher, the quantity of credit has a stronger positive relation with the probability of future crises.	• The level of the quantity of credit is positively related to the probability of a banking crisis. • Other measures of the leverage of the economy, such as the ratio of credit to stock market capitalization, can drive out the explanatory power of the quantity of credit in the logit regressions.
Minsky's financial instability hypothesis: Periods of financial stability may lead to future crisis because they encourage economic agents to borrow more and take more risky and speculative positions. The speculative risk-taking and borrowing may reinforce each other when asset prices increase. But, when negative shocks hit and the asset prices fall, it turns out that people have taken too much risk and debt. As a result, they go into distress, the number of nonperforming loans increases, and the financial positions of financial institutions deteriorate, which can lead to financial crises and worsen the economic downturn.	Minsky (1986)	• A long period of financial stability, deregulation, speculative risk taking, and credit boom precedes the financial crisis. • The time in financial stability could be strongly related to the probability of financial instability.	• Excessive credit growth is positively related to the probability of banking crises, especially when the quantity of credit is large. • The time in financial stability is positively related to the probability of future crisis.

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Theory	References	Implications	Possible Tests
Banks catering to sentiment: When rational profit-maximizing banks cater to the market sentiment, they co-invest in newly securitized loans when asset prices are high and choose to hold on to distressed securities when asset prices are low. Banks borrow short term and accept the risk of having to liquidate their portfolio holdings at below fundamental values at bad times, or risk of fire sales. These behaviors make banks unstable and prone to crises.	Shleifer and Vishny (2010)	• A cyclical relation between bank profit and balance sheet as well as real investment. • The shocks to security prices in the form of sentiment are transmitted to other sectors. • Banks choose to hold on to undervalued securities during bad times. Banks use short-term debt to finance credit expansion. The implications of this model may primarily apply to the experience in the US and other advanced economies that have developed security markets.	The effect of the quantity of finance on the probability of banking crises is stronger in countries that banks are more involved in the security markets.
Financial liberalization: During and after financial liberalization, financial sector reforms can ease legal barriers to entry and enlarge the scope of activities of banks and other financial intermediaries. Competition that comes with these changes may reduce the existing banks' franchise values and lead banks to allocate more credit to lenders that are relatively more opaque to their competitors. As a result, banks lower the standards of lending and lend more to borrowers that have lower quality. Financial liberalization can increase the quantity of credit and the probability of banking crisis when there are too many bad loans.	Keeley (1990), Hellman, Murdock, and Stiglitz (2000), and Dell'Ariccia and Marquez (2004)	• Financial liberalization leads to a stronger positive relation between the quantity of finance and the probability of banking crises. This theory may better explain the experiences in countries that are experiencing or have experienced financial liberalization.	Whether the relation between the occurrence of systemic crises and quantity of private credit is stronger after financial liberalization.

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Theory	References	Implications	Possible Tests
Collateralized borrowing and Value-at-Risk: When banks finance their activities through collateralized borrowing, they adjust exposures so that the probability of default is kept at a constant – a level given by the Value-at-Risk threshold. At the system-wide level, a fall in the permitted leverage of the financial intermediaries as a group can lead to a funding crisis.	Adrian and Shin (2008)	• Leverage is procyclical in the sense that leverage is high when the balance sheet is large. • leverage and balance sheet size are both determined by the riskiness of the intermediary's assets. These implications apply to the banking practices that use collateral to finance activities and use Value-at-Risk.	• Given good measures of the leverage of banks, one can test whether the leverage of banks is driving the positive relation between the quantity of credit and the probability of banking crises. • The effect of the quantity of credit on the probability of banking crises is stronger for countries where the practice of collateralized borrowing and usage of Value-at-Risk is more dominant.
Adverse incentives: In deregulated and competitive environment, investment managers have the incentive to search for good investments and conceal tail risks from investors. Investment managers also have incentives to herd with other managers on investment choices. As plain-vanilla transaction becomes more liquid and amenable to being transacted in the market, banks are moving to more illiquid transactions and bear more risks. These behaviors can introduce systemic risks and higher probability of banking crises.	Rajan (2006)	The behaviors described in this explanation reinforce each other during price boom and credit boom. This theory seems to apply to the recent experience in the US.	This explanation may not apply to a wide range of countries other than the US.

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Theory	References	Implications	Possible Tests
Banking sector problems induced by asset bubbles: When investors investing in risky assets by using money borrowed from banks, they can avoid losses in low payoff states by defaulting on the loan. This risk shifting can cause risky assets to be priced above their fundamental value, creating a bubble. Crises occur when the anticipation of credit expansion is not fulfilled.	Allen and Gale (2000)	Anticipated credit expansion can lead to financial fragility. A crisis occurs if the realized credit expansion is not as large as the expectation. Financial contraction does not need to occur for the crisis to happen. Therefore, the deviation of the credit growth from its trend in the past a few years is negatively related to the probability of future crisis.	One could identify the deviation of credit expansion from its extrapolated trend. When the deviation changes from positive to negative, probability of future crises increases.
Public guarantees: Explicit or implicit government guarantees lead to risk shifting behavior and high asset prices, which in turn causes future financial crises.	Krugman (1998), McKinnon and Pill (1998)	Implicit public guarantee encourages banks to take risky and speculative positions. A measure of the effectiveness of the institutional infrastructure of financial supervision for reducing implicit guarantee drives both the quantity of credit and the probability of future crises.	A measure of the effectiveness of the institutional infrastructure of financial supervision for reducing implicit guarantee would be helpful for testing this theory.

This table describes the theories of the way finance can lead to instability and financial crises.