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ESSAYS ON FINANCIAL STABILITY: MARKET STRUCTURE AND EARLY WARNING SYSTEMS

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SUMMARY

This thesis bundles together two distinct yet overlapping strands of the banking literature, which have received renewed interest following the global financial crisis: market structure and financial stability, and early warning systems for banking crisis forecasting. The thesis consists of three chapters. The first chapter critically reviews the extant theoretical and empirical literature on the ambiguous concentration- stability nexus and the forecasting of banking crises, highlighting the specific gaps addressed in the following empirical chapters. The second chapter investigates the channels through which bank concentration affects financial stability. Recent evidence points to the presence of non-monotonicities in the relationship between market concentration and stability, implying that the channels identified in the theoretical literature may be at play simultaneously with varying magnitude, which crucially depend upon initial levels of concentration. Using panel data, the chapter tests for the simultaneous presence of the channels and finds evidence that the prevalence of one or the other is a function of the initial degree of market concentration. The third chapter provides a systematic analysis of the role played by the duration of a systemic banking crisis in affecting the relative ability of multinomial and binomial logit models in correctly predicting the arrival of a crisis. The specific hypothesis tested is that the longer the duration of the crisis the better is the multinomial logit model in forecasting systemic banking crises relative to the binomial logit model. Results confirm that the multinomial logit model outperforms alternative binomial models in correctly predicting the arrival of a systemic banking crisis. In particular, the performance of the multinomial model improves over the binomial logit when the average duration of the crisis increases: the longer the average duration of crises in the sample, the better the relative performance of the multinomial over alternative binomial specifications.

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ABBREVIATIONS

AUROC	Area under the Receiver Operating Characteristic Curve
EWS	Early Warning System
FN	False Negative
FX	Foreign Exchange
GDP	Gross Domestic Product
GFC	Global Financial Crisis
HHI	Herfindahl-Hirschman Index
IIA	Independence of Irrelevant Alternatives
ROA	Return on Assets
ROE	Return on Equity
TP	True Positive

1 MARKET CONCENTRATION AND THE FORECASTING OF BANKING CRISES: THEORY AND EVIDENCE

This Chapter critically reviews the literature on financial stability, putting particular emphasis on the relationship between market structure and financial stability, and on early warning systems for banking crisis forecasting. The first part of this Chapter provides an overview of the extant literature on banking market concentration and financial stability, highlighting the ambiguity of the theory and the mixed findings of the empirical literature. The second part of the Chapter discusses the theory of banking crises, the relevant empirical literature on early warning indicators and the main methodological issues associated with building early warning systems. The Chapter also summarizes the specific gaps addressed by the empirical chapters of this thesis.

1.1 Market structure and financial stability

The structure of the banking market has historically been an important element of the academic and policy debate on financial stability. As in other, non-financial markets, the structure of the banking market is often seen as an important requisite for an effective system. The past decades have seen a rapid consolidation of banks around the world, which has intensified concerns among policymakers about bank concentration. This consolidation has happened not only within countries, but also across countries.

Consolidation has happened both within business lines but also across business lines, resulting in conglomerates that offer commercial and investment banking, insurance and asset management services. While consolidation has often been justified by efficiency and scale economy arguments, the process of consolidation and the resulting financial conglomerates have given rise to stability concerns. In particular, the size and complexity of these institutions might undermine proper regulation and supervision by both markets and authorities; their size and critical role across different markets might make it difficult for regulators to intervene and potentially close such institutions, a phenomenon known as too-big-to-fail. This problem may have been exacerbated by the regulatory response to the GFC, where structural reforms have led to more concentrated and interconnected banking systems.

What are the effects of bank concentration on the stability of banking systems around the world? The discussion on the relationship between bank market structure and stability has been made difficult by measurement issues. More importantly, both the theoretical literature and the empirical literature have not sanctioned yet either the view that concentration is good or is bad for financial stability, leaving unanswered a number of research questions.

1.1.1 Measuring financial stability and market structure

Testing the relationship between market structure and financial stability requires appropriate measures of both. Bank stability is mostly measured in a negative way, i.e. by considering individual or systemic bank distress. Systemic instability can be broadly defined as periods where the banking system is no longer capable of effectively fulfilling its basic intermediation function, i.e. deposit taking, lending and payment services, for the economy.

There is no single quantitative variable for banking crisis. Banking crisis is an event, so proxies for banking crises would not necessarily be correlated with banking crises themselves. For instance, if we were to use a measure for banking insolvency such as aggregate banking capital, we would need to define a lower bound threshold for a crisis event. However, government intervention or deposit insurance could prevent crisis and the threshold could still be violated. Another issue is that not all crises stem from the liabilities side; as we will see in section 1.2.1, problems in asset quality can also erode banking capital so that a single proxy variable would not pick up all crisis events. As a result, the banking crisis variable is typically created on the basis of several criteria which vary according to the study, and often using accurate, post-crisis data. The main classifications are to be found in Caprio and Klingebiel (1996, 2003), Demirgüç-Kunt and Detragiache (1998, 2005), Reinhart and Rogoff (2009) and Laeven and Valencia (2008, 2012).

Caprio and Klingebiel (1996) have been the first authors to provide a comprehensive dataset of banking crises around the world. The authors define systemic crisis as an event when ‘all or most of banking capital is exhausted’. They specify that non-performing loans as a proportion of the entire loans of the banking system must be in the range of 5–10 percent or less. Insolvency is judged on the basis of official data and published reports by market experts. On this criterion, they judge 58 countries to have experienced systemic crisis over the post-1970s period with many countries experiencing repeated episodes. Caprio and Klingebiel (2003) subsequently updated their database to the period 1980–2002, identifying 93 countries as having experienced systemic distress.

Demirgüç-Kunt and Detragiache (1998) use a more specific set of four criteria where achievement of at least one is a requirement for systemic banking crisis, otherwise bank failure is non-systemic. Specifically, Demirgüç-Kunt and Detragiache (1998) define a full-fledged crisis as an episode characterized by at least one of the following: a) share of non-performing loans to total banking system assets in excess of 10 percent; b) public bailout cost in excess of 2 percent of GDP; c) large scale bank nationalization; and d) extensive bank runs and/or emergency government intervention. On this basis, Demirgüç-Kunt and Detragiache (1998) classified 31 systemic crises in 65 countries over the 1980–1994 period. Demirgüç-Kunt and Detragiache (2005) conducted a follow up study and extended the sample to 1980–2002. Using the same criteria as before, they found 77 systemic crises over 94 countries.

Laeven and Valencia (2008) define a systemic banking crisis as a crisis in which 'a country's corporate and financial sectors experience a large number of defaults, and financial institutions and corporations face great difficulties repaying contracts on time'. As a result, non-performing loans increase sharply and all or most of the aggregate banking system capital is exhausted. This situation may be accompanied by depressed asset prices (such as equity and real estate prices) on the heels of run-ups before the crisis, sharp increases in real interest rates, and a slowdown or reversal in capital flows.

Using this broad definition of a systemic banking crisis that combines quantitative data with some subjective assessment of the situation, Laeven and Valencia (2008) identify the starting year of systemic banking crises around the world since 1970. As a cross-check on the timing of each crisis, the authors examine whether the crisis year coincided with deposit runs, the introduction of a deposit freeze or blanket guarantee, or extensive liquidity support or bank interventions. All in all, Laeven and Valencia (2008) date 124 systemic banking crises over the period 1970 to 2007. More recently, Laeven and Valencia (2012) provided an update of their database, identifying 147 crisis episodes during 1970-2011.

Finally, Reinhart and Rogoff (2009) mark a banking crisis by two types of events: (i) bank runs that lead to the closure, merging or takeover by the public sector of one or more financial institutions, and (ii) in the absence of bank runs, the closure, merging, takeover or large-scale government assistance of an important financial institution (or groups of financial institutions) that marks the start of similar outcomes for other financial institutions. The authors further differentiate between Type I crises (systemic/severe) and Type II (financial distress/milder). Based on these criteria, Reinhart and Rogoff (2009) identify a total of 107 banking crises in 65 countries, some with multiple crises, from countries' independence or 1945 to 2008.

In addition to systemic banking crises, individual bank fragility can also be a concern for bank supervisors and policy makers, as individual bank distress may put countries' financial safety net under pressure. Several systemic banking crises have started as crises in individual banks. Individual bank distress can be measured in terms of proximity to bankruptcy or entry into bankruptcy. Specifically, researchers often use the z-score, which is the sum of capital-asset ratio and return on assets, weighted by the standard deviation of return on assets (Boyd et al., 2006). The z-score indicates the number of standard deviations in return on assets that a bank is away from insolvency and thus the probability of failure. An alternative, widely used indicators of individual bank fragility is the non-performing loan ratio. Unlike the z-score, this variable focuses on credit risk and cannot be related directly to the likelihood of failure. Neither of the two measures considers actual failure of banks.

If measuring financial stability is often a subjective endeavour even when objective indicators are used, the measurement of market structure is *prima facie* less questionable. Typically, market structure is measured by banking concentration, which can be approximated by the number of banks and/or the number of branches or ATMs. However, the most widely used indicators of market concentration are the concentration ratio—the share of assets held by the k largest banks (typically three or five) in a given economy—and the Herfindahl-Hirschman index (HHI) —the sum of the squared market share of each bank in the system. The concentration ratio varies between nearly 0 and 100. The HHI has values up to 10,000. If there is only a single bank that has 100 percent of the market share, the HHI would be 10,000. If there were a large number of market participants with each bank having a market share of almost 0 percent, the HHI would be close to zero. Therefore, the HHI accounts for the market share of all banks in the system and assigns a larger weight to the biggest banks. Instead, concentration ratios completely ignore the smaller banks in the system.

These indicators are not without drawbacks, however. They are rather crude measures that do not consider important qualitative dimensions, which can have an impact on financial stability such as the ownership structure of the banking system. Banks with different ownership behave differently and this can have a bearing on stability outcomes. An additional challenge in measuring concentration is to properly define the relevant market. Cross-country studies typically define an economy as the relevant market but this is not necessarily a correct assumption. Studies for the U.S. have typically focused on the Metropolitan Statistical Areas as the relevant market. Further, market structure indicators are typically measured at the institutional level, rather than the product level; i.e. concentration is assumed to be the same across different product lines, such as deposit, lending and payment services.

1.1.2 Theoretical overview[1]

Theory has made contrasting predictions on the relationship between banking market concentration and financial stability. Some models predict that more concentrated banking systems are more stable, as profits provide a buffer against instability and provide incentives against excessive risk taking. This so called 'charter value' view of banking, as theoretically modelled by Marcus (1984), Chan et al. (1986), and Keeley (1990), considers banks as entities choosing the risk of their asset portfolio. Bank owners, however, have incentives to shift risks to depositors, as in a world of limited liability they only take the upside part of this risk taking. In less concentrated markets with more pressures on profits, banks have higher incentives to take more risks, resulting in higher instability. In highly concentrated banking systems, on the other hand, banks have better profit opportunities, capital cushions and therefore fewer incentives to take excessive risks, with positive repercussions for financial stability. In addition, in more concentrated markets, banks earn more informational rents from their relationship with borrowers, increasing their incentives to properly screen borrowers, again increasing stability (Boot and Greenbaum, 1993; Allen and Gale, 2000a; 2004).

More concentration can also have a positive impact for liability risk. Smith (1984) shows that concentrated banking markets lead to more stability if information about the probability

[1] This section draws extensively from Beck (2008).

distribution of depositors' liquidity needs is private, allowing banking relationships to last longer. Matutes and Vives (1996), however, argue that bank illiquidity can arise in any market structure. Specifically, a bank's distress probability is determined endogenously by depositor' expectations resulting in the possibility of multiple equilibriums.

An additional channel through which banking market structure can affect stability is the interbank market and the payment system. As demonstrated by Allen and Gale (2000a), a low degree of concentration can prevent banks to provide liquidity to another bank that is hit by a temporary liquidity shortage. If all banks are price takers, no bank has incentive to provide liquidity to the bank in difficulty, with the result that this bank will eventually fail with negative consequences for the whole system. A complementary view is offered by Saez and Shi (2004), who argue that in an unconcentrated market banks can cooperate and act strategically to help a bank with temporary liquidity shortages.

Another argument of proponents of the 'concentration-stability' hypothesis is that more concentrated banking systems have larger banks, which in turn allows them to better diversify their portfolios. Diamond (1984), Ramakrishnan and Thakor (1984), Boyd and Prescott (1986), Williamson (1986), Allen (1990), and others predict economies of scale in intermediation. A related argument refers to the number of banks to be supervised by the authorities. If a more concentrated banking system implies a smaller number of banks, this might reduce the supervisory burden and thus improve overall financial stability (Allen and Gale, 2000a).

While the 'charter-value hypothesis' predicts that more concentrated banking systems are more stable, an opposing view, the so called 'concentration-fragility' view, is that a more concentrated banking structure results in more bank instability. Boyd and De Nicoló (2005) argue that the argument that market power in banking boosts profits and hence bank stability does not take into account the potential impact of banks' market power on firm behaviour. Rather than banks choosing the riskiness of their assets, it is actually the borrowers who choose the riskiness of their investment undertaken with bank loans. Boyd and De Nicoló (2005) confirm that concentrated banking systems enhance market power, which allows banks to charge higher interest rates to firms. However, these higher interest rates may induce firms to assume greater risk, which results in a higher probability that loans turn sour. Therefore, Boyd and De Nicoló (2005) find a positive relationship between concentration and bank instability. Similarly, Caminal and Matutes (2002) show that more concentration can lead to less credit rationing, larger loans and higher probability of failure if loans are subject to multiplicative uncertainty.

Advocates of the 'concentration-fragility' view also argue that (i) relative to diffuse banking systems, concentrated markets generally have fewer banks and (ii) policymakers are more concerned about bank failures when there are only a few banks. Based on these assumptions, banks in concentrated systems will tend to receive larger subsidies through implicit 'too-big-too-fail' policies that intensify risk-taking incentives and hence increase banking system insyability (e.g., Mishkin, 1999). Further, having larger banks in a concentrated banking system could also increase contagion risk, resulting in a positive link between concentration and systemic fragility.

Proponents of the 'concentration-fragility' view would also disagree with the proposition that a concentrated banking system characterized by a few banks is easier to supervise than a less concentrated banking system with many banks. The argument here is that bank size is positively correlated with complexity so that large banks are harder to supervise than small banks. Concentrated banking systems tend to have larger banks. Further, the recent consolidation trend has also led to financial conglomerates offering a whole array of financial services, previously offered by specialized institutions, and all this is expected to complicate the life of the supervisor. Thus, this argument predicts a positive relationship between concentration and fragility.

The 'concentration-stability' view and the 'concentration-fragility' view have been recently reconciled in models that show a U-shaped relationship between concentration and stability. Martínez-Miera and Repullo (2010) develop a model which implies a non-monotonic relationship between concentration and financial stability. There, increasing the number of banks in monopolistic markets initially makes the financial system more stable, as borrowers become safer. This is because a larger number of banks lead to a reduction in loan rates, which in turn leads to lower probabilities of default and improved bank metrics. They define such a channel 'risk-shifting effect'. Boyd and De Nicoló (2005) reach the same conclusion in a model with a loan market and perfect correlation among borrowers' default probabilities. By allowing for imperfect correlation of loan defaults, Martínez-Miera and Repullo (2010) show, however, that an increasingly diffuse market leads to lower loan rates which in turn reduces interest income from performing loans and ultimately makes the banking system more fragile. This channel is defined as the ‘margin effect’.

An alternative view can be derived from the general equilibrium banking model with moral hazard examined by De Nicolò and Lucchetta (2011). They show that the impact of market structure on systemic stability depends on the intermediation technology, i.e., on the bank’s screening and monitoring technology. If the intermediation technology employed by banks for screening and monitoring borrowers has constant returns to scale, i.e., the effort cost of screening and monitoring is proportional to the size of the borrower’s investment, lower concentration in the deposit market is sub-optimal: when concentration decreases, bank risk increases and bank capital declines, making concentrated banking sectors more socially desirable. If instead there are increasing returns to scale, i.e., the effort cost of screening and monitoring is independent on the borrower’s investment size, then lower concentration minimizes the likelihood of banking crisis. Under increasing returns to scale, lower concentration increases the supply of funds to the bank and reduces the cost of the intermediation technology. This reduction more than offsets the negative impact of higher funding costs on the bank’s expected profits, lowering the incentives for the bank to take on more risks.

1.1.3 What the data tell us

Up until recently, the empirical literature either focused on one country or on the comparison of two countries. Only recently, the availability of large panel datasets has enabled cross-country studies. In a seminal paper, Keeley (1990) provides evidence that reduced concentration following the relaxation of branching restrictions in the 1980s reduced banks’ capital cushions and increased risk premiums reflected in higher interest rates. Overall, this suggests that a diffuse market in the U.S. eroded charter values and resulted in higher bank instability in the 1980s. This result is consistent with Dick (2006), who finds evidence of increased impairment losses and provisions following deregulation in the 1990s, but contradicts findings by Jayaratne and Strahan (1998) who find that branch deregulation resulted in a sharp decrease in loan losses.

An extensive strand of the literature infers the effect of market structure on bank fragility by assessing the effect of mergers creating larger banks and increasing market concentration. Paroush (1995) points to higher bank stability caused by increases in market power stemming from diversification gains after mergers. Benston et al. (1995) and Craig and Santos (1997) also point to positive diversification and thus stability gains from bank mergers in the U.S. However, empirical work by Chong (1991) and Hughes and Mester (1998) indicates that bank consolidation tends to increase the riskiness of bank portfolios. For Italy, Bofondi and Gobbi (2004) find that a bank's loan default rate increases as the number of banks in a market increases.

More recently, Jiménez et al. (2013) test the hypothesis of non-monotonocity between market concentration and bank stability postulated by Martínez-Miera and Repullo (2010) using data from the Spanish banking system. They find support for this nonmonotonic relationship using standard measures of market concentration in both the loan and deposit markets.

The recent availability of large panels has initiated a new wave of literature assessing the validity of the different theoretical models in a cross-country setting. Beck et al. (2006) is the first paper to assess the 'concentration-stability' and 'concentration-fragility' hypotheses in a large sample of countries. They find that more concentrated banking systems are less likely to suffer systemic banking crises in a sample of 69 countries over the period 1980-1997. In a subsequent paper, Beck et al. (2007) analyse some of the channels through which concentration might be positively associated with banking system stability, and find tentative evidence that more concentrated banking systems allow better possibilities for banks to diversify risk.

Boyd et al. (2006) arrive at a different conclusion using bank individual fragility data. Unlike Beck et al. (2006), they find that banks are more likely to fail in countries with more concentrated banking systems. Along the same lines, Uhde and Heimeshoff (2009) provide evidence that national banking market concentration has a negative impact on European banks' financial soundness as measured by the z-score. Using the same sample of countries but analysing them at both country-level and bank-level, IJtsma et al. (2017) confirm that concentration has a negative impact on financial stability, though the effect is economically small at both levels of analysis. Fu et al. (2014) analyse the trade-off between concentration and financial stability using data on 14 Asia Pacific economies from 2003 to 2010. They find that greater concentration fosters financial fragility. Similarly, Mirzaei et al. (2013) investigate the effects of market structure on profitability and stability for 1,929 banks in 40 emerging and advanced economies over 1999–2008 and find that a more concentrated banking system may be vulnerable to financial instability.

On the other hand, Tabak et al. (2012) address the issue of how bank size and market concentration affect performance and risks in 17 Latin American countries between 2001 and 2008. They show that systemically important financial institutions appear to outperform others in terms of both cost and profit without the need of taking more risks. This result holds even in concentrated markets, i.e., where there are few dominant banks and many others with small size in relation to the market.

More recently, some authors have reconciled the conflicting findings of the empirical literature uncovering the presence of non-monotonicities in the relationship between banking market structure and financial stability. Using data for 8,235 banks in 23 developed nations, Berger et al. (2009) find that—consistent with the traditional 'concentration stability' view—banking systems with a higher degree of concentration proxied by the HHI have less overall risk exposure. However, the data also provides some support for the 'concentration-fragility' view—that concentrated markets increase loan portfolio risk. Cuestas et al. (2017) find an inverse U-shaped relationship between market concentration, proxied by market share, and stability, proxied by the z-score and loss reserves, for a sample of Baltic countries during 2000-14, in line with the theoretical predictions of Martinez-Miera and Repullo (2010).

More formally, Bretschger et al. (2012) investigate the channels through which concentration affects financial stability in a large sample of countries. Using a two-stage binary response model, the authors find support for the hypothesis that stability is indirectly impacted by market structure via a profitability channel and a risk channel. More importantly, the authors find support for both the 'concentration-stability' hypothesis and the 'concentration-fragility' view, with varying effects between high- and low-income countries. However, the authors do not study the net effects of the two channels, which remain ambiguous.

1.1.4 Summary

Overall, both the country-level and the cross-country evidence yield mixed results on the relationship between concentration and stability, which does not clarify the ambiguity of the theory. However, with the exception of Bretschger et al. (2012), all studies examine the direct effect of concentration on financial stability whereas taking the theoretical literature seriously would mean to scrutinize the indirect impact of concentration on financial stability, the effects which run via specific channels. Coupled with the recent theoretical and empirical evidence on the presence of non-monotonicities in the relationship between concentration and stability, this may imply that the channels identified in the theoretical literature through which market structure impacts financial stability may be at play simultaneously with varying magnitude, which may crucially depend upon the initial levels of concentration. To the best of our knowledge, none of the existing studies formally test for all channels operating simultaneously and, most importantly, for the relative strength of the channels at different levels of market concentration. This gap is addressed in Chapter 2.

1.2 Predicting systemic banking crises

The GFC has led researchers and policymakers around the world to put renewed efforts into understanding and predicting systemic banking crises. In doing so, the empirical literature concerned with predicting banking crises has been focusing on developing early warning systems (EWS), which seek to forecast future crises.

The EWS literature can be classified into three waves. The first wave is generally descriptive while trying to identify some regularities in the run-up to the crises. Kindleberger (1978) discusses a large number of crises over a very long period of time and qualitative descriptions of U.S. crises of past decades have been presented, for example, by Friedman and Schwartz (1963). More recent descriptive analyses have been presented, for example, in Connor et al. (2012) for Ireland and the U.S., and in Reinhart and Rogoff (2008a) for advanced economies.

The second wave of the EWS literature emerged once econometric analysis with panel data was possible. Here the occurrence of banking crises is modelled as a function of macroeconomic and financial variables. The breakthrough with the second wave was greatly facilitated by the instrumental contribution of Caprio and Klingebiel (1996, 2003), who produced the first database of banking crises in different parts of the world. The early pioneering studies of the second wave, including the widely-cited works of Kaminsky and Reinhart (1999) and Demirgüç-Kunt and Detragiache (1998), relied on Caprio and Klingebiel (1996, 2003) as a source of data. Most recent contributions include Bordo and Meissner (2012), Schularick and Taylor (2012) and Jordà et al. (2011), who combine data on old and new crises, with sample periods ranging from the late 19th to the 21st century. Recent contributions have also benefited from renewed attempts at building consistent datasets of systemic banking crisis episodes, namely Laeven and Valencia (2008, 2012) and Reinhart and Rogoff (2009).

The GFC has led to the emergence of a third wave of EWS literature. This literature typically compares the impact of the crisis on different countries and tries to explain the differences. The main focus is on the impact on either the financial sector (see Kauko, 2012; Kamin and DeMarco, 2012; Aizenman and Pasricha, 2012) or the real economy (Berkmen et al., 2012; Artha et al., 2011) or an extensive set of economic outcomes (Rose and Spiegel, 2011, 2012; Acosta-González et al., 2012; Frankel and Saravelos, 2010).

1.2.1 The causes of banking crises[2]

Before discussing methodological issues and early warning indicators of banking distress, it is useful to briefly review the theoretical literature on the causes of banking crises. There are two broad set of theories of banking crises: one puts emphasis on the liability side of the banking system balance sheet; the other focuses on the asset side.

A first group of theories treat banking crises as depositor panics characterized by depositor withdrawals that puts pressure on the liquidity position of the bank (Friedman and Schwartz, 1963). Such depositor runs can cause illiquidity at banks that are otherwise solvent. Such liquidity pressures can force banks to sell assets at fire sale prices, rendering the bank insolvent. If not prevented through policy, banking failures can become systemic, creating panics and contagion.

Bank runs may or may not be associated with changes in the real economy. For example, Bryant (1980) and Diamond and Dybvig (1983) show that bank runs are self-fulfilling prophecies in an environment where consumption needs are unknown and long-term investments are costly to liquidate. Bank runs occur when depositors fear others will withdraw as well. In such models, banks are viewed as inherently unstable because they mostly finance long-term, illiquid assets with short term, redeemable deposits. However, bank runs can also occur in anticipation of economic downturns that will reduce the value of bank assets and raise the possibility that banks will not be able to meet their obligations fully and on time (Jacklin and Bhattacharya, 1988; Chari and

[2] This section draws extensively from Laeven (2011).

Jagannathan, 1988; and Allen and Gale, 1998). Such crises are particularly likely when there is asymmetric information across depositors about forthcoming bank problems.

Depositor panics are most damaging when they result in contagion, with liquidity pressures spreading through the banking system as failures of individual banks create externalities for the banking system as a whole. Contagion can arise from direct contractual linkages between banks, such as through interbank loans, or from indirect linkages, such as through balance sheet exposures to common shocks (Bhattacharya and Gale, 1987; Allen and Gale, 2000b).

Traditional bank runs have been, however, infrequent since the onset of deposit insurance. In principle, credible deposit insurance can prevent bank runs (Diamond and Dybvig, 1983) and need not displace market discipline (Martinez Peria and Schmukler, 2001). Yet by reducing debtholder discipline deposit insurance can make banking systems less stable (Keeley, 1990; Calomiris, 1999; Demirgüç-Kunt and Detragiache, 2002; Demirgüç-Kunt et al., 2008). Although banking crises have been frequent since the adoption of deposit insurance, aggregate deposit withdrawals have rarely exceeded 10 percent of total deposits, with the exception of the Argentine crisis in 1989 crisis, when monthly deposit withdrawals reached 26 percent during a single month (Laeven and Valencia, 2008). With banks increasingly funding themselves in wholesale markets through uninsured non-deposit liabilities, modern bank runs typically involve the withdrawal of liquidity from uninsured debtholders in advance of traditional depositor withdrawals. The recent GFC can be characterized as having been triggered by such a wholesale bank run (Gorton, 2008).

A second group of theories consider banking crises as originating from losses on the asset side of banks' balance sheets that make banks insolvent. Losses generally follow a prolonged decline in asset quality and stem from adverse macroeconomic shocks, market failures, government interference, fraud or a combination of these factors. Most of these theories regard banking crises as a natural consequence of business cycles (Minsky, 1982; Gorton, 1998). Credit grows rapidly when the economy is booming, as investors turn more optimistic about the future and lending standards deteriorate. When economic conditions slow, a flight to quality causes a collapse in credit.

The macroeconomic origins of banking crises lie in unsustainable macro policies, global financial conditions, and exchange rate misalignments (Lindgren et al., 1996). Expansionary monetary and fiscal policies may spur lending booms, excessive debt accumulation, and overinvestment in real assets, causing deterioration in the quality of bank assets. Reinhart and Rogoff (2009) find that banking crises are typically preceded by credit booms and asset price bubbles. Such macroeconomic shocks can cause particularly severe bank distress in emerging markets that tend to borrow short-term foreign currency denominated debt. Currency or maturity mismatches in firms' balance sheets can easily translate in losses for banks following exchange rate depreciations or increases in world interest rates, and large shifts in the terms of trade will impair the capacity of exporting firms to service their debts.

Banking crises often follow collapses in asset prices. Asset price bubbles can arise for many reasons (Brunnermeier, 2001). One important factor is the amount of liquidity provided by the central bank as money or credit (Kindleberger, 1978). Indeed, banking crises often follow episodes of high inflation or low interest rates. In Diamond and Rajan (2009), liquidity shocks force banks to sell illiquid assets to repay short-term funds, leading to a sharp increase in interest rates and resulting in a decline in the net worth of the bank, ultimately leading to bank runs. Similarly, De Nicolo et al. (2010) and Dell'Ariccia et al. (2010) argue that low interest rates resulting from lax monetary policy induce banks to take on more risk, as banks shift to higher yielding assets, and increase bank leverage, thereby increasing bank fragility. Farhi and Tirole (2012) and Diamond and Rajan (2009) examine the role of monetary bailouts and collective moral hazard on banks' liquidity decisions. When banks expect a bailout by the monetary authorities, they will tend to take on excessive liquidity risk.

Distortions introduced by government intervention, rapid financial liberalization, and weak supervisory or regulatory policies, have often been a source of banking crises (Rochet, 2008; Caprio and Honohan, 2010). For example, under-priced deposit insurance, by removing depositor discipline, has been a particularly important factor in causing banks to take excessive risks (Bhattacharya and Thakor, 1993; Boot and Greenbaum, 1993; Laeven, 2002; Hovakimian et al., 2003; Demirgüç-Kunt et al., 2008). Similarly, government-subsidized housing policies have often generated real estate booms, resulting in banking crises (Herring and Wachter, 2003). The U.S. mortgage crisis of 2007 or the crisis in Japan in the 1990s followed active government policy toward increasing home ownership.

Financial liberalization and deregulation has been a common precursor to banking crises (Drees and Pazarbasioglu, 1998; Kaminsky and Reinhart, 1999). Domestic financial liberalization expands the volume of credit, and this can lead to a bubble in asset prices (Allen and Gale, 2000c). Similarly, capital account liberalization, by inviting capital inflows, can generate credit booms and asset price bubbles (Ranciere et al., 2008). The post-1970 period during which many countries liberalized their financial markets and capital accounts has been unprecedented in terms of the frequency and severity of banking crises.

Fraud has also been at the root of several large bank failures, some of which culminated in episodes of systemic distress (Caprio and Honohan, 2010). Banks are highly leveraged institutions and even relatively small incidents of fraud can cause insolvency. Famous examples of fraudulent behaviour by banks include Venezuela in 1994 and the Dominican Republic in 2003. The collapse of U.S. investment bank Lehman Brothers was in part also caused by accounting fraud.

1.2.2 Early warning indicators[3]

A relatively wide range of indicators, drawn from the theory of banking crises, is found to be useful in predicting the arrival of a banking crisis. First are credit-related variables. Two kinds of credit-based indicators have been most often used in crisis prediction, namely the credit-to-GDP ratio and the growth rate of real credit. Evidence on the predictive ability of these variables is not very robust. Using panel data, Davis et al. (2011) find that banking crises tend to be commonplace if the credit-to-GDP ratio is high, but this result proved to be particularly sensitive to the inclusion of additional variables. Hahm et al. (2011) and Joyce (2011) find that the level of the credit-to-GDP ratio is not a robust crisis predictor in developing countries when controlled for banks' foreign assets and liabilities. Similarly, Von Hagen and Ho (2007) do not find evidence that the ratio of private credit to GDP affects crisis probability.

When it comes to the the growth rate of the credit stock, authors have found better results. Lag-length selection has become highly relevant for the results, with a few authors obtaining significant results when credit growth is lagged by two years or less. Jordà et al. (2011) find that over the period 1870–2008, the credit-to-GDP ratio grew quickly four years before the outbreak

[3] This section draws extensively from Kauko (2014).

of a crisis. Demirgüç-Kunt and Detragiache (2000) find a statistical relationship between credit growth and crises with a two-year lag. Bunda and Ca'Zorzi (2010) obtain strong evidence of the relationship between credit growth lagged two years and a financial crisis (including both currency and banking crises). On the other hand, Barrell et al. (2011) find that credit growth lagged one year is not a particularly good predictor of crises in developed countries.

In recent times, the trend deviation of the credit-to-GDP ratio has been much discussed as it will be the primary trigger for countercyclical capital requirements in the Basel III framework (see Basel Committee, 2010). Borio and Lowe (2002) are the first to use this variable and find evidence on the general tendency of the credit-to-GDP ratio to reach its maximal trend deviation about three years before the outbreak of a crisis. Drehmann et al. (2011) use the same method and the same explanatory variable and conclude that the trend deviation of the credit-to-GDP ratio seems to perform the best among ten different potential variables based on the noise-to-signal ratio.

Most econometric analyses have found that banking crises are typically preceded by a current account deficit. Lo Duca and Peltonen (2013) find evidence on the role of the current account deficit in both developed and emerging economies. Kauko (2012) finds that a combination of rapid credit growth and a current account deficit made a national banking system more vulnerable in 2009. Rose and Spiegel (2012) obtain further evidence to support the view that the recent crisis was worse in countries with current account deficits than in surplus countries. Some other studies, however, present weaker evidence. For example, Roy and Kemme (2012) find that the current account is a good crisis predictor if and only if private debt and asset prices are omitted from the analysis. A current account deficit normally occurs simultaneously with a trade balance deficit. Kaminsky and Reinhart (1999) conclude that exports tend to be weak before a financial crisis, contributing to a foreign trade deficit.

Kindleberger (1978) and Minsky (1977) focus on the role of asset price bubbles as drivers of financial instability. Reinhart and Rogoff (2008a) present some descriptive statistics and conclude that house price increases are regularly observed before banking crises. Connor et al. (2012) emphasise the role of the housing market in the build-up of risks in the U.S. and Ireland before the GFC. Econometric evidence on the predictive power of house prices has come almost exclusively from developed countries, primarily because of data availability. Drehmann et al.

(2011) find that the trend deviation of housing prices tends to peak about two years before the outbreak of a crisis. Barrell et al. (2010) find that an increase in housing prices predicts banking crises in developed countries with a lag of three years (Barrell et al., 2011). Bunda and Ca'Zorzi (2010) find that house price growth lagged one year is an excellent crisis predictor. Roy and Kemme (2011) find that real estate prices predict banking crises within a period of four years.

The relationship between economic growth and banking crises seems somewhat unstable. In the short run, slow or negative growth is a worrying sign (see Beck et al., 2006; Davis et al., 2011; Davis and Karim, 2008b; or Klomp and de Haan, 2009). According to Demirgüç-Kunt and Detragiache (1998, 2005), Angkinand and Willett (2011) and von Hagen and Ho (2007), economic growth has in most cases been slow immediately before a crisis. Davis and Karim (2008a) show that slow GDP growth predicts banking crises. On the other hand, Joyce (2011) and Domaç and Martinez Peria (2003) do not find any relationship. GDP growth may be rapid during the build-up phase, but the evidence is not unanimous.

Results concerning the level of GDP per capita are not particularly robust either. Rose and Spiegel (2011), Aizenman and Pasricha (2012) and Kauko (2012) find that low-income countries were relatively mildly affected by the subprime-Lehman crisis. This contradicts some findings on earlier crises (Davis and Karim, 2008a; Domaç and Martinez Peria, 2003; Beck et al., 2006). Income inequality, on the other hand, has been a typical characteristic of pre-crisis eras (Roy and Kemme, 2012).

Twin crises, i.e. simultaneous banking crises and collapses of fixed exchange rate regimes, have taken place mainly in emerging markets. By definition, exchange rates are key variables in studies on twin crises. According to Kaminsky and Reinhart (1999), a banking crisis normally precedes a currency collapse, but the currency collapse may worsen the banking crisis. Domaç and Martinez Peria (2003) and Husain et al. (2005) find that stable fixed exchange rate systems diminish the risk of crises in developing countries. Duttagupta and Cashin (2011) find that nominal depreciation of the domestic currency is a regular determinant of banking crises. On the other hand, Demirgüç-Kunt and Detragiache (1998, 2005), von Hagen and Ho (2007) and Beck et al. (2006), for example, do not find evidence of a statistically robust association between currency depreciation and the occurrence of crises. Dollarization of the financial system may render a country more vulnerable to banking crises, but the effect seems to be weak (Hong, 2006). In contrast, Duttagupta and Cashin (2011) identify bank liability dollarization as one of the main crisis determinants.

Some results indicate that rapid inflation increases the risk of banking crises. However, this finding is not widely robust. Demirgüç-Kunt and Detragiache (1998, 2000) find that rapid inflation is associated with crises, but Davis and Karim (2008a), studying a sample consisting mainly of developing and emerging economies, find that the effect depends on the method and the precise definition of banking crisis. Joyce (2011) finds additional evidence on the impact of inflation on the occurrence of crises in emerging markets. Rose and Spiegel (2012) do not find a correlation between inflation and the severity of the GFC in cross-national comparisons.

Banking sector liberalisation also seems to be a central variable. The probability of banking crises increases in the aftermath of liberalisation (Kaminsky and Reinhart, 1999; Demirgüç-Kunt and Detragiache, 1998). Evidence on permanent destabilising effects of liberalised capital inflows is presented by Ranciere et al. (2006). Noy (2004) finds that the abolition of domestic interest rate regulations is a risk factor in emerging and developing markets, but that a relaxation of the regulations on international capital mobility has no impact.

There are relatively few papers that focus on the crisis prediction power of banks' financial indicators such as profitability, solvency or liquidity. Barrell et al. (2010) show that a simple leverage indicator and a liquidity indicator are good predictors of future crises. Duttagupta and Cashin (2011) find further evidence of the role of liquidity. The deposits-to-loans ratio seems to be one of the best explanatory variables in analyses of the cross-national severity of the 2007–2008 crisis (Kamin and DeMarco, 2012) as well as the probability of crises in Western Africa (Angora and Tarazi, 2011).

The evidence is equally mixed for monetary aggregates. It is possible to find evidence of the impact of rapid growth of monetary aggregates on crisis occurrence among Asian countries in the 1990s (Davis et al., 2011). But Drehmann et al. (2011) find that M2 growth has not been a good crisis predictor in developed economies. Jordà et al. (2011) find that the amount of money relative to nominal GDP tended to be high four years prior to a crisis. Schularick and Taylor (2012), using similar data, reach the conclusion that the growth rate of monetary aggregates is a weaker predictor of crises than credit aggregates. The M2 multiplier, i.e. the ratio of M2 to the monetary base, often grows substantially and reaches high levels before the outbreak of a banking crisis (Kaminsky and Reinhart, 1999; Demirgüç-Kunt and Detragiache, 1998, 2000; Büyükkarabacak and Valev, 2010). However, Joyce (2011) does not obtain evidence of the relevance of the money multiplier and Beck et al. (2006) find only weak evidence.

High interest rates affect debtors' solvency by weakening their financial viability and capacity to service debt. Demirgüç-Kunt and Detragiache (1998, 2000, 2002) and Evrensel (2008) conclude that high real interest rates systematically precede banking crises. Jordà et al. (2011) find that short-term real interest rates have no explanatory power as such, but that the difference between economic growth and real rates of interest does. Bordo and Meissner (2012) find that low interest rates promote credit cycles, leading to a heightened risk of a banking crisis.

1.2.3 Methodological issues

Since the early stages of the second wave of the EWS literature there have been two dominant methods for predicting the dichotomous banking crisis variable, namely the signals method and the binary regression.

The signals method assumes that macroeconomic variables can safely fluctuate within certain boundaries, but beyond a threshold level the variation constitutes a menace to financial stability. The method was introduced in this literature by Kaminsky and Reinhart (1999) and has been used by Borio and Lowe (2002), Borio and Drehmann (2009) and Drehmann et al. (2011), among others. The threshold value is chosen to minimise the noise-to-signal ratio: the ratio of false alarms to all possible false signals divided by the ratio of correct alarms to all possible correct signals.[4] For instance, one might conclude that the noise-to-signal ratio would have been minimised during the sample period if a crisis had been predicted whenever house prices increased by more than 10 percent a year. The variable with the lowest minimum noise-to-signal ratio has the strongest predictive power. One can impose the additional restriction that at least a certain percentage of crises must be predicted (see e.g. Borio and Drehmann, 2009). The signals method

[4] The noise-to-signal ratio equals [B/(B+D)]/[A/(A+C)], where A, number of correct alarms; B, number of false alarms; C, number of crises without alarm and D, number of cases without alarm and without crisis.

allows strong nonlinearities between the explanatory variable and crisis occurrence (Alessi and Detken, 2011). A notable limitation of the method is that the basic version cannot be used to test the joint significance of several variables. Moreover, the method itself does not include any tests of statistical significance, so that significance testing must be performed separately.

However, most second wave contributions have used binary regressions, particularly binomial multivariate logit and probit. The early pioneers Demirgüç-Kunt and Detragiache (1998, 2000, 2002) use the binomial multivariate logit method. The same method, or comparable ones such as probit, have been used for instance by Ranciere et al. (2006), von Hagen and Ho (2007), Noy (2004), Angora and Tarazi (2011), Davis et al. (2011), Schularick and Taylor (2012), Angkinand and Willett (2011), Joyce (2011), Bunda and Ca'Zorzi (2010) and Lo Duca and Peltonen (2013). Under the binomial multivariate logit (probit) method, the banking crisis dummy is related to a vector of covariates to provide estimates of the probability of an incoming crisis.

To analyse interaction effects of macro-financial variables, there have been attempts to integrate the signals approach and the binomial multivariate logit method through the use of the binary classification tree or binary recursive tree method (Duttagupta and Cashin, 2011; and Davis and Karim, 2008b). The binary classification tree is well suited for analyses of interaction effects. First, it is tested which variable has the strongest predictive power as a crisis predictor. The sample is split into two child nodes according to the values of the best explanatory variable. Then, each child node is split according to the variable that best divides it into crisis and non-crisis cases; the variable need not be the same one for both child nodes. In the following stage, the nodes are split again.

The literature suggests that the empirical strategy based on the estimation of the binomial multivariate logit outperforms the signals approach. Demirgüç-Kunt and Detragiache (2000), Davis and Karim (2008a; 2008b) and Alessi et al., (2015) show that crisis probabilities estimated through the binomial multivariate logit exhibit lower type I (missed crises) and type II (false alarms) errors than the signals approach and therefore provide a more accurate basis for building an EWS.

Although being an interesting step forward in the prediction of banking crises, the binomial multivariate logit method is not without drawbacks. The availability of large longitudinal datasets would suggest to make use of the desirable features of panel data techniques. In particular, the inclusion of country fixed effects in the empirical model would allow for the possibility that the dependent variable may change cross–country independently of the explanatory variables included in the regression, which is a reasonable assumption. In logit estimations, however, including country fixed effects would require omitting from the panel all countries that did not experience a banking crisis during the period under consideration (Greene, 2011). When it comes to building a EWS, this would imply disregarding a large amount of available information, since the number of countries that did not experience crisis is typically larger than that of countries that experienced a crisis. Furthermore, limiting the panel to countries with crises would produce a biased sample. An alternative strategy would be to estimate a logit model with random effects, since such a methodology would be compatible with using the entire data set. However, this model produces unbiased estimates only if the random effects are uncorrelated with the regressors, which is unlikely to be true in practice. Given these downsides and with all its limitations, estimating the logit model using the full sample but without fixed effects or random effects remains the preferred approach.

Another potential drawback of the binomial multivariate logit approach is related to the presence of reverse causality. After the onset of a banking crisis, the behaviour of some of the explanatory variables is likely to be affected by the crisis itself. For instance, the credit stock, a typical early warning indicator as discussed in the previous section, is likely to fall as a result of the banking crisis. Another regressor that may be affected by the banking crisis is market concentration, which is likely to increase due to bank mergers and closures that often accompany banking sector rescue operations. Clearly, these feedback effects would muddle the relationships at stake. Researchers deal with this issue by either excluding from the sample crisis observations after the onset of a crisis (e.g. Demirgüç-Kunt and Detriagiache, 1998; Beck et al, 2006) or treating crisis years other than the first as non-crisis observations (e.g. Eichengreen and Arteta, 2000; Barell et al, 2010).

While being a crude way to mitigate endogeneity (in addition to using lagged regressors), this approach forces the researcher to ignore information that is potentially valuable, especially in the case of prolonged systemic crises: most macro-financial indicators typically used in empirical EWSs are likely to display a different behaviour during a lengthy crisis relative to both tranquil times and the first year of the crisis. Empirical results might be biased if the assumption that crisis years other than first can be treated as non-crisis years or dropped from the model is not valid. In the former case, crisis years are treated as tranquil periods. In the latter, any data in crisis years other than the first are discarded. In either case, potentially valuable information is not considered. In the context of currency crises this phenomenon is known as ‘post-crisis bias’: after the onset of the crisis, economic variables do not go back immediately to a ‘tranquil’ steady-state but take time to converge to equilibrium. To account for it, transition periods where the economy recovers from the crisis are explicitly modelled (Bussiere and Fratzscher, 2006).

In the context of systemic banking crisis, the existence of some kind of post-crisis bias is even more likely to be present. On the one hand, banking crises are more persistent than currency crises as they tend to last longer (Babecký et al, 2013). On the other hand, due to the credit crunch and the generalized loss of confidence that typically accompany a banking crisis, economic recovery takes longer than after a currency crisis (Frydl, 1999). Put differently, since banking crises are typically long-lasting, in the period after the onset of the crisis the economy is still in a state of crisis, and hence relevant economic variables behave differently from both ‘equilibrium’ periods and the outbreak of a crisis.

1.2.4 Summary

Binary multivariate logit models have proved to be the most reliable EWS for systemic banking crises forecasting. Yet this method suffers from what has been called the ‘crisis duration bias’. i.e. the potential to obtain biased results stemming from the practice to either treat observation after the onset of a crisis as non-crisis years or drop them altogether from the model (Caggiano et al., 2014). One possible way to solve the ‘crisis duration bias’ is to use the multinomial logit model with three outcomes in the dependent variable: (i) the first year crisis regime when the crisis occurs; (ii) the crisis regime for crisis years subsequent to the first year of the crisis; and (iii) the tranquil regime for remaining observations (see Bussiere and Fratzscher, 2006). Caggiano et al. (2014) show that multinomial logit models are better suited relative to alternative binomial logit models in predicting the arrival of a systemic banking crisis for a sample of low income countries, where the average duration of banking crises is longer than in other regions. To the best of our knowledge, however, there is no systematic analysis of the role played by the duration of a systemic banking crisis in affecting the relative ability of multinomial and binomial logit models in correctly predicting the arrival of the crisis itself. This gap in the literature is addressed in Chapter 3.

2 BANKING MARKET STRUCTURE AND FINANCIAL STABILITY: NEW EVIDENCE

This Chapter investigates the indirect effects of banking market concentration on financial stability. Bank concentration affects financial stability through specific channels, whose magnitude may depend upon initial levels of concentration. Using a sample of 68 countries from 1997 to 2015, this Chapter present a unified empirical framework to investigate and test for the simultaneous presence of the channels through which concentration impacts financial stability. Results show that at relatively low levels of concentration, increased concentration makes the banking system more stable via the *charter value channel*. At relatively high levels of concentration, increased concentration makes the banking system more fragile via the *interest rate channel*, the *diversification channel* and the *ease of monitoring channel*. For intermediate levels of concentration, the channels cancel each other out and concentration has no significant effect on financial stability.

2.1 Introduction

The GFC has reignited interest among policymakers and academics in the relationship between concentration in the banking sector and financial stability as the market structure may have played a role in the run up to the financial crisis. More importantly, there are concerns that the problem of banks considered 'too-big-to-fail' has gotten worse since 2008, potentially sowing the seeds of a future financial crisis. Yet despite a growing body of theoretical and empirical research, there is still no consensus on whether concentrated banking systems lead to more (or less) financial stability.

Banking market concentration affects financial stability through four main channels. First is the *charter value channel*. Proponents of the so called 'concentration-stability' view posit that concentration may signal less competition and hence greater market power and profits. Higher bank margins, in turn, boost the charter value of banks, thus decreasing incentives for risk-taking and ultimately making the banking system less prone to crisis (Boot and Greenbaum, 1993; Besanko and Takor, 1993; Hellman et al., 2000; Allen and Gale, 2000; Matutes and Vives, 2000).

A second channel though which concentration affects financial stability is the *interest rate channel*. Advocates of the so called ‘concentration-fragility’ view acknowledge that concentrated markets lead to higher bank market power and higher profits. However, higher market power allows banks to charge higher interest rates to borrowers, which in turn increases the incentive of borrowers to assume greater risks and, ultimately, makes the banking system less stable (Boyd and De Nicoló, 2005).[5]

Third, banking market concentration has a bearing on financial stability through the *diversification channel*. However, the sign of the relationship is ambiguous. On the one hand, concentrated banking systems may entail larger banks with more diversified portfolios due to economies of scale in intermediation, thus increasing stability, in line with the ‘concentration-stability’ view (Diamond, 1984; Ramakrishnan and Thakor, 1984; Boyd and Prescott; 1986; Williamson; 1986; Allen, 1990). On the other hand, larger banks may be implicitly protected by ‘too-big-to-fail’ policies that intensify risk-taking incentives and hence increase banking system fragility, overcoming diversification advantages, in line with the ‘concentration-fragility’ hypothesis (O’Hara and Shaw, 1990; Boyd and Runkle, 1992; Mishkin, 1999; Acharya et al., 2012). Further, having larger banks in a concentrated banking system could also increase contagion risk, leading to more instability (Saez and Shi, 2004).

Finally, concentration affects stability through the *ease of monitoring channel*. Like the previous channel, there is no prior on the sign of the relationship. If a more concentrated banking system implies a smaller number of large banks, this might reduce the supervisory burden and thus enhance overall banking system stability, as suggested by the ‘concentration-stability’ hypothesis (Allen and Gale, 2000). The countervailing argument is that if bank size is positively correlated with complexity then a relatively small number of large banks are harder to monitor than small banks hence increasing the fragility of the banking system, in line with the ‘concentration-fragility’ view (Beck et al., 2007).

[5] The contrasting effects of the *charter value channel* and the *interest rate channel* have been recently reconciled in models that show a non-monotonic relationship between concentration and financial stability (see Martinez-Miera and Repullo, 2010).

The empirical literature, which is mostly concerned with measuring the direct impact of concentration on stability, does not clarify the ambiguity of the theoretical predictions. On the one hand, there is ample evidence that concentrated banking markets may increase financial stability (Keeley, 1990; Demirgüç-Kunt and Detragiache, 2002; Beck et al., 2006; Chang et al., 2008; Evrensel, 2008); on the other hand, as theory predicts, concentrated banking markets may also contribute to financial instability (De Nicoló et al., 2003; Boyd et al., 2006; Schaeck et al., 2009; Uhde and Heimeshoff, 2009; Mirzaei et al., 2013; IJtsma et al., 2017). In concentrated markets, as banks get larger and more diversified they may increase the risks of their portfolios, or strategically choose to operate at a closer distance to default (Chong, 1991; Hughes and Mester, 1998; De Nicoló, 2000; Boyd et al., 2006). Larger banks also become subject to internal inefficiencies and increased operational risk (Beck et al., 2006; Cetorelli et al., 2007; Laeven and Levine, 2007).

More recently, some authors have reconciled the conflicting findings of the empirical literature uncovering the presence of non-monotonicities in the relationship between banking market structure and financial stability (Berger et al., 2009; Bretschger et al., 2012; Beck et al., 2013; Carbó Valverde et al., 2013; Jimenez et al., 2013; Cuestas et al., 2017). This may imply that the channels identified in the theoretical literature through which market structure impacts financial stability are at play simultaneously with varying magnitude, which crucially depend upon the initial levels of concentration.

Against this background, this Chapter aims to provide new evidence on the complex interaction between banking market concentration and financial stability, contributing to the ongoing policy debate on structural reforms in the banking sector. In particular, our contribution to the current academic and policy debate on banking market structure and stability is the following: using panel data, we present a unified empirical framework to study whether the structure of the banking market, proxied by the degree of concentration in the market, affects financial stability, measured by the probability of both systemic and non-systemic banking crisis, via the simultaneous presence of the channels suggested by the economic theory of banking, and whether the magnitude of these effects change with the degree of concentration in the banking sector.

To the best of our knowledge, only a few studies have estimated the impact of market structure mediated by the channels highlighted in the theoretical literature. Bretschger et al. (2012) investigate the effect of banking market concentration on banking, currency and sovereign crises, testing for the presence of both the *charter value channel* and the *interest rate channel*, and finding evidence for both channels operating simultaneously. The net effect of the two channels is, however, left ambiguous. Beck et al. (2007) experiment with the *diversification channel* and the *ease of monitoring channel* and find evidence for only the *diversification channel* to play a role in affecting banking system stability through concentration. However, none of the existing studies formally test for all channels operating simultaneously and, most importantly, for the magnitude of the channels at different levels of market concentration. This Chapter contributes to address this gap, shedding new light on the (indirect) effect of concentration on financial stability.

Our empirical analysis rests on a dataset comprising available cross-country, annual observations for 68 countries over the period 1997-2015. Data on systemic and non-systemic banking crises are taken from an updated version of the Reinhart and Rogoff (2009) dataset. Crisis data are given by a binary dummy which takes value of one if country i at time t has entered a crisis and zero otherwise. The data cover 42 crises episodes. Concentration is measured by the share of banking assets held by the three largest banks, but we also study the impact of an alternative concentration measure such as the share of banking system assets concentrated in the five largest banks. To proxy for the channels through which market concentration affects financial stability, we use the following variables: bank return on assets (ROA) for the *charter value channel*; real lending rate for the *interest rate channel*; bank foreign assets plus bank foreign liabilities to banking system assets for the *diversification channel*; and the number of banks for the *ease of monitoring channel*. Following existing benchmark cross-country studies (for example, Beck et al., 2006), we estimate a binomial logit model and control for the following variables: real GDP growth, inflation, nominal exchange rate depreciation, current account balance, real domestic credit growth, and real GDP per capita. We disentangle the channels through which concentration affects financial stability by estimating a model where proxies for the *charter value channel*, the *interest rate channel*, the *diversification channel* and the *ease of monitoring channel* are included and are allowed to interact with the level of concentration.

We find that all channels through which market concentration affects financial stability operate simultaneously, with varying magnitude that crucially depends upon the initial levels of concentration. In particular, we find strong evidence that at relatively low levels of concentration the *charter value channel* dominates: increased concentration leads to improved financial stability. At relatively high levels of concentration, the *interest rate channel*, the *diversification channel* and the *ease of monitoring channel* all dominate, and increased concentration leads to more financial instability. However, while we find strong support for the *interest rate channel,* we find somewhat weaker evidence for the *diversification channel* and the *ease of monitoring channel*. For intermediate levels of concentration, the channels cancel each other out and concentration has no significant impact on banking system stability. Several robustness checks, including alternative proxies for the channels, an alternative measure of concentration, a different subsample, and different econometric models confirm our findings.

This Chapter is structured as follows. Section 2 provides a description of the data and the econometric methodology while section 3 shows our main results. Section 4 presents a battery of sensitivity tests. Section 5 concludes.

2.2 Data and methodology

2.2.1 Data

Our dataset is composed by annual observations from 68 countries over the period 1997-2015. Both the sample composition and time period are driven by data availability. We take information concerning financial stability from an updated version of the Reinhart and Rogoff (2009) database.[6] Reinhart and Rogoff (2009) mark a banking crisis by two types of events: (i) bank runs that lead to the closure, merging or takeover by the public sector of one or more financial institutions, and (ii) in the absence of bank runs, the closure, merging, takeover or large-scale government assistance of an important financial institution (or groups of financial institutions) that marks the start of similar outcomes for other financial institutions. This classification provides us with 42 annual crisis observations, comprising 25 systemic crisis episodes (severe financial distress, in the authors' definition) and 17 non-systemic crises (milder financial distress) in 38

[6] Available at http://www.hbs.edu/faculty/initiatives/behavioral-finance-and-financial-stability/Pages/global.aspx.

countries, which gives an in-sample frequency of crises of 3.6 percent, which is in line with similar studies (e.g. Barrell et al., 2010) and within acceptable bounds for the style of analysis.

Dating banking crises is not without drawbacks. Crises can be classified too late, because the financial problems usually begin well before a bank (or a group of banks) is finally closed or merged, or too early, because the worst of a crisis may come later. Moreover, unlike other types of financial crises such as external debt crises, which have well defined closure dates, it is difficult if not impossible to pinpoint the year in which a banking crisis ended. For these reasons, and because we are mostly concerned with investigating the effect of market concentration on the arrival of a banking crisis (i.e. the switch between non-crisis and crisis states), our binary crisis variable takes value of one if country i at time t enters into a crisis and zero otherwise. In other words, as in other studies (see, for example, Barrel et al., 2010), we treat crisis years other than the first (i.e. when the crisis arrives) as tranquil times. Such an approach, as well as the use of lagged control variables (see below) also allows us to control for potential endogeneity between concentration and banking crisis, as bank failures typically modify the structure of the banking sector (Perotti and Suarez, 2002).

Our baseline measure of market structure is the aggregate share of banking assets held by the three largest banks. Market structure should ideally be measured by relevant product and geographic markets; however, such disaggregated data are often not available, and most measures cannot be computed separately for these submarkets. Therefore, as is common in the cross-country literature, we resort to an aggregate measure of concentration. To test the validity of our main findings, we also use an alternative indicator of concentration such as the share of total banking assets held by the largest five banks.

To proxy for the channels through which market concentration affects financial stability, we use several indicators, in line with previous studies (see Bretschger at al., 2012; and Beck et al., 2007). The 'concentration-stability' hypothesis assumes that market concentration affects systemic stability or, put differently, the probability of a banking crisis, through higher profits. We, therefore, proxy the *charter value channel* by a standard measure of bank profitability in the literature: the return on assets (ROA). The 'concentration-fragility' view suggests that the effect of higher concentration works through loan rates. Accordingly, we use the real lending rate charged by banks to the private sector as a proxy for the *interest rate channel*. Concentrated banking systems are typically more diversified than banking systems composed of many small banks. Therefore, to proxy for *diversification channel* we construct a measure of cross-border financial activity such as the sum of banks' gross external assets and liabilities relative to total banking system assets. Finally, higher market concentration usually entails a small number of large and diversified banks hence we proxy the *ease of monitoring channel* by the number of banks in the country. We provide robustness checks using alternative indicators for the four channels.

Control variables reflect what the theory of the determinants of systemic banking crises suggests, and include the most common predictors of banking crisis found in the empirical literature (see Kauko, 2014, for a review). A first group of covariates captures macroeconomic developments which can have a direct impact on the performance of the banking system, especially on the quality of assets and the level of nonperforming loans. This group of variables includes real GDP growth and inflation. A second set of control variables reflect structural characteristics of the banking system such as the exchange rate depreciation and the current account balance, which measure the degree of vulnerability of the banking system to currency mismatch and to sudden capital outflows, respectively. Credit growth is also included to reflect the risk that high rates of credit expansion may fuel an asset bubble which can ultimately lead to a banking crisis. Finally, we control for the level of economic development by including the real GDP per capita. To control for potential endogeneity of the regressors, we lag all variables by one year. Moreover, to help interpret how concentration transmits to financial stability through the channels we standardize all variables.

Table 1 provides summary statistics for all variables included in our empirical analysis while Table 2 presents the correlation matrix. Appendix A presents data sources and definitions while Appendix B provides the list of countries with related crisis periods.

2.2.2 *Methodology*

To investigate the relationship between concentration and banking system instability, we estimate a binary logit model that is robust to heteroscedasticity (see, for example, Beck et al., 2006).[7]

In the logit model, the probability of a banking crisis is assumed to be a function of a vector of potential explanatory variables. Let $P_{t,i}$ denote a dummy variable that takes value of one if at time *t* country *i* is experiencing a banking crisis and zero otherwise. Let $\boldsymbol{\beta}$ be the vector of parameters to be estimated, and $F(\boldsymbol{\beta}'\boldsymbol{x}_{t,i})$ the cumulative probability distribution function, assumed to be logistic. Then, the log-likelihood function of the model that must be maximized is:

$$(1) \qquad Ln(L) = \sum_{t=1}^{T}\sum_{i=1}^{n}\{P_{t,i}ln[F(\boldsymbol{\beta}'\boldsymbol{x}_{t,i})] + (1 - P_{t,i})ln[1 - F(\boldsymbol{\beta}'\boldsymbol{x}_{t,i})]\}.$$

It must be noticed that while the signs of the coefficients can be easily interpreted as representing an increasing or a decreasing effect on crisis probability, their values are not as immediate to interpret. As Eq. (1) shows, the coefficients on $x_{t,i}$ reflect the impact of a change in the correspondent explanatory variable upon $\ln(P_{t,i}/(1 - P_{t,i}))$, not on $P_{t,i}$, with the magnitude of the impact depending on the slope of the cumulative distribution function evaluated at $\boldsymbol{\beta}'\boldsymbol{x}_{t,i}$. Therefore, the magnitude of the change depends on the initial value of the variables and their coefficients. This is ideal, given the focus of this Chapter.

Differently from most of the existing studies, we are interested in the effect of market concentration on banking instability mediated by the channels identified in the theoretical literature. To do so, we augment our baseline logit model with interaction terms between the channel variables and concentration, and evaluate the interaction effects of our channels at different levels of concentration, i.e. we estimate the marginal effects of the different channels conditional upon different selected percentiles of the concentration distribution.

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[7] Since observations within each country group may also be correlated, we relax the assumption that errors are independent within each country observations. We present robustness tests below.

2.3 Results

We begin our empirical strategy by estimating a binary logit specification as in other studies (e.g., Beck et al., 2006). Results are reported in Table 3, column (1). We find that concentration enters with a significant negative coefficient. While not original and only suggestive, our results lend support to the view that concentrated banking systems are less vulnerable to instability, in line with other studies (Keeley, 1990; Demirgüç-Kunt and Detragiache, 2002; Beck et al., 2006; Chang et al., 2008; Evrensel, 2008; Uhde and Heimeshoff, 2009). Though our variable of interest is concentration, we find that exchange rate depreciation and current account balance enter negatively and significantly, suggesting that an appreciation of the currency, probably leading to overinvestment in non-tradable sectors, and vulnerability to capital outflows are predictors of banking system instability. We also find that inflation and credit growth enter the regression positively and significantly, suggesting that inflationary bursts and a domestic credit boom are associated with banking problems.

We want to test, however, the indirect effect of concentration on banking system instability so next we augment the previous specification with four empirical proxies of the specific channels through which market structure affects financial instability, i.e. a measure of bank profitability (ROA), the real lending rate, a proxy for banking system cross-border activity, and the number of banks in each country. While imperfect, these measures are in line with similar studies (Bretschger et al., 2012; Beck et al., 1997). Results are reported in Table 3, column (2). We find that all but one channel variables enter the regression significantly. The ROA is negative and statistically significant, in line with the hypothesis that countries with more profitable banks are less prone to financial instability. At the same time, we find that the real lending rate enters positively and significantly, consistently with the view that high interest rates make borrowers riskier, leading to a higher probability of banking crisis. On the other hand, cross-border financial activity (our measure of diversification) enters with a significant positive coefficient, supporting the 'too-big-to-fail' argument. Larger and more diversified banks may be induced to take higher risks, leading to higher banking system instability. The (log) number of banks enters with the positive sign, suggesting that a relatively small number of banks may be easier to monitor, enhancing stability. However, this variable is not significant at standard confidence intervals. Interestingly, the inclusion of the channel variables makes the coefficient associated with concentration insignificant. We take this as evidence in favor of our hypothesis that market concentration has an indirect effect on banking system stability: the distinct impact of concentration on the probability of a banking crisis disappears once the channels highlighted by the theory, i.e. the *charter value channel,* the *interest rate channel*, the *diversification channel* and the *ease of monitoring channel* are allowed to play a role.

The next and crucial step of our empirical strategy is to examine whether the effects of the four different channels identified in the theoretical literature depend upon the level of concentration. Our intuition is that the effect of concentration on banking system instability that we find in our baseline regression, i.e. that higher banking market concentration makes the system less vulnerable to crisis, is induced by the channels, whose magnitude varies with the level of concentration. To test for this, we add to the regression model interactions terms between the four channels and the concentration variable.

Estimation results for this model are reported in Table 3, column (3). In a logit model, the sign of the interaction term does not necessarily indicate the sign of the marginal effect, which could be different from zero even if the coefficient of the interaction term is zero. Moreover, the statistical significance of the interaction effect cannot be tested with a simple *t*-test on the coefficient of the interaction term (Ai and Norton, 2003). Therefore, we present a test for joint significance of the effects of concentration working via our proxies for the channels (ROA, real lending rate, cross-border financial activity and number of banks) as well as a test for joint significance of all these regressors.

More importantly, given our interest in evaluating the effects that concentration has on banking instability via the channels that we have identified, we calculate the marginal effects of the four channels on banking system instability computed at different percentiles of concentration. Results, reported in Table 4, suggest that the four channels are at work simultaneously, and have an impact on the probability of crisis that crucially depends upon the level of concentration.

Table 4, column (1) shows that the *charter value channel*, proxied by the ROA, is negatively related to banking system instability: the lower the level of concentration in the banking sector, the higher the bottom line profitability of the banking sector and the lower the likelihood of a banking crisis. The marginal effect of the ROA is always negative, its magnitude decreases with the level of concentration and becomes insignificant at relatively high levels of concentration. Table 4, column (2), shows that the *interest rate channel* is at work as well. The real lending rate is positively related to our banking crisis dummy, implying that more concentrated banking systems lead to a higher cost of money for borrowers, thereby increasing fragility in the system. The marginal effect of the real lending rate is always positive, its magnitude increases with the levels of concentration and it is statistically insignificant at relatively low levels of concentration. Table 4, column (3), presents results for the *diversification channel*. Except for very low levels of concentration, the cross-border financial activity used as a proxy for the channel, is positively related to banking instability, meaning that the higher the concentration of the banking market, the more banks become diversified and the more likely is the system to experience a crisis. The magnitude of the channel increases with the level of concentration and is significant only at relatively high levels of concentration. Finally, Table 4, column (4), shows that the number of banks, which proxies the *ease of monitoring channel,* is positively related to instability: the higher the level of concentration, the more complex becomes to supervise banks, increasing the likelihood of crisis. The coefficient of the number of banks is always positive, its magnitude increases with the level of concentration, and is always statistically significant, except for very low and very high levels of concentration.

One interesting feature of the results reported in Table 4 is that for concentration values between the 30th and the 60th percentile of its distribution—corresponding to in-sample concentration ratios of 55 percent and 73 percent, respectively—the marginal effects of ROA, real lending rate and number of banks are all significant with opposite sign, i.e. the marginal effect of ROA is positive, while the marginal effects of real lending rate and number of banks are both negative. To gauge a clearer conclusion about what effects dominate, Table 4, column (5), reports the LM-type test statistic for the null hypothesis that the sum of the marginal effects equals zero along with the estimated standard errors. Negative and significant values of the test statistic would signal that the null hypothesis can be rejected and that the *charter value channel* dominates. Similarly, positive and significant values of the test statistic would signal that the null hypothesis can be rejected and that the *interest rate channel* and the *ease of monitoring channel* dominate. Results show that the test statistic is significant and with the positive sign only at the 60th percentile of the concentration distribution, implying that the *interest rate channel* and the *ease of monitoring channel* both dominate the *charter value channel*. For intermediate levels of concentration, the effects with opposite sign cancel each other out and concentration has no significant effect on banking system instability.

Overall, results in Table 4 show that concentration affects banking system instability via the channels identified in the literature, with the cumulative effect crucially depending upon the level of concentration itself. In the left tail of the distribution (20th percentile and below), further increasing concentration in the banking sector reduces financial instability via the *charter value channel*. When concentration in its right tail (60th percentile and above), further increasing concentration increases financial instability via the *interest rate channel*, the *diversification channel* and the *ease of monitoring channel.* For intermediate levels of concentration (between the 30th percentile and the 50th percentile), the channels cancel each other out and the structure of the market has no meaningful impact on financial stability. Our results provide, therefore, support for both the 'concentration-stability' view and the 'concentration-fragility' view, and show that the prevalence of one or another critically depends upon the initial levels of concentration.

2.4 Robustness analysis

Our results may be driven by a number of modelling choices, including the variables used as proxies for the channels, the measure of concentration used, the sample period and the econometric specification. This section presents results from several robustness checks.

First, we use different proxies for the channels. Our results may reflect the specific variables selected to proxy for the different channels through which concentration affects banking system instability. Therefore, we run our regression and calculate marginal effects at different values of concentration using the following alternative indicators: return on equity (ROE) for the *charter value channel*; the deflated lending rate for the *interest rate channel*; a measure of income diversification such as the Herfindahl Hirschman Index (Mercieca et al., 2007) for the *diversification channel*;[8] and a measure of regulatory restrictions on the ability of banks to engage in securities markets, insurance and real estate activities for the *ease of monitoring channel*. Results, which are reported in Tables 5─8, broadly confirm our findings: for relatively low levels

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[8] A lower HHI of income diversification signals higher diversification and hence we would expect a negative sign for this variable if the results of the baseline proxy for the *diversification channel* (cross-border financial activity) were confirmed.

of concentration, increasing concentration reduces the probability of banking crises through the *charter value channel*; for relatively high levels of concentration, increasing concentration makes the baking system more fragile. However, while results confirm a strong effect of the *interest rate channel*, they provide somewhat weaker evidence that both the *diversification channel* and the *ease of monitoring channel* are at play as well.

As additional robustness check, we investigate the sensitivity of our results to using an alternative indicator of market concentration: the share of banking system assets held by the five largest banks. Table 9 reports the results, which confirm our findings. We also investigate the robustness of our results to a different sample period. Specifically, given that one-third of crisis episodes in our sample are related to the GFC, we investigate whether our results are driven by the GFC. In Table 10, we run our regression dropping all observations after 2007. We continue to find that the *charter value channel* is at play for relatively low levels of concentration, while the *interest rate channel*, the *diversification channel* and the *ease of monitoring channel* are at play for relatively high levels of concentration.

A final test concerns the model specification. So far, we have allowed for heteroscedasticity of errors and corrected for it, assuming that errors are independent. However, given that we use panel data, the within-country error terms may be correlated with each other. To control for the fact that omitted country-level characteristics might cause correlation of the error terms within-countries, we allow for clustering within countries. Results, presented in Table 11, confirm our main findings.[9]

2.5 Concluding remarks

This Chapter presents a unified empirical framework to investigate the channels through which bank concentration impacts financial stability, and test for their effects at different levels of concentration. Using data for 68 countries during 1997-2015, we estimate a logit model where

[9] We also estimate a logit model with random country effects and use alternative estimators such as probit, cloglog and LPM. Results, which are not reported for brevity but are available upon request, do not differ significantly from our main findings.

interaction effects between our proxies for the channels and our concentration measure are included and evaluated at different levels of concentration.

Our results show that the channels through which concentration affects banking system operate simultaneously with varying magnitude that crucially depends upon the initial levels of concentration. For levels of concentration up to the 20^{th} percentile of its distribution, corresponding to a concentration ratio of 47 percent in our sample, the marginal impact of concentration on banking system instability is negative, and the *charter value channel* dominates: from here, increasing concentration reduces the likelihood of banking crisis. When concentration hits a given threshold, which we estimate at around the 60^{th} percentile of its distribution or concentration ratio of 73 percent in our sample, the marginal impact of concentration on instability becomes positive, and the *interest rate channel*, the *diversification channel* and the *ease of monitoring channel* prevail. For concentration values in between these thresholds values, the channels cancel each other out and concentration does not significantly affect financial stability. Therefore, our results, which survive several robustness checks, lend support to both the 'concentration-stability' view and the 'concentration-fragility', clarifying and measuring the net effects played by the channels.

Appendix A: Regression tables

Table 1 – Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Banking crisis	1,292	0.03	0.18	0.00	1.00
Log GDP per capita	1,292	9.03	1.38	5.52	11.43
GDP growth	1,292	3.61	3.47	-7.82	15.24
FX depreciation	1,289	5.76	21.78	-16.95	206.48
Inflation	1,292	7.54	13.16	-5.26	115.53
Current account balance	1,287	-0.43	6.67	-19.12	24.74
Credit growth	1,247	7.46	14.34	-40.14	76.66
Concentration	1,263	67.07	20.46	17.29	100.00
ROA	1,272	1.00	1.33	-5.97	5.76
ROE	1,272	11.77	13.70	-74.30	67.23
Real lending rate	1,270	6.45	9.47	-32.54	55.43
Nominal lending rate	1,204	14.59	14.31	1.04	95.97
Cross-border financial activity	1,231	0.00	1.00	-0.64	8.11
Income diversification index	1,274	58.38	9.18	50.00	97.18
Log #banks	1,292	3.85	1.22	1.31	8.79
Activity restrictions	1,292	7.26	1.70	3.25	11.25

Table 2 – Correlation matrix

	Banking crisis	Log GDP per capita	GDP growth	FX deprec.	Inflation	Current account balance	Credit growth	Concentr.	ROA	ROE	Real lending rate	Nominal lending rate	Cross-border financial activity	Income diversif. index	Log #banks	Activity restric.
Banking crisis	1															
Log GDP per capita	-0.0049	1														
GDP growth	0.021	-0.3042*	1													
FX depreciation	-0.0268	-0.1203*	-0.1647*	1												
Inflation	0.0294	-0.2681*	0.0654*	0.6143*	1											
Current account balance	-0.0502*	0.2478*	0.0263	-0.0154	-0.0163	1										
Credit growth	0.0675*	-0.1024*	0.3768*	-0.1127*	-0.0796*	-0.0818*	1									
Concentration	-0.0443	0.1564*	-0.0232	-0.0234	-0.0402	0.1064*	0.029	1								
ROA	-0.0491*	-0.2436*	0.3152*	-0.1199*	0.1249*	-0.0766*	0.2800*	-0.0641*	1							
ROE	-0.0226	-0.1873*	0.3044*	-0.0316	0.1718*	-0.0738*	0.2747*	-0.0018	0.7735*	1						
Real lending rate	0.0241	-0.1500*	-0.0636*	-0.1296*	-0.3400*	-0.2082*	0.1061*	-0.0520*	0.001	-0.0823*	1					
Nominal lending rate	0.0486*	-0.3809*	0.0022	0.4879*	0.6619*	-0.1601*	-0.0046	-0.0818*	0.0954*	0.0744*	0.4352*	1				
Cross-border financial activity	0.0436	0.3950*	-0.1051*	-0.0666*	-0.1385*	0.0687*	-0.0512*	0.1275*	-0.1421*	-0.1028*	-0.0817*	-0.1788*	1			
Income diversification index	-0.0378	-0.1055*	0.0114 `	-0.0067	-0.0198	-0.0132	-0.0517*	0.0696*	-0.0074	-0.0182	-0.0218	-0.0336	-0.0467	1		
Log #banks	0.0386	0.5256*	-0.1135*	-0.0515*	-0.1368*	0.2196*	-0.0777*	-0.2602*	-0.1713*	-0.1346*	-0.1581*	-0.2722*	0.2157*	-0.1032	1	
Activity restrictions	-0.0181	-0.3979*	0.1922*	0.0805*	0.1657*	-0.1735*	0.0766*	-0.2073*	0.1203*	0.0780*	0.0452	0.1935*	-0.2841*	0.0587*	-0.2024*	1

* Indicates signficance at the 10% level.

Table 3 – The indirect impact of concentration on banking system instability

	(1) **Coeff.** ***s.e.***	(2) **Coeff.** ***s.e.***	(3) **Coeff.** ***s.e.***
Constant	-3.5473***	-3.6930***	-3.7504***
	0.1773	*0.1918*	*0.2100*
Log GDP per capita	0.2209	0.0002	-0.0056
	0.2132	*0.2861*	*0.2984*
GDP growth	-0.1001	0.0438	0.0033
	0.1902	*0.1940*	*0.2006*
FX depreciation	-0.7688***	-0.9484***	-0.9488***
	0.2947	*0.3157*	*0.3405*
Inflation	0.5625***	0.7286***	0.7778***
	0.1470	*0.2009*	*0.2181*
Current account balance	-0.3509*	-0.3754*	-0.4988**
	0.1929	*0.2142*	*0.2466*
Credit growth	0.3618***	0.4146**	0.4458***
	0.1117	*0.1372*	*0.1301*
Concentration	-0.2758*	-0.2242	-0.3258
	0.1668	*0.2371*	*0.2507*
ROA		-0.4559***	-0.3962**
		0.1445	*0.1645*
Real lending rate		0.2666**	0.4537***
		0.1062	*0.1641*
Cross-border financial activity		0.2212*	0.1591
		0.1270	*0.1431*
Log #banks		0.3117	0.6279**
		0.2226	*0.2871*
ROA; Real lending rate; Cross-border financial activity; Log #banks			17.46***
			0.0016
Concentration; ROA; Real lending rate; Cross-border financial activity; Log #banks			20.39***
			0.0011
ROA X Concentration; Real lending rate X Concentration; Cross-border financial activity X Concentration; Log #banks X Concentration			5.1300
			0.2741
Concentration; ROA; Real lending rate; Cross-border financial activity; Log #banks; ROA X Concentration; Real lending rate X Concentration; Cross-border financial activity X Concentration; Log #banks X Concentration			25.14***
			0.0028
Observations	1,212	1,162	1,162
Log pseudolikelihood	-176.34	-164.17	-161.38
Wald chi2	36.34	42.55	49.12
Prob > chi2	0.0000	0.0000	0.0000
Pseudo R2	0.0509	0.0914	0.1068

The logit probability model estimated in specification (1) is Banking Crisis$_{[Country = j, Time = t]} = \alpha + \beta 1$ Log GDP per capita$_{j,t-1} + \beta 2$ Real GDP growth$_{j,t-1} + \beta 3$ FX depreciation$_{j,t-1} + \beta 4$ Inflation$_{j,t-1} + \beta 5$ Current account balance$_{j,t-1} + \beta 6$ Credit growth$_{j,t-1} + \beta 7$ Concentration$_{j,t-1} + \varepsilon_{j,t}$. The dependent variable is a crisis dummy that takes on the value of one if there is a banking crisis and the value of zero otherwise. Log GDP per capita is the real GDP per capita expressed in log. GDP growth is the rate of growth of real GDP. FX depreciation is rate of change of the exchange rate. Inflation is the rate of change of the GDP deflator. Credit growth is the real growth of domestic credit. Concentration is calculated as the fraction of assets held by the three largest banks in each country. Crisis observations after the initial year of crisis are take on the value of zero. Specification (2) includes: $\beta 8$ ROA$_{j,t-1} + \beta 9$ Real lending rate$_{j,t-1} + \beta 10$ Cross-border financial activity$_{j,t-1} + \beta 11$ Log #banks$_{j,t-1}$. ROA is the return on assets of the banking system in each country. Real lending rate is the interest rate charged by the banking sector to the private sector adjusted for inflation. Cross-border financial activity is the sum of banks' gross external assets and liabilities relative to total banking system assets. Log #banks is the lof of the number of banks. Specification (3) includes interaction terms between concentration and ROA, Real lending rate, Cross-border financial activity and Log #banks, respectively. All independent variables are lagged by one period. We present the coefficients of the logit regressions with White's heteroskedasticity consistent standard errors given in italic. We also present a test for joint significance of the effects of concentration working *via* ROA, Real lending rate, Cross-border financial activity and Log #banks, as well as a test for joint significance of all these regressors. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

Table 4 – Marginal effects of the channels

	(1)	(2)	(3)	(4)	(5)
Percentile	**ROA**	**Real lending rate**	**Cross-border financial activity**	**Log #banks**	**Test for difference in coefficients (1)+(2)+(3)+(4)**
(%)	**dy/dx**	**dy/dx**	**dy/dx**	**dy/dx**	**Coeff.**
	s.e.	**s.e.**	**s.e.**	**s.e.**	**s.e.**
10	-0.0233**	0.0009	-0.0018	0.0086	-
	0.0115	*0.0083*	*0.0127*	*0.0096*	-
20	-0.0203**	0.0050	0.0003	0.0122	-
	0.0081	*0.0060*	*0.0101*	*0.0084*	-
30	-0.0176***	0.0089*	0.0022	0.0155*	0.0068
	0.0060	*0.0048*	*0.0079*	*0.0085*	*0.0093*
40	-0.0158***	0.0117**	0.0036	0.0180*	0.0140
	0.0053	*0.0048*	*0.0065*	*0.0093*	*0.0104*
50	-0.0141**	0.0145***	0.0050	0.02058*	0.2096
	0.0057	*0.0057*	*0.0053*	*0.0107*	*0.0131*
60	-0.0126*	0.0175**	0.0064	0.0233*	0.0282*
	0.0068	*0.0072*	*0.0044*	*0.0126*	*0.0169*
70	-0.0112	0.0205**	0.0078*	0.0262*	-
	0.0082	*0.0093*	*0.0040*	*0.0150*	-
80	-0.0095	0.0244**	0.0097**	0.0299*	-
	0.0101	*0.0121*	*0.0046*	*0.0181*	-
90	-0.0076	0.0291*	0.0119*	0.0344	-
	0.0126	*0.0154*	*0.0064*	*0.0217*	-
Observations	1,162				
Log pseudolikelihood	-161.38				
Wald chi2	49.12				
Prob > chi2	0.0000				
Pseudo R2	0.1068				

The logit probability model estimated is as in Table 3, specification (3). We present the marginal effects (dy/dx) of the logit regression for ROA, Real lending rate, Cross-border financial activity, and Log #banks computed at different percentiles of the concentration variable, and the LM-type test statistic for the null hypothesis that the sum of the marginal effects equals zero, whenever the estimated effects are significant with opposite signs. White's heteroskedasticity consistent standard errors are given in italic. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

Table 5 – Marginal effects of the channels: alternative proxy for the charter value channel

	(1)	(2)	(3)	(4)	(5)
Percentile	**ROE**	**Real lending rate**	**Cross-border financial activity**	**Log #banks**	**Test for difference in coefficients (1)+(2)+(3)+(4)**
(%)	**dy/dx**	**dy/dx**	**dy/dx**	**dy/dx**	**Coeff.**
	s.e.	**s.e.**	**s.e.**	**s.e.**	**s.e.**
10	-0.0212*	-0.0008	0.0006	0.0076	-
	0.0128	*0.0081*	*0.0128*	*0.0100*	-
20	-0.0184**	0.0038	0.0022	0.0118	-
	0.0091	*0.0059*	*0.0102*	*0.0086*	-
30	-0.0153***	0.0079	0.0037	0.0158*	0.0004
	0.0064	*0.0048*	*0.0080*	*0.0087*	*0.0096*
40	-0.0132**	0.0110**	0.0048	0.0188**	0.0165
	0.0052	*0.0048*	*0.0066*	*0.0095*	*0.0107*
50	-0.0113**	0.0140**	0.0059	0.0217**	0.0244*
	0.0049	*0.0055*	*0.0054*	*0.0109*	*0.0131*
60	-0.0094*	0.0172**	0.0071	0.0249*	0.0327*
	0.0055	*0.0070*	*0.0045*	*0.0129*	*0.0168*
70	-0.0076	0.0204**	0.0083**	0.0282*	-
	0.0067	*0.0090*	*0.0041*	*0.0152*	-
80	-0.0055	0.0245**	0.0098**	0.0323*	-
	0.0085	*0.0117*	*0.0047*	*0.0183*	-
90	-0.0029	0.0295**	0.0116*	0.0376*	-
	0.0108	*0.0148*	*0.0065*	*0.0216*	-
Observations	1,162				
Log pseudolikelihood	-163.25				
Wald chi2	56.33				
Prob > chi2	0.0000				
Pseudo R2	0.0965				

The logit probability model estimated is as in Table 3, specification (3). We present the marginal effects (dy/dx) of the logit regression for ROE, Real lending rate, Cross-border financial activity, and Log #banks computed at different percentiles of the concentration variable, and the LM-type test statistic for the null hypothesis that the sum of the marginal effects equals zero, whenever the estimated effects are significant with opposite signs. White's heteroskedasticity consistent standard errors are given in italic. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

Table 6 – Marginal effects of the channels: alternative proxy for the interest rate channel

	(1)	(2)	(3)	(4)	(5)
Percentile	**ROA**	**Nominal lending rate**	**Cross-border financial activity**	**Log #banks**	**Test for difference in coefficients (1)+(2)+(3)+(4)**
(%)	**dy/dx**	**dy/dx**	**dy/dx**	**dy/dx**	**Coeff.**
	s.e.	**s.e.**	**s.e.**	**s.e.**	**s.e.**
10	-0.0234*	0.0101	-0.0048	0.0083	-
	0.0122	*0.0092*	*0.0138*	*0.0102*	-
20	-0.0206**	0.0111	-0.0006	0.0115	-
	0.0084	*0.0069*	*0.0105*	*0.0089*	-
30	-0.0179***	0.0112**	0.0027	0.0140	-0.0061
	0.0061	*0.0058*	*0.0082*	*0.0089*	*0.0070*
40	-0.0160***	0.0125**	0.0052	0.0159*	0.0123
	0.0056	*0.0056*	*0.0068*	*0.0096*	*0.0109*
50	-0.0144**	0.0131**	0.0074	0.0177	-0.0013
	0.0060	*0.0061*	*0.0056*	*0.0108*	*0.0065*
60	-0.0128*	0.0137*	0.0096**	0.0195	0.0105
	0.0070	*0.0071*	*0.0048*	*0.0124*	*0.0087*
70	-0.0113	0.0145*	0.01189***	0.0214	-
	0.0084	*0.0085*	*0.0045*	*0.0145*	-
80	-0.0097	0.0155	0.0147***	0.0239	-
	0.0104	*0.0107*	*0.0054*	*0.0177*	-
90	-0.0078	0.0169	0.0183**	0.0272	-
	0.0128	*0.0137*	*0.0080*	*0.0221*	-
Observations	1,102				
Log pseudolikelihood	-159.46				
Wald chi2	64.4				
Prob > chi2	0.0000				
Pseudo R2	0.1062				

The logit probability model estimated is as in Table 3, specification (3). We present the marginal effects (dy/dx) of the logit regression for ROA, Nominal lending rate, Cross-border financial activity, and Log #banks computed at different percentiles of the concentration variable, and the LM-type test statistic for the null hypothesis that the sum of the marginal effects equals zero, whenever the estimated effects are significant with opposite signs. White's heteroskedasticity consistent standard errors are given in italic. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

Table 7 – Marginal effects of the channels: alternative proxy for the diversification channel

	(1)	(2)	(3)	(4)	(5)
Percentile	**ROA**	**Real lending rate**	**Income diversification index**	**Log #banks**	**Test for difference in coefficients (1)+(2)+(3)+(4)**
(%)	**dy/dx**	**dy/dx**	**dy/dx**	**dy/dx**	**Coeff.**
	s.e.	**s.e.**	**s.e.**	**s.e.**	**s.e.**
10	-0.0238*	0.0021	0.0088	0.0076	-
	0.0122	*0.0084*	*0.0136*	*0.0104*	-
20	-0.0206**	0.0052	0.0035	0.0119	-
	0.0086	*0.0063*	*0.0099*	*0.0090*	-
30	-0.0181***	0.0079	-0.0012	0.0157*	-0.0024
	0.0063	*0.0050*	*0.0077*	*0.0090*	*0.0099*
40	-0.0165***	0.0101**	-0.0046	0.0187*	0.0122
	0.0055	*0.0045*	*0.0070*	*0.0097*	*0.0104*
50	-0.0151***	0.0122**	-0.0078	0.0217*	0.0187
	0.0057	*0.0048*	*0.0072*	*0.0111*	*0.0127*
60	-0.0139**	0.01445**	-0.0113	0.0250*	0.0256
	0.0068	*0.0056*	*0.0083*	*0.0129*	*0.0161*
70	-0.0126	0.0169**	-0.0149	0.0286*	-
	0.0084	*0.0069*	*0.0103*	*0.0150*	-
80	-0.0112	0.0197**	-0.0191	0.0327*	-
	0.0105	*0.0087*	*0.0132*	*0.0172*	-
90	-0.0095	0.0223**	-0.0239	0.0374*	-
	0.0132	*0.0110*	*0.0174*	*0.0197*	-
Observations	1,174				
Log pseudolikelihood	-162.22				
Wald chi2	46.73				
Prob > chi2	0.0000				
Pseudo R2	0.1043				

The logit probability model estimated is as in Table 3, specification (3). We present the marginal effects (dy/dx) of the logit regression for ROA, Real lending rate, Income diversification index, and Log #banks computed at different percentiles of the concentration variable, and the LM-type test statistic for the null hypothesis that the sum of the marginal effects equals zero, whenever the estimated effects are significant with opposite signs. White's heteroskedasticity consistent standard errors are given in italic. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

Table 8 – Marginal effects of the channels: alternative proxy for the ease of monitoring channel

	(1)	(2)	(3)	(4)	(5)
Percentile	**ROA**	**Real lending rate**	**Cross-border financial activity**	**Activity restrictions index**	**Test for difference in coefficients (1)+(2)+(3)+(4)**
(%)	**dy/dx**	**dy/dx**	**dy/dx**	**dy/dx**	**Coeff.**
	s.e.	**s.e.**	**s.e.**	**s.e.**	**s.e.**
10	-0.0244**	0.0032	-0.0045	-0.0076	-
	0.0110	*0.0079*	*0.0131*	*0.0123*	-
20	-0.0209***	0.0062	-0.0015	-0.0079	-
	0.0078	*0.0056*	*0.0100*	*0.0097*	-
30	-0.0178***	0.0086*	0.0011	-0.0081	-0.0093
	0.0059	*0.0045*	*0.0076*	*0.0079*	*0.0062*
40	-0.0157***	0.0101**	0.0027	-0.0081	-0.0056
	0.0052	*0.0045*	*0.0060*	*0.0070*	*0.0060*
50	-0.0138**	0.0115**	0.0042	-0.0082	-0.0024
	0.0054	*0.0050*	*0.0048*	*0.0066*	*0.0065*
60	-0.0121**	0.0127**	0.0055	-0.0082	0.0006
	0.0060	*0.0060*	*0.0039*	*0.0067*	*0.0075*
70	-0.0106	0.0138	0.0067	-0.0082	-
	0.0068	*0.0072*	*0.0035*	*0.0071*	-
80	-0.0090	0.0150	0.0080	-0.0083	-
	0.0079	*0.0090*	*0.0038*	*0.0080*	-
90	-0.0074	0.0165	0.0095	-0.0085	-
	0.0091	*0.0114*	*0.0049*	*0.0092*	-
Observations	1,162				
Log pseudolikelihood	-163.19				
Wald chi2	47.32				
Prob > chi2	0.0000				
Pseudo R2	0.0968				

The logit probability model estimated is as in Table 3, specification (3). We present the marginal effects (dy/dx) of the logit regression for ROA, Real lending rate, Cross-border financial activity, and Activity restrictions index computed at different percentiles of the concentration variable, and the LM-type test statistic for the null hypothesis that the sum of the marginal effects equals zero, whenever the estimated effects are significant with opposite signs. White's heteroskedasticity consistent standard errors are given in italic. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

Table 9 – Marginal effects of the channels: alternative measure of concentration

	(1)	(2)	(3)	(4)	(5)
Percentile	**ROA**	**Real lending rate**	**Cross-border financial activity**	**Log #banks**	**Test for difference in coefficients (1)+(2)+(3)+(4)**
(%)	**dy/dx**	**dy/dx**	**dy/dx**	**dy/dx**	**Coeff.**
	s.e.	**s.e.**	**s.e.**	**s.e.**	**s.e.**
10	-0.0346***	0.0049	-0.0019	0.0072	-
	0.0130	*0.0071*	*0.0139*	*0.0137*	-
20	-0.0242***	0.0089*	0.0017	0.0149	-0.0153**
	0.0075	*0.0050*	*0.0092*	*0.0103*	*0.0074*
30	-0.0196***	0.0107**	0.0033	0.0182	-0.0089
	0.0062	*0.0047*	*0.0073*	*0.0103*	*0.0066*
40	-0.0154**	0.0124**	0.0048	0.0214*	0.0183
	0.0060	*0.0048*	*0.0057*	*0.0113*	*0.0125*
50	-0.0115*	0.0141**	0.0062	0.0246*	0.0272*
	0.0066	*0.0056*	*0.0045*	*0.0133*	*0.0162*
60	-0.0086	0.0156**	0.0074*	0.0273*	-
	0.0074	*0.0065*	*0.0041*	*0.0155*	-
70	-0.0065	0.0166**	0.0083**	0.0293*	-
	0.0081	*0.0073*	*0.0041*	*0.0174*	-
80	-0.0043	0.0178**	0.0093**	0.0316	-
	0.0089	*0.0083*	*0.0046*	*0.0195*	-
90	-0.0028	0.0188**	0.0010*	0.0333	-
	0.0096	*0.0090*	*0.0051*	*0.0210*	-
Observations	1,160				
Log pseudolikelihood	-159.40				
Wald chi2	52.1				
Prob > chi2	0.0000				
Pseudo R2	0.1174				

The logit probability model estimated is as in Table 3, specification (3). However, the concentration measure used is the share of banking system assets held by the five largest banks. We present the marginal effects (dy/dx) of the logit regression for ROA, Real lending rate, Cross-border financial activity, and Log #banks computed at different percentiles of the concentration variable, and the LM-type test statistic for the null hypothesis that the sum of the marginal effects equals zero, whenever the estimated effects are significant with opposite signs. White's heteroskedasticity consistent standard errors are given in italic. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

Table 10 – Marginal effects of the channels: alternative sample period

	(1)	(2)	(3)	(4)	(5)
Percentile	**ROA**	**Real lending rate**	**Cross-border financial activity**	**Log #banks**	**Test for difference in coefficients (1)+(2)+(3)+(4)**
(%)	**dy/dx**	**dy/dx**	**dy/dx**	**dy/dx**	**Coeff.**
	s.e.	**s.e.**	**s.e.**	**s.e.**	**s.e.**
10	-0.0237	-0.0074	-0.0031	0.0106	-
	0.0178	*0.0148*	*0.0216*	*0.0171*	-
20	-0.0211**	0.0033	0.0012	0.0166	-
	0.0112	*0.0088*	*0.0155*	*0.0142*	-
30	-0.0193**	0.0097	0.0038	0.0201	-
	0.0080	*0.0072*	*0.0119*	*0.0142*	-
40	-0.0181**	0.0142*	0.0056	0.0226	-0.0038
	0.0071	*0.0076*	*0.0095*	*0.0153*	*0.0087*
50	-0.0172**	0.0178*	0.0071	0.0245	0.0006
	0.0074	*0.0089*	*0.0079*	*0.0168*	*0.0106*
60	-0.0165*	0.0213*	0.0085	0.0266	0.0048
	0.0087	*0.0108*	*0.0066*	*0.0186*	*0.0131*
70	-0.0159	0.0244*	0.0098*	0.0285	-
	0.0103	*0.0128*	*0.0058*	*0.0204*	-
80	-0.0152	0.0279*	0.0111*	0.0306	-
	0.0125	*0.0146*	*0.0057*	*0.0222*	-
90	-0.0143	0.0309*	0.0123*	0.0322	-
	0.0149	*0.0156*	*0.0065*	*0.0233*	-
Observations	659				
Log pseudolikelihood	-100.37				
Wald chi2	36.88				
Prob > chi2	0.0013				
Pseudo R2	0.1335				

The logit probability model estimated is as in Table 3, specification (3). However, the sample period is 1997-2007. We present the marginal effects (dy/dx) of the logit regression for ROA, Real lending rate, Cross-border financial activity, and Log #banks computed at different percentiles of the concentration variable, and the LM-type test statistic for the null hypothesis that the sum of the marginal effects equals zero, whenever the estimated effects are significant with opposite signs. White's heteroskedasticity consistent standard errors are given in italic. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

Table 11 – Marginal effects of the channels: error terms clustered within countries

	(1)	(2)	(3)	(4)	(5)
Percentile	**ROA**	**Real lending rate**	**Cross-border financial activity**	**Log #banks**	**Test for difference in coefficients (1)+(2)+(3)+(4)**
(%)	**dy/dx**	**dy/dx**	**dy/dx**	**dy/dx**	**Coeff.**
	s.e.	**s.e.**	**s.e.**	**s.e.**	**s.e.**
10	-0.023**	0.0009	-0.0018	0.0086	-
	0.0115	*0.0091*	*0.0110*	*0.0067*	-
20	-0.0203**	0.0050	0.0003	0.0122*	-
	0.0083	*0.0071*	*0.0086*	*0.0065*	-
30	-0.0176***	0.0089	0.0022	0.0155**	-0.0021
	0.0063	*0.0058*	*0.0065*	*0.0071*	*0.0085*
40	-0.0158***	0.0117**	0.0036	0.0180*	0.0140
	0.0057	*0.0053*	*0.0050*	*0.0080*	*0.0114*
50	-0.0141**	0.0145***	0.0050	0.0206**	0.0210
	0.0061	*0.0054*	*0.0037*	*0.0091*	*0.0234*
60	-0.0126*	0.0175***	0.0064**	0.0233**	0.0346*
	0.0072	*0.0061*	*0.0026*	*0.0107*	*0.0169*
70	-0.0112	0.0205***	0.0078***	0.0262**	-
	0.0086	*0.0073*	*0.0019*	*0.0124*	-
80	-0.0095	0.0243***	0.0097***	0.0299**	-
	0.0107	*0.0093*	*0.0026*	*0.0147*	-
90	-0.0076	0.0291**	0.0119***	0.0344**	-
	0.0134	*0.0117*	*0.0046*	*0.0172*	-
Observations	1,162				
Log pseudolikelihood	-161.38				
Wald chi2	90.96				
Prob > chi2	0.0000				
Pseudo R2	0.1068				

The logit probability model estimated is as in Table 3, specification (3). However, error terms are clustered within countries. We present the marginal effects (dy/dx) of the logit regression for ROA, Real lending rate, Cross-border financial activity, and Log #banks computed at different percentiles of the concentration variable, and the LM-type test statistic for the null hypothesis that the sum of the marginal effects equals zero, whenever the estimated effects are significant with opposite signs. White's heteroskedasticity consistent standard errors are given in italic. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

Appendix B: Description and sources of data

Variable Name	Definition	Source
Banking crisis	Dummy takes on value of one during episodes identified as a systematic and non-systemic banking crises.	Reinhart and Rogoff (2009)
Log GDP per capita	Real GDP per capita.	World Development Indicators (World Bank)
GDP growth	Rate of growth of real GDP.	World Development Indicators (World Bank)
Inflation	Rate of change of GDP deflator.	World Development Indicators (World Bank)
Depreciation	Nominal exchange rate depreciation (average of the year).	World Development Indicators (World Bank)
Current account balance	Current account to GDP.	World Development Indicators (World Bank)
Credit growth	Rate of growth of domestic credit to the private sector adjusted for inflaion as measured by the by the GDP deflator.	International Financial Statistics (IMF); European Central Bank; National central banks.
Concentration	Degree of concentration in the banking industry, calculated as the fraction of assets held by the three largest banks.	Global Financial Development Database(World Bank)
ROA	Commercial banks' after-tax net income divided by yearly averaged assets.	Global Financial Development Database(World Bank)
ROE	Commercial banks' after-tax net income divided by yearly averaged equity.	Global Financial Development Database(World Bank)
Real lending rate	Lending interest rate charged by the banking sector to the private sector adjusted for inflation as measured by the GDP deflator.	World Development Indicators (World Bank); National central banks
Nominal lending rate	Lending interest rate charged by the banking sector to the private sector.	World Development Indicators (World Bank); National central banks
Cross-border financial activity	Sum of banks' gross external assets and liabilities relative to total banking system assets.	International Financial Statistics (IMF); Global Financial Development Database(World Bank)
Income diversification index	HHI of relative share of interest income and noninterest income to total banking revenue.	Global Financial Development Database (World Bank)
Log #banks	Number of banks (average).	Financial Access Survey (IMF)
Activity restrictions	Measure of regulatory restrictions on the ability of banks to engage in securities markets, insurance and real estate activities.	Barth et al. (2013)

Appendix C: List of countries and crisis period

Country	Systemic crisis	Non systemic crisis	Country	Systemic crisis	Non systemic crisis
Algeria			Kenya		
Angola			Korea, Rep.	1997	
Argentina	2001		Malaysia	1997	
Australia			Mauritius		
Austria	2008		Mexico		
Belgium	2008		Morocco		
Bolivia		1999	Myanmar	2002	
Brazil			Netherlands	2008	
Canada			New Zealand		
Central African Republic			Nicaragua		2000
Chile			Nigeria	2009	1997
China	1998	1997	Norway		
Colombia	1998		Panama		
Costa Rica			Paraguay		2002
Cote d'Ivoire			Peru	1999	
Denmark	2008		Philippines	1997	
Dominican Republic	2003		Poland		
Ecuador			Portugal		2008
Egypt, Arab Rep.			Romania		
El Salvador		1998	Russian Federation	1998	2008
Finland			Singapore		
France		2008	South Africa		
Germany	2007		Spain		2008
Ghana		1997	Sri Lanka		
Greece	2008		Sweden		2008
Guatemala		2001, 2006	Switzerland		
Honduras		1999, 2001	Thailand		
Hungary	2008		Tunisia		
Iceland	2007		Turkey	2000	2008
India			United Kingdom		2008
Indonesia	1997		United States		
Ireland	2007		Uruguay	2002	
Italy	2008		Venezuela, RB	2009	
Japan	1997		Zambia		

Appendix D: Discussion

This section presents the referee reports for the Chapter along with the responses provided by the author.

Referee #1: Prof. Damiano Bruno Silipo

The chapter uses data for 68 economies during 1997-2005, and adopts a unified framework to estimate the channels through which concentration affects financial stability.

The chapter finds the interesting results, well anchored in the theoretical literature, that at relatively low levels of concentration, increased concentration makes the banking system more stable via the charter value channel. At relatively high levels of concentration, increased concentration makes the banking system more fragile via the interest rate channel, the diversification channel and the ease of monitoring channel. For intermediate levels of concentration, the channels cancel each other out and concentration has no significant effect on financial stability. Therefore, the chapter leads to the conclusions that the initial level of concentration determines also the channels through which concentration affects banking stability.

Points to address:

C1: An alternative explanation of these results may be bank size. Recent evidence actually shows that the size of the banking sector is non-linearly correlated with financial stability, implying that “too much finance” is bad for stability (see for example the paper by Arcand, Berkes and Panizza, “Too much finance?”. Journal of Economic Growth, 2015). The specification used in the analysis should include the size of the banking sector and possibly its squared term.

R1: Thank you for this comment. The reasons for not including a proxy for banking sector size, typically measured by the credit-to-GDP ratio, is twofold: 1) size is not a traditionally good predictor of banking system instability, as discussed in the first paragraph of section 1.2.2.; and 2) the credit-to-GDP ratio is highly correlated with GDP per capita (the Pearson’s correlation coefficient is 0.68, and is significant at the 1 percent level), giving rise to potential collinearity problems. Moreover, the paper referred to in the comment (Arcand et al., 2015) examines the relationship between financial depth and economic growth, while our focus is on financial instability. Nonetheless, Table 1 below reports the baseline results with the inclusion of the credit-to-GDP ratio among the control variables. The latter covariate turns out to be significant and with a positive sign, implying that countries with larger banking systems are more prone to crisis. However, this does not affect the general conclusions of the Chapter, i.e. that concentration affects instability through channels (the marginal effects of the channels at different levels of concentration are not reported for the sake of brevity). At relatively low levels of concentration, increased concentration makes the banking system more stable via the *charter value channel*. At relatively high levels of concentration, increased concentration makes the banking system more fragile via the *interest rate channel*, the *diversification channel* and the *ease of monitoring channel*. For intermediate levels of concentration, the channels cancel each other out and concentration has no significant effect on financial stability.

Table 1 – The indirect impact of concentration on banking system instability: controlling for banking system size

	(1) **Coeff.** ***s.e.***	(2) **Coeff.** ***s.e.***	(3) **Coeff.** ***s.e.***
Constant	-3.6148*** *0.1773*	-3.7510*** *0.1980*	-3.8256*** *0.2206*
Log GDP per capita	-0.1655 *0.2651*	-0.2280 *0.3036*	-0.2752 *0.3098*
Credit-to-GDP	0.4911** *0.2057*	0.4273** *0.2193*	0.4867** *0.2196*
GDP growth	-0.1145 *0.1822*	0.0396 *0.1834*	-0.0108 *0.1886*
FX depreciation	-0.8089*** *0.2969*	-1.0268*** *0.3054*	-1.0571*** *0.3345*
Inflation	0.6659*** *0.1459*	0.8679*** *0.1867*	0.9666*** *0.2072*
Current account balance	-0.2773 *0.1757*	-0.2961 *0.1916*	-0.4374** *0.2287*
Credit growth	0.4132*** *0.1164*	0.4381** *0.1373*	0.4802*** *0.1340*
Concentration	-0.3026* *0.1546*	-0.2910 *0.2305*	-0.4090* *0.2407*
ROA		-0.4342*** *0.1414*	-0.3697** *0.1657*
Real lending rate		0.3273*** *0.1088*	0.5170*** *0.1592*
Cross-border financial activity		0.1822 *0.1202*	0.1064 *0.1366*
Log #banks		0.2049 *0.2218*	0.5924** *0.2859*
ROA; Real lending rate; Cross-border financial activity; Log #banks			18.37*** *0.0010*
Concentration; ROA; Real lending rate; Cross-border financial activity; Log #banks			21.15*** *0.0008*
ROA X Concentration; Real lending rate X Concentration; Cross-border financial activity X Concentration; Log #banks X Concentration			6.0100 *0.1987*
Concentration; ROA; Real lending rate; Cross-border financial activity; Log #banks; ROA X Concentration; Real lending rate X Concentration; Cross-border financial activity X Concentration; Log #banks X Concentration			24.12*** *0.0041*
Observations	1,212	1,162	1,162
Log pseudolikelihood	-173.40	-162.28	-159.01
Wald chi2	40.89	47.16	51.63
Prob > chi2	0.0000	0.0000	0.0000
Pseudo R2	0.0667	0.1018	0.1199

The logit probability model estimated in specification (1) is Banking Crisis$[\text{Country} = j, \text{Time} = t] = \alpha + \beta 1$ Log GDP per capita$_{j,t-1} + \beta 2$ Real GDP growth$_{j,t-1} + \beta 3$ FX depreciation$_{j,t-1} + \beta 4$ Inflation$_{j,t-1} + \beta 5$ Current account balance$_{j,t-1} + \beta 6$ Credit growth$_{j,t-1} + \beta 7$ Concentration$_{j,t-1} + \varepsilon_{j,t}$. The dependent variable is a crisis dummy that takes on the value of one if there is a banking crisis and the value of zero otherwise. Log GDP per capita is the real GDP per capita expressed in log. GDP growth is the rate of growth of real GDP. FX depreciation is rate of change of the exchange rate. Inflation is the rate of change of the GDP deflator. Credit growth is the real growth of domestic credit. Concentration is calculated as the fraction of assets held by the three largest banks in each country. Crisis observations after the initial year of crisis are take on the value of zero. Specification (2) includes: $\beta 8$ ROA$_{j,t-1} + \beta 9$ Real lending rate$_{j,t-1} + \beta 10$ Cross-border financial activity$_{j,t-1} + \beta 11$ Log #banks$_{j,t-1}$. ROA is the return on assets of the banking system in each country. Real lending rate is the interest rate charged by the banking sector to the private sector adjusted for inflation. Cross-border financial activity is the sum of banks' gross external assets and liabilities relative to total banking system assets. Log #banks is the lof of the number of banks. Specification (3) includes interaction terms between concentration and ROA, Real lending rate, Cross-border financial activity and Log #banks, respectively. All independent variables are lagged by one period. We present the coefficients of the logit regressions with White's heteroskedasticity consistent standard errors given in italic. We also present a test for joint significance of the effects of concentration working *via* ROA, Real lending rate, Cross-border financial activity and Log #banks, as well as a test for joint significance of all these regressors. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

C2: Related to the previous point, is the motivation of the control variables used in the analysis. I understand that these variables come from the literature, but the chapter should discuss a bit more the economic rationale for the use of these variables.

R2: Thank you for the comment. The economic rationale of the proxies used for the channels has been added to the text (section 2.2.1).

C3: In line with previous studies, the chapter adopts a binomial logit model to test the hypothesis that concentration affects stability through different channels. However, chapter 3 shows that the multinomial logit model outperforms the binomial model on the predictive power of the banking crises. So, the chapter could include an exercise with the multinomial logit model, to see how the results compare with those reported.

R3: We estimate the multinomial logit model as in Chapter 3. We assume that each economy $i=1,\dots,n$ can be in one of the following $j+1=3$ states: tranquil period ($j=0$), first year of crisis ($j=1$), or crisis years other than the first ($j=2$). The probability that an economy is in state j is given by

$$(1) \qquad Pr\left(Y_t = j|\boldsymbol{X_{i,t}}\right) = \frac{e^{\beta'_j X_{i,t}}}{1+\sum_{l=1}^{J} e^{\beta'_l X_{i,t}}}, \boldsymbol{\beta_0} = \boldsymbol{0}, J = 2$$

where $\boldsymbol{X}_{i,t}$ is the vector of regressors of dimension k and β is the vector of parameters to be estimated. The log-likelihood function to be maximized is

$$(2) \qquad Ln(L) = \sum_{i=1}^{n} \sum_{j=0}^{J} d_{i,j} lnPr(Y_i = j)$$

where $d_{ij}=1$ if the economy i is in state j.

We set the tranquil regime as the base outcome in order to provide identification for the multinomial logit model, which gives the following J=2 log-odds ratio:

$$(3) \qquad \frac{Pr\left(Y_{i,t}=1\right)}{Pr\left(Y_{i,t}=0\right)} = e^{\beta'_1 X_{i,t}} \text{ and}$$

$$(4) \qquad \frac{Pr\left(Y_{i,t}=2\right)}{Pr\left(Y_{i,t}=0\right)} = e^{\beta'_2 X_{i,t}}.$$

The vector of parameters β_1 measures the effect of a change in the independent variables $\boldsymbol{X}_{i,t}$ on the probability of entering a systemic banking crisis *relative* to the probability of being in tranquil times. Accordingly, β_2 measures the effect of a change in the independent variable $\boldsymbol{X}_{i,t}$ on the probability of remaining in a state of crisis *relative* to the probability of being in tranquil times. Eq. (2) is a generalization of the log-likelihood for the binomial logit model, where only two states are allowed, i.e. $\Pr(Y_t=2)=0$.

Table 2 below reports the marginal effects of the channels estimated at different percentiles of the concentration distribution in the first-year crisis regime. The results confirm our main findings: the channels through which concentration affects banking system operate simultaneously with varying magnitude that crucially depends upon the initial levels of concentration.

C4: Minor comments: p. 19. Indirect effect should be direct effect.

R4: Thank you for the comment. The typo has been corrected.

Table 2 – Marginal effects of the channels: the multinomial logit model

	(1)	(2)	(3)	(4)	(5)
Percentile	**ROA**	**Real lending rate**	**Cross-border financial activity**	**Log #banks**	**Test for difference in coefficients (1)+(2)+(3)+(4)**
(%)	**dy/dx**	**dy/dx**	**dy/dx**	**dy/dx**	**Coeff.**
	s.e.	**s.e.**	**s.e.**	**s.e.**	**s.e.**
10	-0.0263**	0.0007	-0.0023	0.0066	-
	0.0128	*0.0083*	*0.0123*	*0.0100*	-
20	-0.0226**	0.0051	0.0001	0.0094	-
	0.0090	*0.0056*	*0.0096*	*0.0085*	-
30	-0.0194***	0.0089**	0.0022	0.0118	-0.0061
	0.0066	*0.0045*	*0.0074*	*0.0082*	*0.0070*
40	-0.0171***	0.0116**	0.0036	0.0134	0.0123
	0.0060	*0.0046*	*0.0060*	*0.0086*	*0.0109*
50	-0.0150**	0.0139**	0.0049	0.0148	-0.0013
	0.0064	*0.0054*	*0.0049*	*0.0064*	*0.0065*
60	-0.0131*	0.0160**	0.0062	0.0160	0.0105
	0.0074	*0.0067*	*0.0040*	*0.0105*	*0.0087*
70	-0.0114	0.0176**	0.0073**	0.0169	-
	0.0087	*0.0082*	*0.0037*	*0.0119*	-
80	-0.0096	0.0192*	0.0085**	0.0178	-
	0.0103	*0.0103*	*0.0039*	*0.0138*	-
90	-0.0080	0.0202	0.0098*	0.0185	-
	0.0120	*0.0129*	*0.0053*	*0.0163*	-
Observations	1,162				
Log pseudolikelihood	-495.67				
Wald chi2	196.04				
Prob > chi2	0.0000				
Pseudo R2	0.2345				

The multiniomial logit probability model estimated is as in Table 3, specification (3). The dependent variable takes three outcomes: Yj,t = 1 for the first year of crisis, Yj,t = 2 for crisis years subsequent to the first, Yj,t = 0 for all other times.We present the marginal effects (dy/dx) of the logit regression for ROA, Real lending rate, Cross-border financial activity, and Log #banks computed at different percentiles of the concentration variable in the first-year crisis regime (Yj,t = 1), and the LM-type test statistic for the null hypothesis that the sum of the marginal effects equals zero, whenever the estimated effects are significant with opposite signs. White's heteroskedasticity consistent standard errors are given in italic. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

Referee #2: Prof. Silvia Fedeli

The thesis is well structured and complete. The topics are interesting and each of the empirical chapters is both well motivated and grounded in the theoretical literature, and adopts appropriate techniques, thus contributing to the relevant literature. One empirical chapter (Chapter 3) has been already published in the Journal of Empirical Finance, and the candidate must be commended for this achievement. I do not have anything to add/suggest on this chapter.

The other empirical chapter (Chapter 2) also appears publishable in journals of equivalent ranking. I have only few comments on it.

Q1: The objective of the chapter is to analyze the relationship between banking market structure and banking stability. However, market structure may also have an impact on competition and in my opinion the chapter (also in the light of the literature review presented in Chapter 1) should also elaborate this issue.

R1: Thank you for this excellent point. The reason why competition is not discussed in the thesis is that to my understanding concentration and competition refer to two distinct concepts. It is true that in some studies market concentration is used as a proxy for competition. This approach is based on the traditional Industrial Organisation (IO) literature, which uses structural tests to assess banking competition based on the Structure-Conduct-Performance (SCP) model derived in Bain (1951). The SCP hypothesis argues that greater concentration causes less competitive bank conduct and leads to greater profitability. According to this theory, competition can be measured by concentration indices such as the market share of the three (five) largest banks, or by the Herfindahl index. However, these tools, which were applied until the 1990s, suffer from the fact that they infer the degree of competition from indirect proxies. On the other hand, the new empirical IO approach is based on non-structural tests to circumvent the problems of measuring competition by the traditional IO approach. The new empirical IO theory determines banks' conduct directly (widely used proxies include the Lerner index, the Boone indicator, and the H-statistic derived from the Panzar-Rosse methodology). Furthermore, it allows us to consider the actual behaviour of banks by taking market contestability into account. Empirically, it has been shown that concentration is not a good predictor of competition (see, for example, Cetorelli, 1999; Claessens and Laeven, 2004; and Demirguc-Kunt et al., 2004, among others). For all these reasons, this Chapter (and the literature review in Chapter 1) keeps its focus on the relationship between market structure (as opposed to competition) and financial stability only.

Q2: The chapter should also refine the analysis by taking into account institutional characteristics of the countries included in the sample in order to consider the relative weight of the financial systems.

R2: Institutional features of economies are taken into account in the analysis through the (log) GDP per capita. The latter is a widely-used summary variable to proxy for institutional development. Specific proxies for institutional development would be significantly and positively correlated with the GDP per capita, giving rise to potential collinearity problems. For example, the Person's correlation coefficient of the World Bank Governance Indicator (the average of six summary components) and the (log) GDP per capita is 0.89, and is significant at the 1 percent level. Therefore, like with the size of the banking system discussed above, specific institutional variables are not included in the analysis.

Q3: Robustness tests could also include alternative indicators used in the literature such as the Herfindahl index or the Lerner index.

R3: Thank you for the comment. The Herfindahl index would be a natural proxy for market structure along with the concentration variable used in the analysis. Unfortunately, it is not available for the panel used in the analysis. On the other hand, the Lerner index, as mentioned above, is a direct measure of competition (it measures pricing power by examining the price markup over marginal cost: higher values for this index indicate greater market power and lower levels of bank competition) while we are concerned with the relationship between market structure and financial stability.

Q4: The chapter could also consider alternative measures of banking instability such as the z-score.

R4: Thank you for the comment. The focus of the Chapter is on systemic stability as opposed to individual fragility measured by the z-score, as discussed in Chapter 1 (see section 1.1.1). For this reason, we do not consider this variable as an alternative proxy for banking crisis. Moreover, the z-score is a continuous variable and as such its consideration would require a different econometric approach, making difficult to compare the results with those based on the logit model.

Q5: It is possible that developed and developing economies behave differently from each other, hence some subsample analysis would be useful.

R5: Thank you for this comment. We report in Table 3 and Table 4 below the results of the analysis based on two subsamples identified by the income level. In particular, we split our sample into a subsample for developed economies and one for developing economies. Countries belonging to the World Bank high income group are classified as developed economies, while those belonging to the middle-income group and low income group are considered developing countries. We continue to find that concentration affects financial stability indirectly and only in the tails of the concentration distribution. However, the significance and magnitude of the channels varies. For developed economies, the *charter value channel* dominates only at very low levels of concentration (10^{th} percentile and below) while the *ease of monitoring channel* is the only channel through which market structure impacts the probability of a systemic crisis at higher levels of concentration (50^{th} percentile and above). For developing economies, the charter value channel is significant at low levels of concentration (30^{th} percentile and below) while the interest rate channel dominates at high levels of concentration (80^{th} percentile and above).

Table 3 – Marginal effects of the channels: developed economies

	(1)	(2)	(3)	(4)	(5)
Percentile	**ROA**	**Real lending rate**	**Cross-border financial activity**	**Log #banks**	**Test for difference in coefficients (1)+(2)+(3)+(4)**
(%)	**dy/dx**	**dy/dx**	**dy/dx**	**dy/dx**	**Coeff.**
	s.e.	**s.e.**	**s.e.**	**s.e.**	**s.e.**
10	-0.0896**	0.0399	0.0045	0.0217	-
	0.0389	*0.0156*	*0.0202*	*0.0156*	-
20	-0.0576**	0.0207	0.0053	0.0297*	-0.2800
	0.0389	*0.0209*	*0.0134*	*0.0161*	*0.0251*
30	-0.0371**	0.0034	0.0057	0.0344*	-0.0026
	0.0156	*0.0225*	*0.0094*	*0.0176*	*0.0212*
40	-0.0247**	-0.0069	0.0060	0.0372**	0.0125
	0.0123	*0.0249*	*0.0074*	*0.0183*	*0.0216*
50	-0.0118	-0.0077	0.0063	0.0402**	-
	0.0110	*0.0288*	*0.0061*	*0.0186*	-
60	-0.0024	-0.0256	0.0065	0.0425**	-
	0.0112	*0.0326*	*0.0060*	*0.0190*	-
70	-0.0082	-0.0346	0.0068	0.0451**	-
	0.0117	*0.0381*	*0.0070*	*0.0204*	-
80	0.0169	-0.0423	0.0070	0.0476**	-
	0.0144	*0.0438*	*0.0085*	*0.0231*	-
90	0.0241	-0.0488	0.0073	0.0500*	-
	0.0175	*0.0494*	*0.0100*	*0.0265*	-
Observations	454				
Log pseudolikelihood	-61.68				
Wald chi2	53.11				
Prob > chi2	0.0000				
Pseudo R2	0.2182				

The logit probability model estimated is as in Table 3, specification (3). However, the sample includes high income only. We present the marginal effects (dy/dx) of the logit regression for ROA, Real lending rate, Cross-border financial activity, and Log #banks computed at different percentiles of the concentration variable, and the LM-type test statistic for the null hypothesis that the sum of the marginal effects equals zero, whenever the estimated effects are significant with opposite signs. White's heteroskedasticity consistent standard errors are given in italic. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

Table 4 – Marginal effects of the channels: developing economies

	(1)	(2)	(3)	(4)	(5)
Percentile	**ROA**	**Real lending rate**	**Cross-border financial activity**	**Log #banks**	**Test for difference in coefficients (1)+(2)+(3)+(4)**
(%)	**dy/dx**	**dy/dx**	**dy/dx**	**dy/dx**	**Coeff.**
	s.e.	**s.e.**	**s.e.**	**s.e.**	**s.e.**
10	-0.0184	-0.0029	-0.0640	-0.0005	-
	0.0115	*0.0095*	*0.0598*	*0.0199*	-
20	-0.0160*	0.0028	-0.0414	0.0048	-
	0.0083	*0.0071*	*0.0402*	*0.0137*	-
30	-0.0143**	0.0063	-0.0274	0.0080	-
	0.0065	*0.0059*	*0.0290*	*0.0116*	-
40	-0.0129**	0.0096*	-0.0143	0.0110	-0.0033
	0.0054	*0.0051*	*0.0199*	*0.0117*	*0.0063*
50	-0.0121**	0.0115**	-0.0068	0.0128	-0.0006
	0.0051	*0.0050*	*0.0156*	*0.0129*	*0.0061*
60	-0.0115**	0.0138**	0.0012	0.0150	0.0023
	0.0053	*0.0056*	*0.0125*	*0.0150*	*0.0062*
70	-0.0111*	0.0168**	0.0102	0.0179	0.0057
	0.0059	*0.0072*	*0.0117*	*0.0187*	*0.0072*
80	-0.0113	0.0205**	0.0195	0.0215	-
	0.0070	*0.0097*	*0.0154*	*0.0234*	-
90	-0.0120	0.0281*	0.0374	0.0291	-
	0.0094	*0.0144*	*0.0300*	*0.0329*	-
Observations	708				
Log pseudolikelihood	-88.38				
Wald chi2	43.48				
Prob > chi2	0.0001				
Pseudo R2	0.1288				

The logit probability model estimated is as in Table 3, specification (3). However, the sample includes low income and middle income countries only. We present the marginal effects (dy/dx) of the logit regression for ROA, Real lending rate, Cross-border financial activity, and Log #banks computed at different percentiles of the concentration variable, and the LM-type test statistic for the null hypothesis that the sum of the marginal effects equals zero, whenever the estimated effects are significant with opposite signs. White's heteroskedasticity consistent standard errors are given in italic. Detailed variable definitions and sources are given in the data appendix.

* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

3 COMPARING LOGIT-BASED EARLY WARNING SYSTEMS: DOES THE DURATION OF SYSTEMIC BANKING CRISES MATTER?[10]

This Chapter compares the performance of binomial and multinomial logit models in the context of building EWSs for systemic banking crises. The Chapter tests the hypothesis that the predictive performance of binomial logit models is hampered by what we define as the 'crisis duration bias', arising from the decision to either treat crisis years after the onset of a crisis as non-crisis years or remove them altogether from the sample. In line with our hypothesis, results from a large sample of world economies suggest that i) the multinomial logit outperforms the binomial logit model in predicting systemic banking crises, and ii) the longer the average duration of the crisis in the sample, the larger the improvement.

3.1 Introduction

'I see two broad tasks ahead: [...]; 2) Dealing with the longer-term global architecture - i.e. …fixing an inadequate regulatory system and developing a reliable early warning and response system' (D. Strauss-Kahn, Managing Director of the IMF, Letter to the G-20 Heads of Governments and Institutions, November 9, 2008).

The GFC has stimulated a new wave of policy and academic research aimed at developing empirical models able to provide alerts about the risk of the onset of a systemic banking crisis, the so-called early warning systems, EWSs (for a review of the literature on EWSs see, for example, Gaytan and Johnson, 2002; Demirgüç-Kunt and Detragiache, 2005; Babecký et al; 2013; and Kauko, 2014).

The empirical literature on EWSs for systemic banking crises has come up with two dominant analytical techniques for predicting signs of banking distress, namely the signals approach and the binomial multivariate logit framework. The signals approach, first developed by Kaminsky and Reinhart (1998) and adopted, among others, by Borio and Lowe (2002), Borio and Drehmann (2009) and Drehmann and Juselius (2014), considers

[10] This chapter has been jointly co-authored with G. Caggiano, L. Leonida and G. Kapetanios and published in the Journal of Empirical Finance, Volume 37, June 2016, Pages 104-116 (https://doi.org/10.1016/j.jempfin.2016.01.005). I contributed 50 percent of the work.

the impact of covariates in isolation and benchmarked against specific threshold values. The fluctuation of the covariate beyond a threshold level, chosen to minimize the noise-to-signal ratio, is interpreted as a threat to financial stability. The binomial multivariate logit, pioneered by Demirgüç-Kunt and Detragiache (1998) and used, among others, by Beck et al. (2006), Davis and Karim (2008a); Barrell et al. (2010) and Schularick and Taylor (2012), relates a binary banking crisis dummy to a vector of explanatory variables to provide estimates of the probability of an incoming crisis.

In spite of recent attempts to integrate the two approaches to analyze interaction effects of macro-financial variables through, for example, the use of the binary classification tree technique (Duttagupta and Cashin, 2008; Davis and Karim, 2008b), the literature suggests that the empirical strategy based on the estimation of the binomial multivariate logit outperforms the signals approach. Demirgüç-Kunt and Detragiache (2000), Davis and Karim (2008a; 2008b) and Alessi et al., (2015) show that crisis probabilities estimated through the binomial multivariate logit exhibit lower type I (missed crises) and type II (false alarms) errors than the signals approach and therefore provide a more accurate basis for building an EWS.

While being an interesting step forward in the prediction of banking crises, in instances where the crisis is longer than one year the use of the binomial multivariate logit model forces the researcher either to treat crisis years other than the first as non-crisis observations (Eichengreen and Arteta, 2000; Barell et al, 2010) or to exclude them from the sample (Demirgüç-Kunt and Detriagiache, 1998; Beck et al, 2006). However, treating years after the crisis as tranquil periods or removing them from the sample implies discarding information that is potentially valuable: most macroeconomic and financial indicators typically used in empirical EWSs display a different behavior during a prolonged systemic crisis relative to both tranquil times and the first year of the crisis.[11] More formally, ignoring such heterogeneous dynamics might give rise to what we call the crisis duration bias, i.e. the inability of binomial logit multivariate models to correctly capture the arrival of a crisis when the crisis itself lasts more than one year.

[11] Empirical evidence in support of this claim is reported in Table 1 and will be discussed more at length in the next Section.

The issue related to the crisis duration bias is not new in the empirical finance literature. In the context of currency crises, Bussiere and Fratzscher (2006) use a multinomial logit model that allows the dependent variable to take three outcomes: (i) the first year crisis regime, i.e. the outbreak of the crisis; (ii) the crisis regime, for crisis years subsequent to the first one; and (iii) the tranquil regime, for all the remaining observations. Their results show that multinomial logit models are better suited relative to alternative binomial logit models in predicting the arrival of a currency crisis.[12]

In this Chapter we build on Caggiano et al. (2014), who show that the above results hold for systemic banking crises as well for a sample of low income countries (LICs), and provide, to the best of our knowledge, the first systematic analysis of the role played by the duration of a systemic banking crisis in affecting the relative ability of multinomial and binomial logit models in correctly predicting the arrival of the crisis itself.

More specifically, we perform two exercises using a large and heterogeneous sample of 92 world economies observed between 1982 and 2010. In the first of these, we estimate EWSs based on the multinomial logit model and two binomial logit models, one that treats crisis years other than the first as tranquil times and one that discards them. The arrival, and the duration, of a systemic banking crisis is measured using the classification by Reinhart and Rogoff (2011). A number of commonly used control variables are included as potential predictors: measures of broad macroeconomic conditions (GDP per capita, GDP growth, real interest rate, inflation rate, depreciation of exchange rate, changes in terms of trade); measures of a country's monetary conditions (M2 to reserves, credit to GDP growth); and measures of the banking systems' structural factors (currency mismatch, liquidity, leverage). In the second exercise, we study whether and by how much the duration of the crisis matters in forecasting its arrival by estimating the three alternative logit models using subsamples of countries built in terms of the average duration of crises they experienced in the observed time span.

Our main results can be summarized as follows. First, using the full sample of world economies, we find the multinomial logit model to outperform both alternative binomial models in correctly predicting the arrival of the crisis. Not only the multinomial model helps better predict the arrival of crisis; it also improves over the number of false alarms, as shown

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[12] The authors refer to a *post crisis bias* in their analysis.

by the Area Under the Receiver Operating Characteristics curve (AUROC). Second, according to the best selected model specification, we find that the credit to GDP growth rate, the ratio of money supply (M2) to reserves, the rate of inflation, and the liquidity position and the net open position of the banking system are the best predictors of the arrival of a systemic banking crisis. Third, and more importantly given the focus of this Chapter, our main finding is that the performance of the multinomial model, as measured by the AUROC, improves over the binomial logit when the average duration of the crisis increases: the longer the average duration of crises in the sample, the better the relative performance of the multinomial over the two alternative binomial specifications. Further robustness checks show that these results hold true for other commonly used definitions of systemic banking crisis, such as Laeven and Valencia (2012).

Our findings have important implications for empirical analyses aimed at building EWSs as well as for policy makers. Our results on the role played by the duration of the crisis show that multinomial logit models are better equipped to correctly gauge the probability of the arrival of a crisis as well as to avoid costly false alarms. From a policy perspective, our results show that regulators and policymakers aiming to minimize the overall costs of banking crises should target not only the variables that are most correlated with the arrival of a crisis but should also act to minimize the impact of macro-financial variables on the duration of a crisis. Our empirical evidence shows that the first objective is best achieved by keeping inflation under control and allowing for sound domestic and external liquidity conditions, and managing credit booms; the latter, i.e. speeding up recovery from the crisis, is better achieved by targeting general macroeconomic conditions.

This Chpater is organized as follows. Section 2 presents the dataset and discusses the econometric methodology employed for the empirical analysis. Section 3 shows the empirical results obtained from using the full sample of world economies. Section 4 presents the subsample analysis and discusses the role played by the average duration of crisis. Section 5 concludes and draws some policy implications.

3.2 Data and empirical framework

3.2.1 Data

Our sample comprises yearly data for 92 economies observed between 1982 and 2010. We draw evidence about systemic banking crises from Reinhart and Rogoff (2011), who define a crisis as systemic if either of the following occurs: (i) bank runs which lead to the liquidation or the restructuring of one or more financial institutions, or (ii) in the absence of bank runs, the closure, restructuring or large-scale government assistance of one or more institutions which marks the beginning of similar outcomes for other financial institutions. This classification provides us with 97 systemic crisis episodes in 92 countries between 1982 and 2010, with an average duration of 4.35 years.[13]

We select the set of explanatory variables following the relevant literature on EWSs (see Kauko, 2014, for a recent review). Accordingly, and given data availability, we use three groups of explanatory variables to estimate our EWS:

a) Macroeconomic fundamentals: (log) GDP per capita, real GDP growth, changes in terms of trade, real interest rate and inflation. The level and growth of output are expected to affect the credit quality of the banking system by impacting the ability of borrowers to pay back their debt. Similarly, a deterioration in the terms of trade of an economy and high interest rates affect debtors' solvency by weakening their financial viability and capacity to service debt. On the other hand, high inflation is associated with macroeconomic instability and impacts the real return on assets, discouraging savings and incentivizing borrowing, increasing this way the likelihood of experiencing a crisis.

b) Monetary conditions: broad money (M2) cover of international reserves and growth of the credit-to-GDP ratio. The ratio of M2 to official reserves captures the ability of the country to withstand a sudden stop and reversal in capital inflows, especially in the presence of a currency peg. Therefore, the higher the value for this variable, the higher the vulnerability to capital outflows, and hence the probability of incurring a banking crisis. Similarly, excessive credit growth can trigger bank problems through a generalized deterioration in banks' asset quality (as a result of over-indebtedness of borrowers and loosening credit standards) and/or a reduction in liquidity (due to aggressive maturity transformation and reliance on wholesale sources of funding). Accordingly, the probability of a crisis is expected to increase when credit grows too fast. We use growth of the credit-

[13] We also consider the alternative definition of systemic banking crisis given by Laeven and Valencia (2012), who classify systemic crisis based on either of the following measures: (i) deposit runs proxied by a monthly percentage decline in deposits in excess of 5 percent; or (ii) the introduction if deposit freezes or blanket guarantees; or (iii) liquidity support defined as monetary authorities' claims on banks of at least 5 percent of total deposits. According to this classification, we identify 74 episodes of crises, with average duration equal to 2.37 years.

to-GDP ratio instead of growth of real credit due to data availability and practical implications. The credit-to-GDP ratio has been adopted as a common reference point under Basel III to guide the build-up of countercyclical capital buffers (BCBS, 2010; Drehmann et al., 2011).

c) Banking system structural factors: foreign exchange (FX) net open position and liquidity position. A negative FX net open position is a signal of currency mismatch between the value of banks' assets and liabilities, which exposes banks to potentially substantial losses in the event the domestic currency depreciates, especially for developing economies. The liquidity position of the banking system is proxied by the ratio of private credit to deposits. The higher the ratio, the lower the capacity of the banking system to withstand deposit withdrawals or the inability to rollover short-term debt in wholesale markets, hence a positive relation with the likelihood of a crisis is expected.

Appendix A provides a detailed description of the variables and their sources.

3.2.2 The crisis duration bias

As discussed, binomial multivariate logit models have become the benchmark empirical framework for building EWSs since the seminal work by Demirgüç-Kunt and Detragiache (1998). When binomial EWSs are of interest, the dependent variable takes the form of a two-outcome dummy variable, with the value of 1 denoting the first year of a systemic banking crisis, and the value of 0 denoting all remaining observations. Hence, in a binomial logit framework, crisis years other than the first are either treated as normal (non-crisis) times or discarded from the sample. In both cases, potentially valuable information is not taken into account when estimating EWSs, particularly if the proportion of post-crisis observations is not negligible. In the context of currency crises this phenomenon is known as the post-crisis bias: after the onset of the crisis, economic variables do not go back immediately to 'normal', i.e. to the pre-crisis steady-state level, but take time to converge to equilibrium. In order to account for such a different behavior, transition periods where the economy recovers from the crisis are explicitly modeled in a multinomial logit framework. The issue of post-crisis bias, and the use of multinomial logit models to deal with it, has been considered in the empirical literature on currency crises (Bussiere and Fratzscher, 2006).

In the context of systemic banking crises, the existence of a similar bias is even more likely to be present. On the one hand, banking crises are more persistent than currency crises as they tend to last longer (Babecký et al, 2013). On the other hand, due to the credit crunch and the generalized loss of confidence that typically accompany a banking crisis, economic recovery takes longer than after a currency crisis (Frydl, 1999), disproportionately affecting those sectors of the economy which are heavily dependent on bank finance (Kroszner et al., 2007; Dell'Ariccia et al., 2007). Put differently, since banking crises are typically long-lasting, in the periods following the onset of the crisis the economy is likely to be still in a state of crisis, and hence relevant economic variables behave differently from both 'equilibrium' periods and the outbreak of a crisis. We call crisis duration bias this phenomenon related to the existence of a state of prolonged distress in the context of banking crises: not accounting for the existence of a third state in the economy, i.e., a period of adjustment after the outbreak of a banking crisis before going back to normal, might reduce the predictive power the estimated EWS (see Caggiano et al., 2014, for an analysis of the crisis duration bias in a sample of LICs).

The existence of three scenarios – 'normal' times, the first year of crisis, and the crisis years after the first – that are likely to be significantly different from each other in our sample of economies is strongly supported by the preliminary evidence we report in Table 1. The Table presents the average values of our independent variables for all years (column 2); when the crisis occurs (column 3); in the combined tranquil periods and crisis years (column 4); in tranquil times (column 5) and in crisis years other than the first (column 6). Comparison of columns (5) and (6) suggests that, when the economy is in a prolonged state of crisis, its behavior is different compared to tranquil times. More formally, as reported in Column (7), the null hypothesis of equality of means is rejected for all but two of our control variables, supporting the hypothesis that these periods, i.e. the post-crisis adjustment period and tranquil times, should be treated differently when building the EWS. The descriptive evidence reported in Table 1 suggest that mixing up information about tranquil times and post-crisis periods (as in column 4) is likely to be misleading and that it might lead to a potential crisis duration bias. The same suggestive evidence holds if the Laeven and Valencia (2012) classification of banking crisis is adopted. We take the evidence of Table 1 as a rationale for the use of models that explicitly account for a post-crisis state.

3.3 The multinomial logit model

In building the EWS for predicting systemic banking crises, we consider the multinomial logit model, previously employed by Bussiere and Fratzscher (2006) in the context of currency crises and by Caggiano et al. (2014) in the context of banking crises in LICs, as an alternative to the commonly used binomial models previously discussed. The estimated model returns a predicted measure of fragility of the banking sector, i.e. the estimated probability of a crisis, as a function of a vector of potential explanatory variables.[14]

More formally, we assume that each economy *i=1,…,n* can be in one of the following *j+1=3* states: tranquil period (*j=0*), first year of crisis (*j=1*), or crisis years other than the first (*j=2*). The probability that an economy is in state *j* is given by

$$(5) \qquad Pr\left(Y_t = j|\boldsymbol{X_{i,t}}\right) = \frac{e^{\beta_j' X_{i,t}}}{1+\sum_{l=1}^{J} e^{\beta_l' X_{i,t}}}, \boldsymbol{\beta_0} = \boldsymbol{0}, J = 2$$

Where $\boldsymbol{X}_{i,t}$ is the vector of regressors of dimension k and β is the vector of parameters to be estimated. The log-likelihood function to be maximized is

$$(6) \qquad Ln(L) = \sum_{i=1}^{n} \sum_{j=0}^{J} d_{i,j} lnPr(Y_i = j)$$

where *dij=1* if the economy *i* is in state *j*.

We set the tranquil regime as the base outcome in order to provide identification for the multinomial logit model, which gives the following J=2 log-odds ratio:

$$(7) \qquad \frac{Pr\left(Y_{i,t}=1\right)}{Pr\left(Y_{i,t}=0\right)} = e^{\beta_1' X_{i,t}} \; and$$

$$(8) \qquad \frac{Pr\left(Y_{i,t}=2\right)}{Pr\left(Y_{i,t}=0\right)} = e^{\beta_2' X_{i,t}}.$$

[14] When using panel data, country fixed effects are often included in the empirical model to allow for the possibility that the dependent variable may change cross-country independently of the explanatory variables included in the regression. In logit estimations, including country fixed effects would require omitting from the panel all countries that did not experience a banking crisis during the period under consideration (Greene, 2011). This would imply disregarding a large amount of information. Moreover, limiting the panel to countries with crises only would produce a biased sample. Therefore estimating the model without fixed effects is usually the preferable approach.

The vector of parameters β_1 measures the effect of a change in the independent variables $\boldsymbol{X}_{i,t}$ on the probability of entering a systemic banking crisis relative to the probability of being in tranquil times. Accordingly, β_2 measures the effect of a change in the independent variable $\boldsymbol{X}_{i,t}$ on the probability of remaining in a state of crisis relative to the probability of being in tranquil times. Eq. (2) is a generalization of the log-likelihood for the binomial logit model, where only two states are allowed, i.e. Pr(Yt=2)=0.[15]

However, one caveat is in order. Although the multinomial logit model classifies observations into multiple states (three in our case), it nonetheless rests on a questionable assumption, i.e. that the Independence of Irrelevant Alternatives (IIA) holds.[16] In the next section, we provide evidence for its validity based on the Hausman and McFadden (1984) test.[17]

3.4 Empirical results

We begin by estimating our multinomial logit using the full sample at hand, and by including all selected regressors. As in Barrell et al (2010), we adopt the general-to-specific approach to obtain the final specification of the empirical model.

Results about the estimated probability of entering a crisis compared to being in tranquil times coming from our final specification are summarized in column (1) of Table 2. As the Table shows, we find that the banking system credit-to-deposit ratio and FX net open position, the rate of inflation, the change in credit as a fraction of GDP, and the M2 reserves to GDP ratio are all positively correlated with the probability of experiencing a systemic banking crisis. Unsurprisingly, these results are in line with previous studies focusing on heterogeneous samples such as ours, i.e. including both advanced and developing economies (Demirgüç-Kunt and Detragiache, 1998; 2000; 2002; Beck et al., 2006; Davis and Karim, 2008a). Hence, in terms of early warning for policy makers, our

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[15] Given that the focus of our study is on building a EWS, we lag all variables by one year. This also helps deal with potential endogeneity of regressors.
[16] The Indipendence of Irrelevant Alternatives hypothesis maintains that the characteristics of a given choice alternative have no impact on the probability of choosing other alternatives.
[17] The Hausman and McFadden test rests on the estimation of two multinomial logit models, one based on the full set of alternatives (all three states in our case) and the other based on a subset of these alternatives, and the subsamples with choices from this subset (states '0', i.e. tranquil times, and '1', first year of crisis, in our case. The IIA holds if the estimated parameters from the two models are not statistically different. Under the null hypothesis that the IIA holds, the test has a chi-square distribution.

results indicate that banking systems that one year prior to the crisis engage in excessive credit activity relative to the deposit base are more likely to experience a systemic crisis. In addition to liquidity risk, external vulnerabilities as proxied by the ratio of M2 to reserves and banking system exposure to FX risk significantly increase the probability of experiencing systemic financial distress as do excessive credit growth and monetary instability. It is important to notice that the Hausman test for the IIA hypothesis reads 2.170, which leads to not rejecting at any standard significance level the null hypothesis that the IIA holds.

The multinomial model also provides an indication of which factors are more likely to drive the economy into a prolonged period of crisis. The results, i.e. the estimated probability of experiencing a crisis lasting more than one year compared to being in a no-crisis period, are shown in column (2) of Table 2. Interestingly, some variables which are not associated with the arrival of a crisis become significant in explaining the permanence in a state of crisis, while others change their signs or the intensity of the coefficients. Again, the results are intuitively convincing and are as expected. In particular, the level and growth of economic activity usually deteriorate after the onset of systemic banking crisis, contributing to a longer period of distress, as shown by the statistically significant negative sign associated with GDP per capita and GDP growth, while credit activity typically diminishes following the arrival of a crisis, hence a statistically significant negative coefficient for the rate of growth of credit-to-GDP.

The second step in our empirical strategy is to estimate the binomial logit models where the observations related to crisis years other than the first are (i) treated as non-crisis observations (Table 3) and (ii) discarded from the sample (Table 4). In both cases, the results about the determinants of the arrival of a systemic banking crisis point to very similar conclusions to those coming from the multinomial logit model, the only exception being the net open position in the binomial model where crisis observations other than the first are removed from the sample, which is no longer significant.

Next, we move to the main question of our empirical analysis: How good is the in-sample performance of the multinomial logit relative to the more commonly used binomial logit model? Assessing the goodness-of-fit of alternative EWSs can be done by looking at the rate of True Positives (TP) and False Positives (FP) they generate, i.e. the percentage of correctly called crises and the percentage of false alarms. In particular, we look at the

AUROC. The ROC curve plots the rate of true positive against the rate of false positive generated by a binary classification model as its discrimination threshold is varied. The AUROC is then a measure of the signalling quality of the estimated EWS, which overcomes the problem of assuming a specific utility function for the policy maker in order to properly weight the costs associated to a given signal (see Hsieh and Turnbull,1996, and Peterson, 2013, for a general discussion of the AUROC; Drehmann and Juselius, 2013, and Caggiano et al., 2014, for an application to banking crises). A value of the AUROC equal to 0.5 refers to a completely uninformative signal, e.g. tossing a coin, while a value equal to 1 refers to a perfectly informative signal.

Estimates of the percentages of crises correctly called, of false alarms and AUROC for our multinomial logit model are reported in Table 5. The top panel of Table 5 reports the results for our baseline definition of systemic banking crisis, i.e. Reinhart and Rogoff (2011). The bottom panel of the Table reports the same results for the alternative crisis definition we consider, i.e. Laeven and Valencia (2012). For our baseline definition of crisis, the multinomial logit outperforms both binomial models. In particular, as reported in column (1), for the multinomial model we get a value of 0.5670 of TP, 0.2447 of FN and a value of the AUROC equal to 0.7338. Columns (2) and (4) report the same values for the binomial logit where the crisis years are treated as normal times (column (2)) and where they are dropped from the sample (column (4)). Column (3) and (5) report the percentage difference between the two binomial logit models and the multinomial. As the Table shows, the multinomial model has a better performance relative to both specifications of the binomial logit models, with a relative improvement in the AUROC of 3.9 percent and 1.7 percent respectively.

3.5 Subsample analysis and crisis duration

The previous section shows that, in a large sample of world economies with average duration of systemic banking crisis longer than one year, multinomial logit models are better equipped than commonly used binomial logit specifications to build up EWSs. But is the superior performance of multinomial logit models relative to binomial models a function of the duration of the crises or is it due to other, unspecified factors?

To dig deeper into the relation between the duration of crises and the relative performance of different logit specifications, we perform the following exercise. We rank the 92 countries included in our sample according to the average duration of systemic banking crises they have experienced in the observed time span. We then split the full sample of countries into four groups. Group A comprises of 32 countries that have never experienced a crisis in the observed sample or have experienced a one year duration banking crisis; the other three groups (Group B, C and D) include 20 countries each, which are ranked according to the average duration of crisis, so that Group B includes the 20 countries that have experienced at least one crisis with the lowest average duration, and group D including the 20 countries that have experienced at least one crisis with the highest average duration (group C includes the middle countries in terms of crisis duration).

Table 6 reports details about the number of observations and the average duration of crisis for each group, and for each definition of banking crisis employed in the empirical analysis. Details on the specific countries included in each group are provided in Appendix B. Based on these groups, we create three subsamples which are subsequently used for estimation: i) A+B, ii) A+C, iii) A+D. Each subsamples includes 52 countries, the 32 countries that never experienced a crisis or experienced a one year crisis plus one of the three groups selected according to the average duration of crisis. For each subsample, we compare our EWS based on the multinomial logit with the EWS based upon the binomial logit models to check whether there is any evidence in favour of what we call the crisis duration bias. Evidence of the crisis duration bias would be consistent with a superior performance of the multinomial relative to the binomial models increasing with the average duration of crisis.

Table 7 shows the results obtained for each subsample for the Reinhart and Rogoff (2011) definition of systemic banking crisis. As column (2) shows, the AUROC for the multinomial increases when the average duration of crisis increases: it moves from 0.7473 in a model that uses the subsample A + B, whose average duration of crisis is equal to 1.18 years, to 0.7708 when the subsample is A + D, whose average duration of crisis is 3.52 years. More importantly, the relative performance of the multinomial vis-à-vis the binomial logit models turns out to be a positive function of the duration of crisis. This is particularly evident when the binomial logit that treats the post-crisis period as tranquil times is considered: as shown in column (4), the relative difference in the AUROC moves from 1.30 percent to 4.99 percent. This is also true relative to the binomial where the post-crisis observations are discarded: the percentage difference in the AUROC moves from 0.31

percent to 1.05 percent. Finally, column (7) shows that the binomial logit where the post-crisis observations are dropped from the sample improves over the alternative binomial logit specification, and that the relative performance is greater the longer the duration of the crisis. A similar pattern holds true if we look at both the percentage of correctly called crises and the percentage of false alarms. Table 8 shows that these results are robust to the use of the alternative definition of banking crises provided by Laeven and Valencia (2012).[18]

Overall, we find evidence in favour of the multinomial logit as a superior empirical framework relative to the binomial model in predicting banking crises in countries where historically the duration of crises has been long lasting. The rationale is that the multinomial model allows accounting for the information content provided by the explanatory variables during the crisis years subsequent to the beginning of a crisis, which represents a promising way to solve what we call the crisis duration bias.

3.6 Conclusions

This Chapter compares the performance of alternative logit models for EWS for predicting systemic banking crises. Using a panel data set of 92 economies observed during the period 1982-2010, we show that the average duration of historically observed systemic crises is an important determinant in discriminating among alternative models. In samples where the average duration of crisis is relatively long, the multinomial logit model, which explicitly distinguishes between first year of the crisis and post-crisis years, improves over the more commonly employed binomial logit models. Within the class of binomial logit models, discarding the observations that refer to post-crisis periods is empirically superior to treating them as tranquil times.

The main message that arises from this Chapter, i.e. the average duration of systemic crisis matters in determining the relative performance of different logit models, deserves further analysis. Specifically, our empirical analysis rests on the use of low frequency, yearly data. At least in samples of advanced economies, recent papers have developed EWSs based on the binomial logit model using quarterly measures of systemic distress (see Alessi et al., 2015, for a review of the literature). Compared to yearly data, quarterly observations

[18] Results are also robust to the use of the systemic banking crisis classifications provided by Caprio et al. (2005) and Demirguc-Kunt and Detragiache (2005). Results, which are not reported for the sake of brevity, are available upon request.

would allow for a more refined analysis of the role played by the duration of crisis in driving our conclusions. This is in our agenda.

Appendix A: Regression tables

Table 1 – Averages of independent variables

(1) Variable	(2) All times	(3) First year of crisis	(4) Tranquil times and crisis years after the first	(5) Tranquil times	(6) Crisis years after the first	(7) Test for difference in mean (5) vs (6)
Average duration of the crisis according to:						
Rainhart and Rogoff (2011): 4.35 years						
Number of observations	2668	97	2571	2269	302	
Real GDP growth (-1)	3.54	3.44	3.54	3.77	1.80	8.277***
Log GDP per capita (-1)	7.73	7.83	7.72	7.76	7.47	2.835***
M2 to reserves (-1)	9.68	16.53	9.42	8.73	14.59	-7.079***
Real interest rate (-1)	3.66	4.65	3.62	3.55	4.17	-0.920
Change in terms of trade (-1)	1.35	1.18	1.35	0.86	5.05	-3.714***
Inflation (-1)	11.38	19.23	11.08	10.89	12.50	-1.238
Credit to deposits (-1)	97.38	118.06	96.60	94.00	116.13	-7.747***
Change in credit to GDP (-1)	2.92	6.17	2.80	2.98	1.40	2.007**
Net open position (-1)	9.11	2.41	9.36	10.19	3.08	5.582***
Leaven and Valencia (2012): 2.37 years						
Number of observations	2668	74	2594	2417	177	
Real GDP growth (-1)	3.54	2.89	3.56	3.81	0.14	12.261***
Log GDP per capita (-1)	7.73	7.68	7.73	7.73	7.77	-0.298
M2 to reserves (-1)	9.68	18.31	9.43	8.83	17.58	-8.332***
Real interest rate (-1)	3.66	3.31	3.67	3.58	4.84	-1.460
Change in terms of trade (-1)	1.35	1.06	1.35	0.96	6.79	-4.040***
Inflation (-1)	11.38	16.23	11.24	10.55	20.57	-6.001***
Credit to deposits (-1)	97.38	125.65	96.57	95.06	117.24	-6.121***
Change in credit to GDP (-1)	2.92	6.49	2.82	3.02	0.04	2.986***
Net open position (-1)	9.11	3.87	9.25	9.93	0.03	6.136***

Table 2 – The multinomial logit model

The multinomial logit probability model estimated in this table is a discrete dependent variable taking value 0, 1 and 2 for Tranquil, Systemic Banking Crisis and Post Crisis years, respectively, using the dating approach by Reinhart and Rogoff (2010). We estimate $Pr(Y_{it} = 1,2) = \alpha + \beta_1$Real GDP growth$_{i,t-1}$ + β_2Real interest rate$_{i,t-1}$ + β_3Inflation$_{i,t-1}$ + β_4Depreciation$_{i,t-1}$ + β_5Terms of trade changes$_{i,t-1}$ + β_6M2/reserves$_{i,t-1}$ + β_7Credit-to-GDP growth$_{i,t-1}$ + β_8Liquidity$_{i,t-1}$ + β_9Net open position$_{i,t-1}$ + $e_{i,t-1}$. We present the coefficients of the multinomial logit regressions. Heteroschedasticity and autocorrelation conistent standard errors are given in parentheses. ***, ** and * indicate that the coefficient is significant at the 1%, 5% and 10% level, respectively.

	(1)	(2)
Variables	*Initial year of crisis*	*Crisis years following first year crisis*
Constant	-4.103*** (0.580)	-1.333*** (0.305)
Credit to deposits (-1)	0.007*** (0.002)	0.008*** (0.001)
Change in credit to GDP (-1)	0.017*** (0.007)	-0.013** (0.006)
Inflation (-1)	0.012*** (0.003)	0.001 (0.003)
M2 to reserves (-1)	0.027*** (0.006)	0.019*** (0.004)
Net open position (-1)	-0.012* (0.006)	-0.008** (0.003)
Real GDP growth (-1)	0.015 (0.028)	-0.106*** (0.017)
Log GDP per capita (-1)	-0.053 (0.066)	-0.188*** (0.040)
Real interest rate (-1)	0.010 (0.008)	0.013*** (0.006)
Change in terms of trade (-1)	0.001 (0.006)	0.007** (0.003)
Pseudo-R^2	0.0869	
Log-pseudolikelihood	-1,229.93	
Hausman Test	2.170 (0.994)	

Table 3 – The binomial logit model (post crisis treated as tranquil times)

The binomial logit probability model estimated in this Table is a discrete dependent variable taking value 1 for Systemic Banking Crisis and 0 otherwise, using the dating approach by Reinhart and Rogoff (2010). We estimate $\Pr(Y_{it} = 1) = \alpha + \beta_1 \text{Real GDP growth}_{i,t-1} + \beta_2 \text{Real interest rate}_{i,t-1} + \beta_3 \text{Inflation}_{i,t-1} + \beta_4 \text{Depreciation}_{i,t-1} + \beta_5 \text{Terms of trade changes}_{i,t-1} + \beta_6 \text{M2/reserves}_{i,t-1} + \beta_7 \text{Credit-to-GDP growth}_{i,t-1} + \beta_8 \text{Liquidity}_{i,t-1} + \beta_9 \text{Net open position}_{i,t-1} + e_{i,t-1}$. We present the coefficients of the binomial logit regressions. Heteroschedasticity and autocorrelation conistent standard errors are given in parentheses. ***, ** and * indicate that the coefficient is significant at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Constant	-4.331***	-4.476***	-4.501***	-4.471***	-4.468***
	(0.232)	(0.264)	(0.271)	(0.589)	(0.585)
Credit to deposits (-1)	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Change in credit to GDP (-1)	0.020***	0.021***	0.019***	0.019***	0.019***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Inflation (-1)	0.010***	0.011***	0.011***	0.011***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
M2 to reserves (-1)	0.021***	0.022***	0.022***	0.022***	0.022***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Net open position (-1)	-0.010*	-0.011*	-0.011*	-0.011*	-0.011*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Real GDP growth (-1)		0.036	0.036	0.036	0.036
		(0.026)	(0.026)	(0.027)	(0.027)
Real interest rate (-1)			0.007	0.007	0.007
			(0.008)	(0.008)	(0.008)
Log GDP per capita (-1)				-0.004	-0.004
				(0.064)	(0.064)
Change in terms of trade (-1)					-0.0004
					(0.006)
Pseudo-R^2	0.0600				
Log-pseudolikelihood	-391.70				

Table 4 – The binomial model (post crisis are excluded)

The binomial logit probability model estimated in this Table is a discrete dependent variable taking value 1 for Systemic Banking Crisis and 0 for tranquil times, using the dating approach by Reinhart and Rogoff (2010). We estimate $Pr(Y_{it} = 1) = \alpha + \beta_1 \text{Real GDP growth}_{i,t-1} + \beta_2 \text{Real interest rate}_{i,t-1} + \beta_3 \text{Inflation}_{i,t-1} + \beta_4 \text{Depreciation}_{i,t-1} + \beta_5 \text{Terms of trade changes}_{i,t-1} + \beta_6 \text{M2/reserves}_{i,t-1} + \beta_7 \text{Credit-to-GDP growth}_{i,t-1} + \beta_8 \text{Liquidity}_{i,t-1} + \beta_9 \text{Net open position}_{i,t-1} + e_{i,t-1}$. We present the coefficients of the binomial logit regressions. Heteroschedasticity and autocorrelation conistent standard errors are given in parentheses. ***, ** and * indicate that the coefficient is significant at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-4.512***	-4.375***	-4.411***	-4.056***	-4.156***	-4.165***
	(0.222)	(0.246)	(0.256)	(0.524)	(0.588)	(0.585)
Credit to deposits (-1)	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Change in credit to GDP (-1)	0.021***	0.021***	0.019***	0.019***	0.019***	0.019***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Inflation (-1)	0.013***	0.011***	0.012***	0.012***	0.012***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
M2 to reserves (-1)	0.026***	0.025***	0.025***	0.026***	0.026***	0.026***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Net open position (-1)		-0.010	-0.010	-0.009	-0.009	-0.009
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Real interest rate (-1)			0.009	0.010	0.010	0.010
			(0.008)	(0.008)	(0.008)	(0.008)
Log GDP per capita (-1)				-0.049	-0.044	-0.044
				(0.063)	(0.065)	(0.065)
Real GDP growth (-1)					0.016	0.017
					(0.030)	(0.030)
Change in terms of trade (-1)						0.001
						(0.006)
Pseudo-R^2	0.0707					
Log-pseudolikelihood	-376.18					

Table 5 – Multinomial model vs. binomial models

EWS based upon:	(1) Multinomial	(2) Binomial where 0s substitute 2s	(3)	(4) Binomial where 2s are dropped	(5)
	Statistic	Statistic	% difference from (1)	Statistic	% difference from (1)
Definition of crisis by:					
Rainhart and Rogoff (2011)					
Number of observations	2,668	2,668	0.00	2,365	12.81
% Correct crisis	0.5670	0.5155	10.00	0.5361	5.77
% False alarms	0.2447	0.2952	-17.13	0.2659	-7.98
Pseudo-R^2	0.0869	0.0600	44.83	0.0707	22.91
AUC	0.7356	0.7061	4.18	0.7217	1.93
Leaven and Valencia (2012)					
Number of observations	2,668	2,668	0.00	2,365	12.81
% Correct crisis	0.6216	0.6081	2.22	0.5811	6.98
% False alarms	0.2413	0.2783	-13.30	0.2715	-11.11
Pseudo-R^2	0.1432	0.0665	115.34	0.0809	77.01
AUC	0.7487	0.7265	3.06	0.7399	1.19

Table 6 – Subsamples description

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Observations					
Sample	All times	First year of crisis	Tranquil times and crisis years after the first	Tranquil times	Crisis years after the first	Average duration of the crisis
Subsamples from						
Rainhart and Rogoff (2011)						
(a)	928	16	912	906	6	0.305
(b)	580	31	549	502	47	2.583
(c)	580	28	552	465	87	4.083
(d)	580	22	558	396	162	8.675
(a)+(b)	1508	47	1461	1408	53	1.181
(a)+(c)	1508	44	1464	1371	93	1.758
(a)+(d)	1508	38	1470	1302	168	3.524
Leaven and Valencia (2012)						
(a)	928	2	926	926	0	0.063
(b)	580	21	559	533	26	1.750
(c)	580	28	552	495	57	3.083
(d)	580	23	557	463	94	5.250
(a)+(b)	1508	23	1485	1459	26	0.712
(a)+(c)	1508	30	1478	1421	57	1.224
(a)+(d)	1508	25	1483	1389	94	2.058

Table 7 – Subsample analysis (Reinhart and Rogoff, 2011)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Multinomial	Binomial where 0s substitute 2s		Binomial where 2s are dropped		Binomial comparison
	Statistic	Statistic	(2) vs (3) % difference	Statistic	(2) vs (5) % difference	(3) vs (5) % difference
			AUC			
(a)+(d)	0.7708	0.7342	4.99	0.7628	1.049	3.895
(a)+(c)	0.7573	0.7446	1.71	0.7540	0.438	1.262
(a)+(b)	0.7473	0.7377	1.30	0.7450	0.309	0.990
			Pseudo-R^2			
(a)+(d)	0.1227	0.0699	75.54	0.0844	45.379	20.744
(a)+(c)	0.0788	0.0499	57.92	0.0599	31.553	20.040
(a)+(b)	0.1367	0.0845	61.78	0.1001	36.563	18.462
			% Correct crisis			
(a)+(d)	0.6053	0.5789	4.55	0.5526	9.524	-4.545
(a)+(c)	0.6364	0.6136	3.70	0.6136	3.704	0.000
(a)+(b)	0.6383	0.6383	0.00	0.7045	-9.403	10.379
			% False alarms			
(a)+(d)	0.2231	0.2680	-16.75	0.2475	-9.847	-7.658
(a)+(c)	0.2558	0.2721	-6.00	0.2564	-0.223	-5.790
(a)+(b)	0.2503	0.2442	2.51	0.2392	4.641	-2.039

Table 8 – Subsample analysis (Laeven and Valencia, 2012)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Multinomial	Binomial where 0s substitute 2s		Binomial where 2s are dropped		Binomial comparison
	Statistic	Statistic	(2) vs (3) % difference	Statistic	(2) vs (5) % difference	(3) vs (5) % difference
			AUC			
(a)+(d)	0.8253	0.7836	5.322	0.8062	2.369	2.884
(a)+(c)	0.7931	0.7479	6.044	0.7827	1.329	4.653
(a)+(b)	0.7898	0.8097	-2.458	0.8149	-3.080	0.642
			Pseudo-R^2			
(a)+(d)	0.1734	0.1036	67.375	0.1220	42.131	17.761
(a)+(c)	0.1902	0.0906	109.934	0.1174	62.010	29.581
(a)+(b)	0.1998	0.0963	107.477	0.1037	92.671	7.684
			% Correct crisis			
(a)+(d)	0.8000	0.7200	11.111	0.7600	5.263	5.556
(a)+(c)	0.6000	0.5667	5.882	0.5667	5.882	0.000
(a)+(b)	0.6522	0.7826	-16.667	0.7391	-11.765	-5.556
			% False alarms			
(a)+(d)	0.2198	0.2589	-15.104	0.2405	-8.582	-7.135
(a)+(c)	0.2077	0.2388	-13.031	0.2132	-2.587	-10.721
(a)+(b)	0.2424	0.2606	-6.977	0.2351	3.119	-9.790

Appendix B: Description and sources of data

Variable	Data definition	Source
Banking crisis	In the binomial logit model, the variable takes on value of 1 if banking distress occurs and 0 otherwise. In the multinomial logit model, the variable takes on the value of 1 on the first year of the crisis, the value of 2 on crisis years other than the first, and 0 for all other times.	Reinhart and Rogoff (2011) Laeven and Valencia (2012) Demirgüç-Kunt and Detragiache (2005) Caprio et al. (2005)
GDP growth	Annual percentage change of real GDP.	World Development Indicators (World Bank)
GDP per capita	Log of real GDP per capita.	World Development Indicators (World Bank)
Inflation	Annual percentage change of the GDP deflator.	World Development Indicators (World Bank)
Terms of trade change	Rate of change in the terms of trade of goods and services.	World Development Indicators (World Bank)
M2 / Reserves	Ratio of M2 to foreign exchange reserves of the Central Bank.	World Development Indicators (World Bank)
Real interest rate	Lending interest rate adjusted for inflation as measured by the GDP deflator.	World Development Indicators (World Bank)
Credit-to-GDP growth	Rate of growth of the ratio of real domestic private credit to GDP.	Global Financial Development Database (World Bank)
Net open FX position	Ratio of net foreign assets to GDP.	IMF IFS: line 31N divided by GDP
Liquidity	Ratio of banking system private credit to deposits.	IMF IFS: 22d divided by lines 24 + 25

Appendix C: Subsample composition

(A)	(B)	(C)	(D)
Bahamas, The	Algeria	Australia	Bangladesh
Bahrain	Argentina	Colombia	Burkina Faso
Barbados	Austria	Cote d'Ivoire	Burundi
Belize	Belgium	Denmark	Cameroon
Bhutan	Benin	Ecuador	Central African Republic
Botswana	Bolivia	Finland	Chad
Cape Verde	Brazil	Ghana	China
Cyprus	Canada	Greece	Congo, Rep.
Dominica	Chile	Ireland	Egypt, Arab Rep.
Ethiopia	Costa Rica	Kenya	India
Gabon	France	Korea, Rep.	Italy
Gambia, The	Germany	Malaysia	Japan
Grenada	Indonesia	Portugal	Mexico
Guatemala	Mali	Senegal	Niger
Honduras	Morocco	Sri Lanka	Norway
Israel	Netherlands	Sweden	Philippines
Lesotho	Nigeria	Togo	Sierra Leone
Malawi	Panama	Tunisia	Thailand
Mauritius	Singapore	Uganda	United States
Nepal	Switzerland	Uruguay	Venezuela, RB
New Zealand			
Pakistan			
Papua New Guinea			
Rwanda			
Seychelles			
South Africa			
Swaziland			
Syrian Arab Republic			
Trinidad and Tobago			
Turkey			
United Kingdom			
Zambia			

Appendix D: Discussion

This section presents the referee reports for the chapter along with the responses provided by the author.

Referee #1: Prof. Damiano Bruno Silipo

This chapter compares the performance of alternative logit models for EWS for predicting systemic banking crises, using a panel data set of 92 economies observed during the period 1982-2010. It shows that the average duration of historically observed systemic crises is an important determinant in discriminating among alternative early warning models. Specifically, it shows that the longer the average duration of crisis the higher the predictive power of the multinomial logit model over the more commonly employed binomial logit models.

C1: Since financial crisis differ not only on duration but also with respect to their severity, I wonder whether similar results hold with respect to the last variable. At least, the author may infer on the latter by providing a correlation matrix between length and deepness of the financial crisis used in the sample.

R1: Thank you for the comment. Financial crises in general, and banking crises in particular, do differ in terms of duration and severity. The latter is a broad concept and typically refers to an outcome of the crisis, which is measured by output losses or fiscal costs (see for example Laeven and Valencia, 2012). Systemic banking crises have often resulted in significant real effects, including output losses and a deterioration of public finances. While there is a strand of the literature concerned with the real effects of banking crises (for example, Dell'Ariccia et al., 2008; Lane, 2011; Laeven and Valencia, 2013; Amaglobeli et al., 2015) these cannot be intuitively modelled in a EWS, which is mostly concerned with predicting the arrival of a banking crisis. However, the intuition that the duration of a banking crisis may be associated with higher real costs is correct. Table 1 below presents a correlation matrix reporting crisis duration (in years), output losses and fiscal costs of crises (both as a percentage of GDP) while Figure 1 and Figure 2 show a graphical representation of the relationship between these variables. The costs of banking crises are taken from Laeven and Valencia (2012). The results clearly show a significant positive association between the duration of a systemic banking crisis and the real costs for the economy.

Table 1 – Correlation matrix: duration and costs of systemic banking crises

	Crisis duration	Output losses	Fiscal costs
Crisis duration	1		
Output losses	0.2896*	1	
Fiscal costs	0.2719*	0.3922*	1

Source: Laeven and Valencia (2012); author.

Figure 1: Crisis duration and output losses

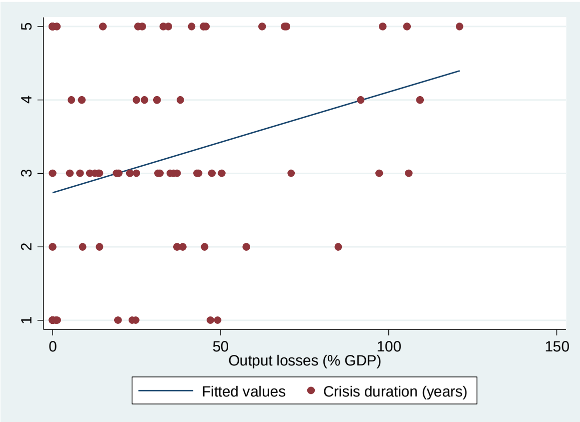
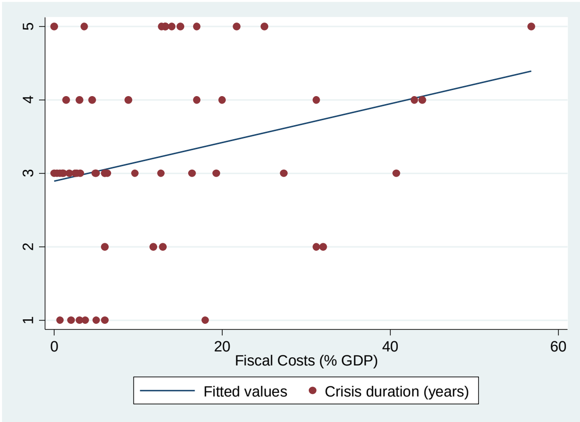


Figure 2: Crisis duration and fiscal costs



Source: Laeven and Valencia (2012); author.

C2: The author should discuss more deeply the implications of the results. Since we are dealing with EWS, and we know the duration of financial crisis only ex post, I wonder how we can use the conclusion of the paper to assess the relative performance of the two econometric models.

R2: Thank you for this valid point. The objective of the Chapter is to show that by explicitly modelling transition periods where the economy is still in a state of crisis the performance of the EWS improves. This is possible through the multinomial logit model, which is shown to outperform the binomial logit model in samples where the duration of the banking crisis is longer. The main message of the Chapter is, therefore, that the duration of the crisis matters when estimating a EWS, which by definition is based on historical data and is only as good to predict crisis as the data themselves.

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