Bank Capital Redux: Solvency, Liquidity, and Crisis*

Òscar Jordà† Björn Richter‡ Moritz Schularick§ Alan M. Taylor¶

March 2017

Abstract

Higher capital ratios are unlikely to prevent a financial crisis. This is empirically true both for the entire history of advanced economies between 1870 and 2013 and for the post-WW2 period, and holds both within and between countries. We reach this startling conclusion using newly collected data on the liability side of banks' balance sheets in 17 countries. A solvency indicator, the capital ratio has no value as a crisis predictor; but we find that liquidity indicators such as the loan-to-deposit ratio and the share of non-deposit funding do signal financial fragility, although they add little predictive power relative to that of credit growth on the asset side of the balance sheet. However, higher capital buffers have social benefits in terms of macro-stability: recoveries from financial crisis recessions are much quicker with higher bank capital.

Keywords: financial crises, crisis prediction, local projections, bank liabilities, capital ratio.

JEL classification codes: E44, G01, G21, N20.

*This work is part of a larger project kindly supported by research grants from the Bundesministerium für Bildung und Forschung (BMBF) and the Institute for New Economic Thinking. We are indebted to a large number of researchers who helped with data on individual countries. We are particularly thankful to João Azevedo and Marco Wysietzki for outstanding research assistance. All errors are our own. The views expressed herein are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Federal Reserve Bank of San Francisco or the Board of Governors of the Federal Reserve System.

†Federal Reserve Bank of San Francisco; and Department of Economics, University of California, Davis (oscar.jorda@sf.frb.org; ojorda@ucdavis.edu).

‡Department of Economics, University of Bonn (brichter@uni-bonn.de).

§Department of Economics, University of Bonn; and CEPR (moritz.schularick@uni-bonn.de).

¶Department of Economics and Graduate School of Management, University of California, Davis; NBER; and CEPR (amtaylor@ucdavis.edu).

A well-run bank needs no capital. No amount of capital will rescue a badly run bank.
—Walter Bagehot

1. Introduction

The institutional response to the global financial crisis has centered on higher capital buffers and regulation of bank leverage. Bagehot's quip, however, reminds us that trouble starts when a bank decides how much to lend, and to whom: no amount of provisioning can make up for poor business acumen. In theory, larger shock buffers should reduce both the probability and the cost of financial crises, just as higher levees protect against major floods. However, opinions differ on how high this financial levee should be, from the intended Basel III leverage ratio of three cents capital per dollar of assets to levels ten times as high, as argued by Admati and Hellwig (2013).[1] Banking industry representatives emphasize that higher capital requirements reduce the availability of credit, while Admati *et al.* (2013) and Miles *et al.* (2013) argue that there are no social costs associated with higher capital ratios and significant increases in regulatory capital are therefore desirable.[2]

This is an important debate that, ultimately, can only be settled by empirical evidence. In recent years, long-run and cross-country perspectives have increasingly gained in importance and informed central debates in monetary and financial policy (Reinhart and Rogoff (2009), Schularick and Taylor (2012), Jordà *et al.* (2013)). To the best of our knowledge, this is the first paper to bring a long-run perspective to the debate about capital buffers. We ask two fundamental questions. First, what is the long-run relationship between capital buffers and systemic financial instability? Second, does more capital positively mitigate the social economic costs of financial crises?

We answer these questions by constructing a new dataset for the liability side of banking systems from 1870 to today. In particular, the data cover three broad categories: capital, deposits, and other debt instruments, which we refer to as non-core liabilities. These data complement our prior measures of the asset side of banking systems (bank credit in particular) and other macroeconomic data in Jordà *et al.* (2017). The combination allows us to study how bank leverage and other balance sheet ratios affect the probability and

[1] The denominator in the Basel III leverage ratio is the total exposure measure which includes, in addition to on-balance sheet assets, adjustments for derivative and securities transaction financing exposures as well as off-balance sheet items.

[2] Determining optimal regulatory capital ratios requires quantitative estimates of the impact of capital requirements on financial intermediation and the effects on output. See Dagher *et al.* (2016) for a detailed discussion of benefits and costs associated with higher capital requirements and for a survey of estimates of steady-state impacts as well as the transitional impact of capital requirements on cost and volume of bank credit. They arrive at the result that risk weighted capital ratios in the range of 15%–23% would have been sufficient to cover bank losses during past crises.

costs of systemic banking crises. Looking ahead, we also hope these data could become a fruitful resource for future research. Crucially, by creating a complete, historical database that now encompasses both sides of banking-system balance sheets we make possible for the first time an evidence-based assessment of the competing claims made about the role of solvency versus liquidity buffers in mitigating financial crises and their deleterious effects.

Our paper has three parts. First, we explore the basic properties of the new data on bank liabilities and show that bank leverage has risen dramatically between 1870 and the second half of the 20th century. In our sample, the average country's capital ratio decreased from around 30% capital-to-assets to less than 10% in the post-WW2 period (see Figure 1 below), before fluctuating in a range between 5% and 10% in the past decades. This trend is visible across all sample countries, as we will show in greater detail.

Next, we investigate whether the funding choices of the banking sector —the structure of the liability side of the balance sheet—are systematically related to financial instability risk. Theoretical predictions about this relationship are ambiguous. A high capital ratio is a direct measure of a well-funded loss-absorbing buffer. However, more bank capital could reflect more risk-taking on the asset side of the balance sheet. Indeed, we find in fact that there is no statistical evidence of a relationship between higher capital ratios and lower risk of systemic financial crisis. If anything, higher capital is associated with higher risk of financial crisis. Such a finding is consistent with a reverse causality mechanism: the more risks the banking sector takes, the more markets and regulators are going to demand banks to hold higher buffers. In line with this finding, Haldane (2011), using recent bank level data, reports that pre-crisis capital ratios performed no better than a coin toss in predicting which institutions in a sample of large international banks would be distressed during the turmoil of 2007 and 2008.

We also consider other features of the funding structure. The loan-to-deposit ratio can serve as a measure of aggregate maturity mismatch or illiquidity, which can be a risk to financial stability (Farhi and Tirole (2012); Diamond and Dybvig (1983)). We find some evidence that higher levels and faster growth of the loan-to-deposit ratio are associated with a higher probability of crisis. The same applies to non-core liabilities: a greater reliance on wholesale funding is also a significant predictor of financial distress. That said, the predictive power of these two alternative funding measures relative to that of credit growth is relatively small. The tried-and-tested credit growth measure is still by far the best single indicator for macroprudential policy-makers to watch as a crisis warning signal (Schularick and Taylor (2012)). Bagehot, it turns out, was right after all.

In the third part of the paper, we ask a different question. The recent macro-finance literature (Brunnermeier and Sannikov (2014); Adrian and Boyarchenko (2012)) has emphasized the central role of financial intermediary balance sheets, and in particular leverage, for asset prices and macroeconomic dynamics. With higher bank leverage, more capital or net worth is lost for a given shock to assets, in turn reducing intermediaries' ability to extend credit, and increasing the likelihood of distressed fire sales (He and Krishnamurthy (2013); Geanakoplos (2010); Kiyotaki and Moore (1997)). Following a similar logic, Adrian *et al.* (2014) show that book leverage of the broker-dealer sector has predictive power for asset prices. The costs of a financial crisis may accordingly vary with the leverage of the intermediary sector. We therefore examine these mechanisms empirically using our long-run data.

Specifically, we study how bank capital modulates the economic costs of financial crises with local projections (Jordà (2005)). Here we find that capital matters considerably: a more highly levered financial sector at the start of a financial-crisis recession is associated with slower subsequent output growth and a significantly weaker cyclical recovery. Depending on whether bank capital is above or below its historical average, the difference in social output costs are economically sizable. We find a substantial 5 percentage point difference in real GDP per capita, 5 years after the start of the recession, in one case versus the other. Our long-run data thus confirm the cross-country findings in Cecchetti *et al.* (2011) and Berkmen *et al.* (2012) for the 2007 crisis and its aftermath. Like Cerutti *et al.* (2015), we find that macroprudential policy, in the form of higher capital ratios, can lower the costs of a financial crisis even if it cannot prevent it.

2. Data

The new dataset presented in this paper is part of an extensive and ongoing data collection effort. The data include balance sheet liabilities of financial institutions on an annual basis from 1870 to 2013 for 17 advanced economies. Moreover, we disaggregate bank liabilities into capital, deposits, and other (non-core) liabilities. Schularick and Taylor (2012), and the updated series in Jordà *et al.* (2017) focused on the asset side of bank balance sheets (and on macroeconomic aggregates). The new data, by focusing on the liability side of financial intermediaries, completes the circle. Table 1 describes the current coverage of these new data.

Except for a few countries, notably Belgium, the Netherlands, and Portugal, we located data for the entire 1870–2013 period. The data come from a variety of sources, such as journal articles, central bank publications, historical yearbooks from statistical offices, as well as archived annual reports from individual banks. In most cases there is no source that covers the entire sample period and hence we had to link various sources to construct

Table 1: *Coverage of the new bank liabilities dataset*

	Total	Capital	Deposits	Other (non-core)
Australia	1870–1945	1870–1945	1870–1945	1870–1945
	1950–2013	1950–2013	1950–2013	1950–2013
Belgium	1920–2013	1920–2013	1920–2013	1920–2013
Canada	1870–2013	1870–2013	1870–2013	1870–2013
Denmark	1870–2013	1870–2013	1870–2013	1870–2013
Finland	1872–2013	1872–2013	1872–2013	1872–2013
France	1888–2013	1888–2013	1945–2013	1945–2013
Germany	1871–1920	1871–1920	1871–1920	1871–1920
	1924–1941	1924–1941	1924–1941	1924–1941
	1950–2013	1950–2013	1950–2013	1950–2013
Great Britain	1880–2013	1880–2013	1880–2013	1880–2013
Italy	1870–2013	1870–2013	1870–2013	1870–2013
Japan	1893–2013	1893–2013	1893–2013	1893–2013
Netherlands	1900–2013	1900–2013	1900–2013	1900–2013
Norway	1870–2013	1870–2013	1870–2013	1870–2013
Portugal	1920–2013	1920–2013	1920–2013	1920–2013
Spain	1874–1934	1874–1934	1874–1934	1874–1934
	1942–2013	1942–2013	1942–2013	1942–2013
Sweden	1870–2013	1870–2013	1871–2013	1871–2013
Switzerland	1870–2013	1870–2013	1870–2013	1870–2013
United States	1870–2013	1870–2013	1870–2013	1870–2013

a continuous time series. Compiling long run series in such a manner requires a number of concessions. Reported balance sheet categories change over time, and category definitions differ across and within countries.

Later we account for country-specific institutional differences in our econometric analysis. Here we put special emphasis on the within-country consistency of our data series. We generally chose data sources that are comparable across time for one country over recent cross-country data sources. Nevertheless, we obviously double-checked the consistency of our series with other datasets (e.g. Organisation for Economic Co-operation and Development (2010)).

In this paper, we take *book values* from banking sector balance sheets and aggregate funding into three broad categories: capital, deposits, and other liabilities. Table 2 displays, in simplified form, the structure of aggregate banking sector balance sheets in 1929 for the United States as an example.

2.1. Capital

We include in *Capital* items that correspond to the Basel III definition of Tier 1 capital, i.e., shareholders' funds that allow banks to absorb losses on an ongoing basis. These are

Table 2: *Example of a banking system balance sheet: United States in 1929*

Cash/liquid	17 %	Deposits	79 %
Loans	56 %	Non-core	8 %
Securities	22 %		
Other	5 %	Capital	13 %
Total assets	100 %	Total liabilities and capital	100 %

Source: Historical Statistics of the United States

normally common stock (paid-up capital), reserves, and retained earnings. As defined in Basel III (Basel Committee on Banking Supervision (2011)), paragraph 52, Common Equity Tier 1 capital consists of the sum of the following elements: (1) common shares issued by the bank that meet the criteria for classification as common shares for regulatory purposes (or the equivalent for non-joint stock companies); (2) stock surplus (share premium) resulting from the issue of instruments included in Common Equity Tier 1; (3) retained earnings; and (4) accumulated other comprehensive income and other disclosed reserves.[3] Dividing this definition of Tier 1 capital by total assets yields an unweighted capital ratio in the spirit of the "leverage ratio" under Basel III (Basel Committee on Banking Supervision (2014)).[4] This ratio is currently tested and shall be a minimum requirement starting in 2018.

The historical data allow us to analyze the long-run trend of our capital ratio that closely corresponds to this Basel-style leverage ratio and study its association with financial instability. Paid-up capital, retained earnings, and reserves have been reported in almost all cases throughout the entire period. Evaluating these variables relative to total balance sheet assets is less prone to measurement problems. Other capital ratio measures based on risk-weighted assets are often prone to changes in the underlying assessment of risk attributed to certain asset classes and suffer from various problems discussed in Admati *et al.* (2013). Furthermore, in contrast to capital measures based on current market values, such as market capitalization, our book value measure is not affected by short-term fluctuations in asset prices.

An important point to keep in mind is that when we use this simple capital ratio, we do not account for various forms of contingent shareholder liability, such as double or unlimited liability. Such additional buffers were not uncommon in the U.S., Canada, and the U.K. until the early 20th century. Double-liability provisions essentially implied that

[3] Additionally, the Basel definition includes "common shares issued by consolidated subsidiaries of the bank and held by third parties (i.e., minority interest) that meet the criteria for inclusion in Common Equity Tier 1 capital" and "regulatory adjustments applied in the calculation of Common Equity Tier 1."

[4] Our definition of total assets differs slightly from the definition of total exposure used in the Basel III framework as we observe only balance sheet data on total assets without being able to adjust assets (as outlined in Basel Committee on Banking Supervision (2011)) in order to arrive at the total exposure measure.

shareholders would be held personally liable by debt holders for the par value of the shareholder's investment. As a result, shareholders could lose up to twice their original investment. Such provisions were phased out in the 1930s. The aggregate capital ratios reported here for these countries may therefore by biased downwards in the early years. If we could account for these provisions (which is practically impossible) it would likely strengthen the trends we document below.

2.2. Deposits and debt instruments

Deposits include term and sight deposits, and both checking and savings accounts by residents. Whenever possible we exclude interbank deposits and deposits by foreigners in an attempt to calculate total domestic deposits by non-financial residents. Yet in some instances this was not possible as different types of deposits were not reported separately. Interbank deposits as well as wholesale funding through interbank loans are included in the third category, *Other Liabilities*. Indeed, this latter category includes *all* forms of debt financing other than deposits as they were defined above. Balance sheet items picked up by this category have changed over the course of time, but it mainly consists of bonds, repos, and interbank loans. We will refer to these liabilities as *non-core liabilities*.

2.3. Balance sheet ratios

Our new data allow us to calculate and track several key balance-sheet ratios of financial intermediaries over more than 140 years. Central to our analysis will be the *capital ratio* defined in a similar way to today's Basel III "leverage ratio" as the ratio of Tier 1 capital over total assets, namely

$$\text{Capital ratio} = \frac{\text{Capital}}{\text{Total assets}}\,. \tag{1}$$

Next we compute the ratio of *loans to deposits*, which is often considered a measure of banking sector illiquidity or vulnerability (Cecchetti *et al.* (2011)). This ratio is defined as:

$$\text{LtD ratio} = \frac{\text{Loans}}{\text{Deposits}}\,. \tag{2}$$

Finally, we compute the share of other liabilities (excluding capital). In order to avoid confusion, we will refer to this measure as the *non-core ratio*, defined as:

$$\text{Non-core ratio} = \frac{\text{Other liabilities}}{\text{Deposits + Other liabilities}}\,. \tag{3}$$

The non-core ratio has taken on significance since 2008 given the role of non-core funding in the crisis. Recent studies have argued that large inflows of non-core funds can destabilize the banking system (Hahm *et al.* (2013)).

3. Key trends

In most countries, capital ratios decreased rapidly from 1870 up to WW2 and have remained relatively stable thereafter. In tandem, capital was gradually replaced by deposits, a process that was mostly complete by 1950. From a broad historical perspective, there has been relatively little change in terms of leverage since then. Capital ratios did not change in a major way in the run up to the 2007–08 financial crisis.

Loan-to-deposit ratios show a pronounced V-shape over the full sample period, with the lowest values during WW2 and, conversely, high levels at the beginning and the end of the full sample period. Non-core liabilities increasingly replaced deposits in the last quarter of the 20th century and remained at high levels until the 2007 crisis. We provide further details on these trends below.

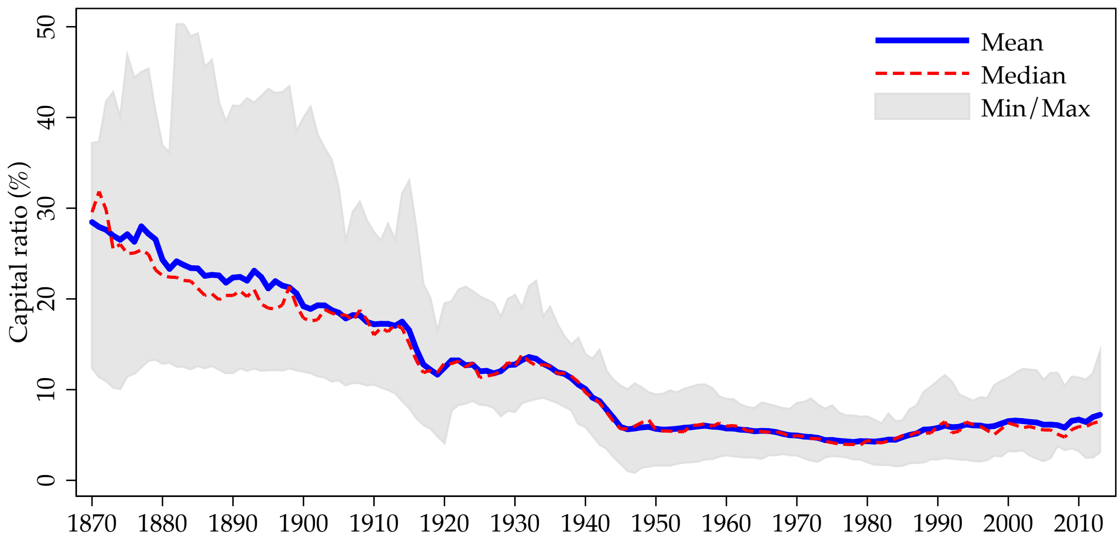
3.1. Capital ratio

Bank leverage rose dramatically from 1870 until the mid-20th century. The cross-country average capital ratio decreased from around 30% to less than 10% in the post-WW2 period (see Figure 1), before fluctuating in a range 5–10% over the past decades. Saunders and Wilson (1999) have studied the decline of capital ratios in Canada, the U.S., and the U.K. This finding is similar to that in Grossman (2010), who shows a decreasing capital ratio between 1840 and 1940 for a subsample of our countries; it is also similar to developments discussed by banking historians for many smaller sub-samples at the individual country level. We show that similar patterns can be found across a broader set of advanced economies.

The capital ratio is rather stable for the second half of the 20th century. A gradual increase is visible after 1970, which is only reversed in the early 2000s, shortly before the global financial crisis and great recession. Yet it is equally clear that while the decade before the global financial crisis saw a very marked increase in the volume of credit, the increase in leverage was comparatively small. A similar picture emerges at the disaggregate country level as we show in Figure A.1 in the appendix. Many countries share a similar pattern of decreasing capital ratios between 1870 and 1945 and relative stability of leverage afterwards. In 1870, capital ratios in most sample countries exceeded 30%.

What explains these historical developments? In theory, the tradeoff between debt and equity financing is determined by the relative costs of the two funding sources. The

Figure 1: *Capital ratio, averages by year for 17 countries, full sample.*



Notes: The blue line plots the mean of capital ratios in the sample countries between 1870 and 2013. The red line refers to the median of the sample countries. The grey area is the min-max range for the 17 countries in our sample.

Modigliani and Miller (1958) theorem suggests that these costs reflect the relative riskiness of each claim—and, hence, that the capital structure per se is irrelevant. An extant literature has explored how taxes and agency problems can create deviations from this irrelevance proposition. Focusing on the long run increase in bank leverage, prominent explanations can be broadly differentiated into those based on (i) market mechanisms, and (ii) responses to a changing political and regulatory environment.

Grossman (2010) argues that the decline in capital ratios was a function of the evolution of the business model of commercial banks. Commercial banking was a fairly new business model in the 19th century, informational frictions and risks were high so that bank creditors required large amounts of equity funding as a buffer against the risk they attached to the banking business. These market-based requirements often increased after financial crises and as a result capital ratios were often higher after a crisis, as observed in the 1920s and 1930s, and shown in detail later in Figure 7. Over time, financial innovation led to higher liquidity in markets. Increasing sophistication of financial instruments allowed banks to better hedge against uncertain events. As a result, the business model of banks became safer, implying a lower need for capital buffers (Kroszner (1999), Merton (1995)). Furthermore, diversification and consolidation in banking systems may have reduced the equity buffers required to cope with risk (Saunders and Wilson (1999)).

A second (but not mutually exclusive) explanation rests on political and institutional

Table 3: *Lowest sample capital ratio by country*

Country	Year	Capital ratio in %	Country	Year	Capital ratio in %
Australia	1976	2.8	UK	1982	4.1
Belgium	1984	1.6	Italy	1952	1.6
Canada	1980	2.4	Japan	1952	2.0
Switzerland	1998	4.5	Netherlands	1980	3.5
Germany	1951	3.0	Norway	1991	2.6
Denmark	2008	4.9	Portugal	1978	3.0
Spain	1956	3.7	Sweden	1981	3.4
Finland	1981	3.2	USA	1974	5.7
France	1951	2.3			

Notes: This table displays the country-year observation with the lowest capital ratio between 1870 and 2008 for each country, excluding war years and 5 year windows around wars.

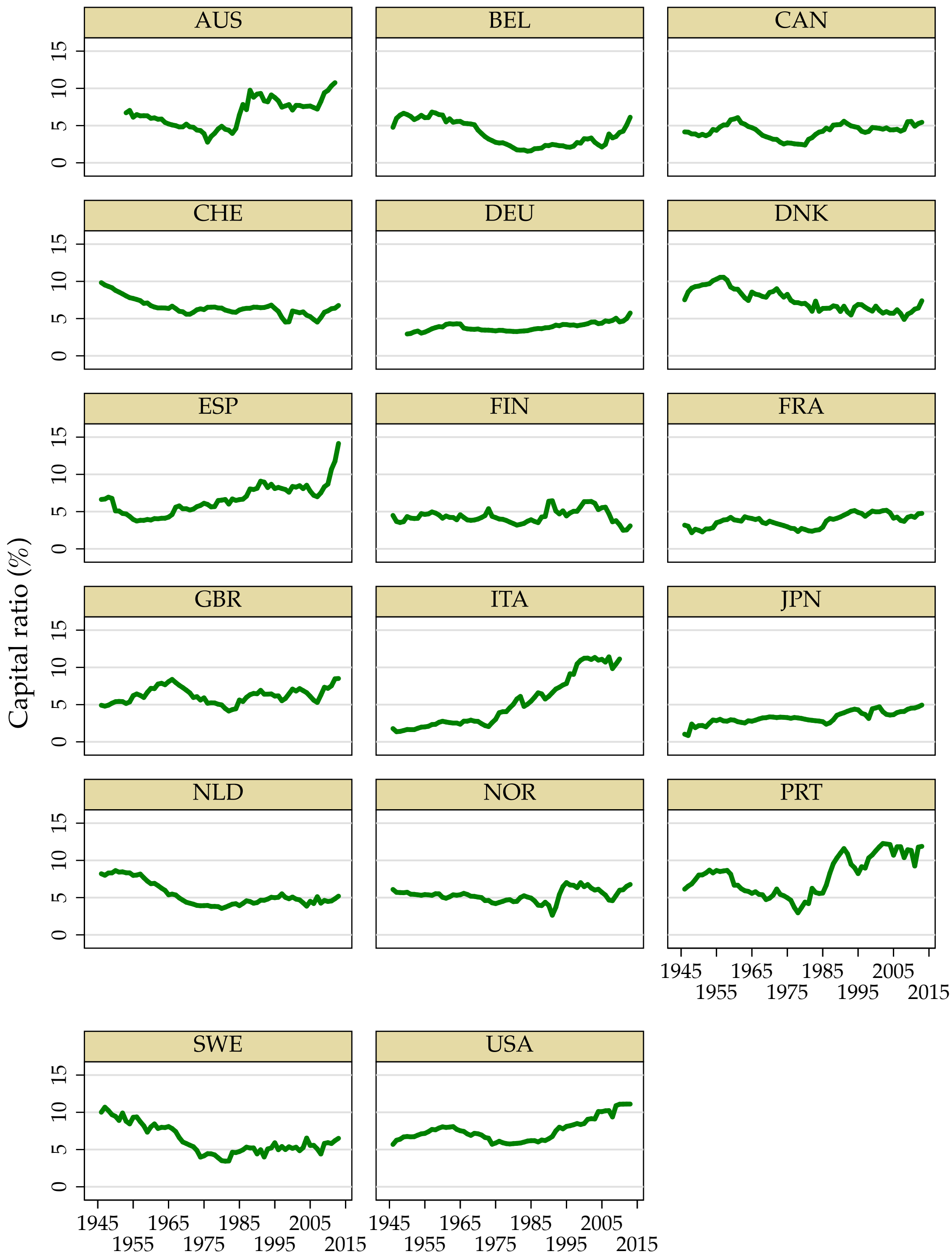
change that affected the business of financial intermediation. Probably the most prominent innovation in this respect was the establishment of a public or quasi-public safety net for the financial sector. Central banks progressively took on the role of lender of last resort, allowing banks to manage short-term liquidity disruptions by borrowing from the central bank through the discount window (Calomiris *et al.* (2016)). The second main innovation in the 20th century regulatory landscape was the introduction of deposit insurance. Deposit insurance mitigates the risks of self-fulfilling panic-based bank runs (Diamond and Dybvig (1983)); but it may, however, also induce moral hazard if the insurance policy is not fairly priced (Merton (1974)). As of today, central banks and deposit insurance have been introduced in nearly all countries in the world (Demirgüc-Kunt *et al.* (2014)).

A last and arguably more recent extension of guarantees for bank creditors relates to systemically important or "too-big-to-fail" banks. While explicit deposit insurance tends to be limited in most countries to retail deposits up to a certain threshold, large banks may enjoy an implicit guarantee by taxpayers. This implicit guarantee could also help account for the observed increase in aggregate financial sector leverage, although the subsidy is difficult to quantify.[5]

Since scaling issues can make it difficult to track developments after 1945, we separately present these trends in Figure 2. In general, these graphs confirm that leverage ratios have moved sideways over the post-WW2 period. If anything, it seems that in the late 20th century, and in the years preceding the global financial crisis, capital ratios increased slightly in many countries. In any case, 2007 does not stand out as a time of particularly

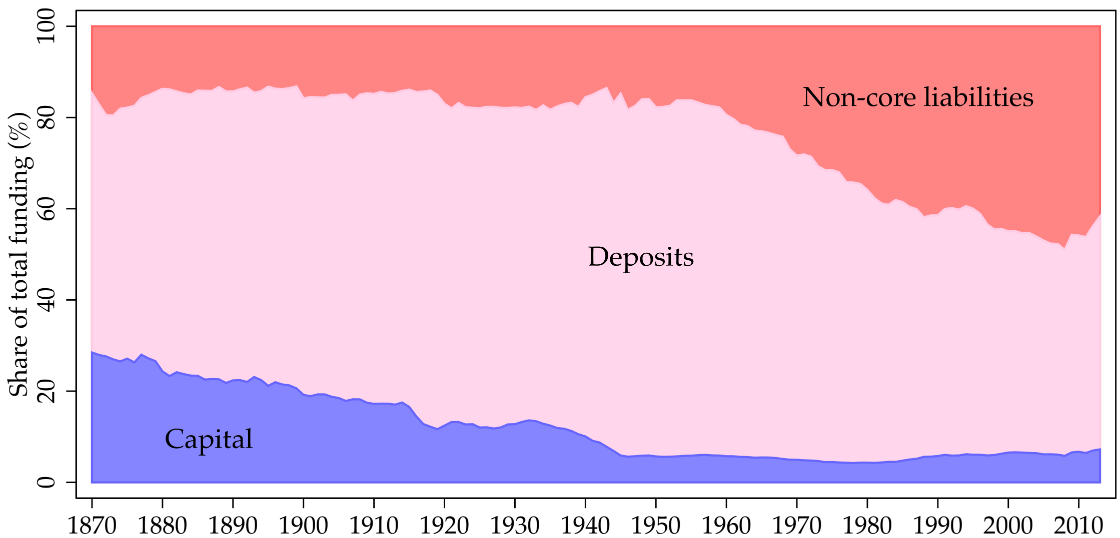
[5]A recent estimate by Haldane (2010) puts the annual TBTF subsidy at several hundred billion dollars for global systemically important banks. Another set of explanations relates to corporate taxation and its decreasing effect on capital ratios as outlined in Pennacchi (2016). Furthermore, there exist indirect effects of corporate taxation, since taxation also determines how attractive bank loans are for firms as a means of financing as opposed to issuing equity, thereby indirectly affecting bank leverage through loan demand.

Figure 2: *Capital ratio, averages by year for 17 countries, post-WW2 sample.*



Notes: This figure plots the capital ratio for all sample countries for the period between 1945 and 2013. See text.

Figure 3: *Composition of liabilities, averages by year for 17 countries, full sample.*



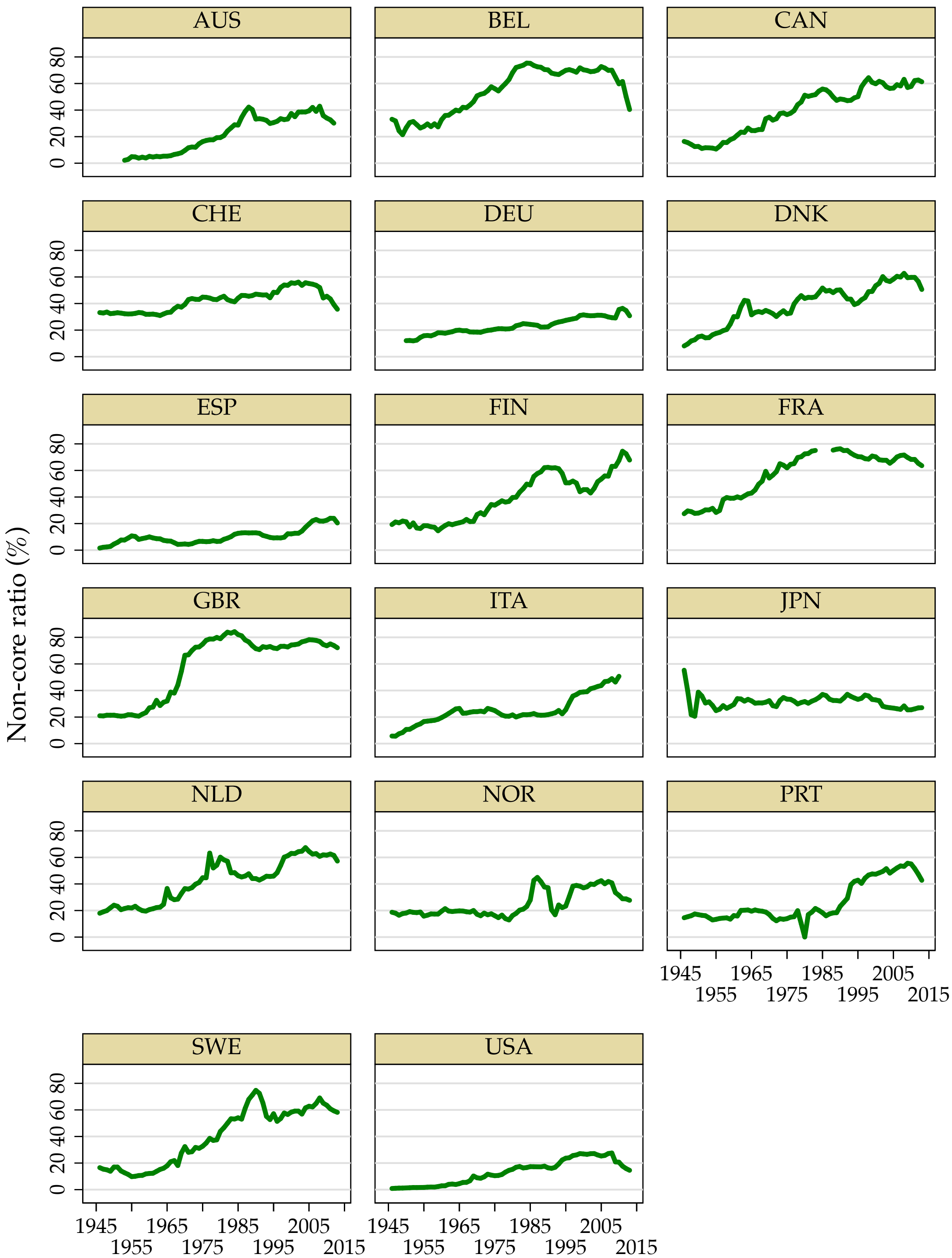
Notes: Averages over 17 sample countries. This figure plots the shares of capital (blue), deposits (pink) and non-core (red) in total funding. Categories add up to one (100%).

high leverage by historical standards. We illustrate this in Table 3, showing for each country in our sample the year with the lowest capital ratio. These dates are spread out over the 60 years between the end of WW2 and the global financial crisis. In Scandinavia and Australia, capital ratios increased after financial crises in the late 1980s and early 1990s. This is probably due to a mixture of regulatory requirements and market discipline. Regulatory changes have been a driver of the slow capital build-up in US banking during the 1990s (Flannery and Rangan (2008)). Capital ratios also increased in Portugal, France and Italy during the 1980s, having been particularly low in the 1970s.

3.2. Debt structure

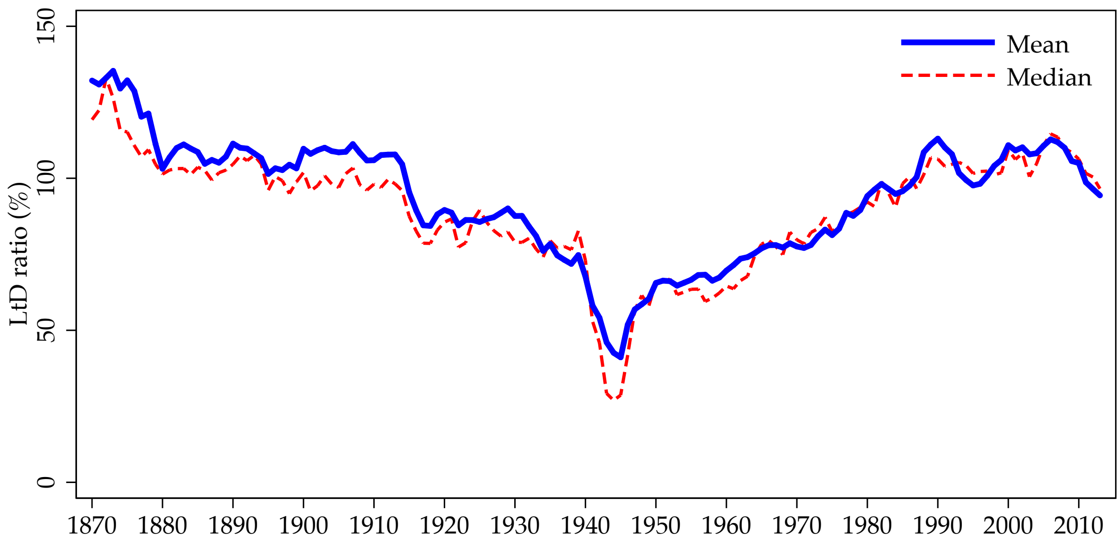
So far we have discussed broad trends in debt and equity. But with our data on banks' balance sheets, we can also look at the trends of the different debt instruments. In Figure 3 we plot the share of capital, deposits, and non-core liabilities. While deposits make up the largest share of funding at all times, the patterns change substantially over time. Until about 1950, the share of deposits in total funding increased as the capital ratio decreased. There was little change in the share of non-core liabilities. Deposits made up 80% of all liabilities in the immediate post-WW2 period. By the early 2000s, the share of deposits had fallen to little more than 50%. This illustrates the increasing importance in recent decades of non-core (e.g., wholesale) funding sources, which is central to the growing separation of

Figure 4: *Non-core ratio by country, averages by year for 17 countries, post-WW2 sample.*



Notes: This figure plots the non-core ratio for all countries from 1945 to 2013. See text.

Figure 5: *LtD ratio, averages by year for 17 countries, full sample.*



Notes: This figure plots the average of the aggregate LtD ratio over all sample countries from 1870 to 2013. See text.

money and credit in the post-WW2 period discussed by Schularick and Taylor (2012) as well as Jordà *et al.* (2013). The debt funding mix between non-core liabilities and deposits changed from being almost exclusively deposit-based in 1950 to a high non-core share in the early 2000s. In Figure 4 we show the evolution of non-core funding share for each country in the post-WW2 period. It is striking that a rising trend is seen in virtually all countries. It is also evident that the non-core ratio typically declines after financial crises, as in the Scandinavian crises of the late 1980s and early 1990s, and after the global financial crisis of 2008.

3.3. Loans-to-deposits ratio

We also track the aggregate loan-to-deposit ratio (LtD) over time. In banking textbooks, banks intermediate funds between borrowers and savers. This intermediation model entails maturity transformation as a bank borrows short and lends long. In our data on balance sheets this mechanism is reflected by deposits, callable on short notice on the liability side; and loans, with longer maturities, on the asset side. The LtD ratio is a common metric of bank illiquidity, since a higher level means that banks find it more difficult to withstand large deposit outflows. Table 1 in Cecchetti *et al.* (2011) shows large heterogeneity of this ratio across banking systems today.

Figure 5 shows the mean LtD ratio for all 17 countries over the entire period. The chart displays a V-shape pattern with a low near 50% at the end of WW2 when banks held a large share of their assets in government securities, clearly a side-effect of war-time government finance policies rather than a market outcome. Hand in hand with the increase of deposits as a source of funds, the average LtD ratio declined from above 100% in 1870 until 1945. It increased afterwards, from 75% in the early 1950s to more than 100% before the global financial crisis. After the crisis, the LtD ratio has decreased as banks have deleveraged and reduced non-core funding. Figure 6 shows long-term LtD ratios at the country level. The trends appear very similar again. In most countries, the LtD ratio reaches a trough in WW2 and rises thereafter. As mentioned earlier, in WW2 banks invested heavily in public debt, not in loans, explaining the unusually low wartime LtD ratio.

4. Bank capital and financial crises

Do balance sheet ratios help predict financial crises in a standard crisis prediction framework? At the macroeconomic level, Schularick and Taylor (2012) have shown that rapid credit expansion serves as a powerful predictor of future financial turmoil with long-run data. This message has later been refined by Jordà *et al.* (2015) who underscored the interaction of credit growth and asset prices (see also Mendoza and Terrones (2012)).[6] In this section we want to evaluate the predictive ability of the capital ratio and other bank balance sheet ratios for systemic financial distress at the country level, an investigation motivated by the focus on such metrics in contemporary financial stability and macroprudential debates.

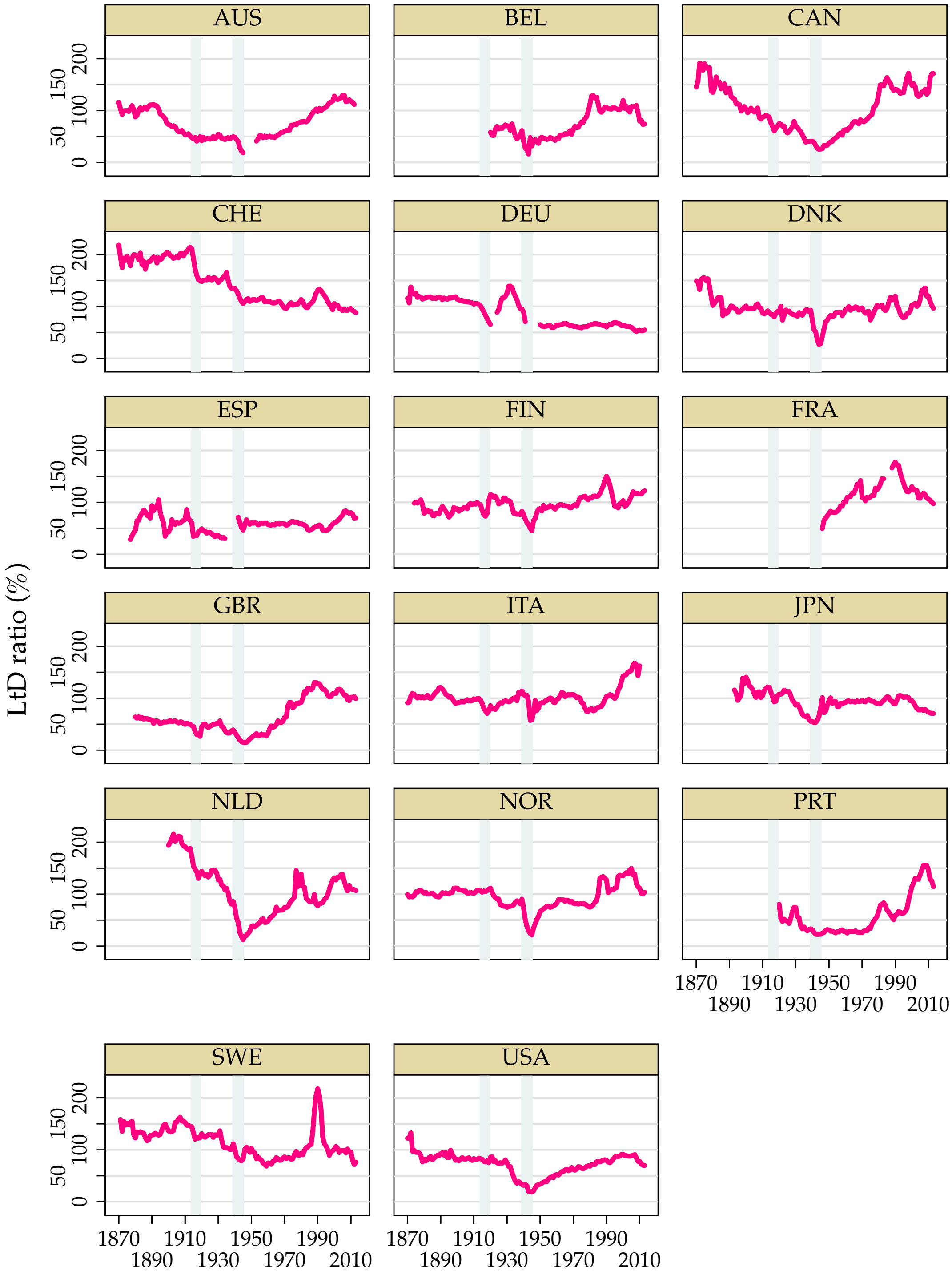
4.1. Balance sheet ratios around financial crises

As a starting point, we describe the typical evolution of banking sector balance sheet ratios in the run-up to and in the aftermath of a systemic financial crisis event. Presenting our first cut of the data, Figure 7 plots average balance sheet ratios and the size of the banking sector relative to the value in the year of the systemic financial crisis, where, as a scaling, the value in the crisis year 0 is fixed to equal 1. Note that financial crises here relate to systemic distress events that affect the entire banking system as defined in Laeven and Valencia (2012). We do not aim to identify isolated bank runs or solvency issues related to a single institution only. For all countries, these dates can be found in the Appendix.

The first two graphs show the behavior of deposits and capital as a source of financing. Before a financial crisis, banks are on average financing their balance sheet increasingly with non-deposit funding. After the crisis, banks increasingly turn to deposits as a source of funds. For capital, the patterns are less clear. Before a financial crisis, capital ratios seem to

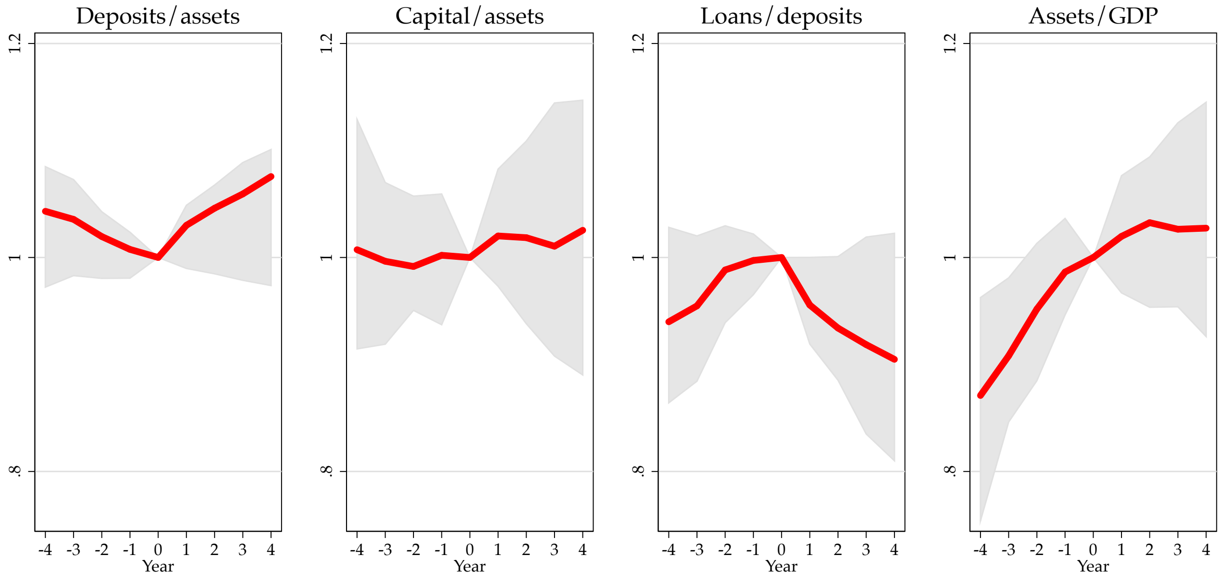
[6] Recent studies focused on the importance of private or public debt, as well as mortgage debt (Jordà *et al.* (2016b), Jordà *et al.* (2016a)) and on the incentives of political actors (Herrera *et al.* (2014)). While these studies focus on the country-level dimension, recent evidence suggests that the link between fast loan growth and bank performance also holds at the bank level (Fahlenbrach *et al.* (2016)).

Figure 6: *LtD ratio by country, averages by year for 17 countries, full sample.*



Notes: Years of world wars are shown in shading.

Figure 7: *Event study of key bank balance sheet ratios centered on the crisis year.*



Notes: This figure presents the path of balance sheet ratios around financial crisis. Year 0 corresponds to a systemic financial crisis. The values of the respective variable are scaled to equal 1 in year 0. The solid line corresponds to the mean and the grey bands to the interquartile range.

be rather stable. After a financial crisis, banks rebuild their capital base relative to pre-crisis levels. This reaction seems plausible as a financial crisis may well lead to increased market discipline so that creditors will penalize low levels of capitalization with higher funding rates for weakly capitalized banks. Moreover, a financial crisis may lead to changes in the regulatory environment. However, as a first pass, it is hard to identify large downward shifts in capital ratios in the run-up to financial crises.

Turning to the asset side of banking system balance sheets, the third graph shows that the LtD ratio increases before a financial crisis and falls afterwards. This behavior partly mirrors the path of deposits presented above, but it also mirrors the growing share of loans in total assets. The fourth graph shows that the size of aggregate banking assets (or liabilities) relative to GDP grows markedly before a financial crisis. Yet the trend slows down when the crisis begins, and 2 years into the crisis the ratio flattens off.

4.2. Bank liabilities and financial crises

We now use formal econometric techniques to investigate the relationship between balance sheet ratios and financial instability. Specifically, we investigate the predictive ability of our three key balance sheet measures, namely the capital ratio, the LtD ratio, and the non-core ratio. As is standard in the literature, we will estimate a probabilistic model, where the binary dependent variable $S_{i,t}$ takes the value of 1 when systemic financial crises occur. The log-odds ratio of a crisis conditional on observables $X_{i,t}$ is assumed to be an affine function. This model is estimated separately for our full and post-WW2 samples. In particular, let

$$\log\left(\frac{Pr[S_{i,t}=1|X_{i,t}]}{Pr[S_{i,t}=0|X_{i,t}]}\right) = \alpha_i + \beta X_{i,t}\,, \tag{4}$$

for all years t and countries i in the sample. Here β will be the vector of coefficients of interest in the various specifications. $X_{i,t}$ starts with Schularick and Taylor's (2012) average annual change of the ratio of credit to GDP over the previous 5-year window and evaluates the additional predictive power of the lagged level in each of the three balance-sheet ratios introduced earlier, one at a time. To soak up cross-country heterogeneity, we will include a country fixed effect α_i for each of the 17 countries. Pooled models are included in the appendix as well.

We are particularly interested in understanding whether balance sheet ratios add valuable information for crisis prediction. Therefore, we move away from likelihood-based measures of fit and instead focus on the AUC statistic, which stands for *area under the curve*. This standard classification statistic measures the ability of the model to correctly sort the data into the financial crisis bin. The AUC is close to 0.5 for models that have little ability to sort the data, and approaches 1 for models that perfectly classify the data based on observables. Our benchmark null prediction model includes country-fixed effects and has AUC=0.62 in the full and AUC=0.60 in the post-WW2 sample. Since some countries are more prone to financial crises than others over the sample, fixed-effects already have the ability to sort the data somewhat. We use this as our benchmark null that observables add no additional information rather than the more customary 0.5 level.

To get a sense for the underlying correlations, we started with a naked model that only used capital ratios and their 5-year changes as regressors, along with country fixed effects. In these regressions, the capital ratio always has the "wrong" positive sign. As a stylized fact, capital ratios and crisis risks are positively correlated in modern economic history. Unconditionally, financial systems with higher capital ratios are more likely to experience financial crises. Put differently, banks' capitalization looks the best before the crash. We report this stylized fact in Table A.2 in the appendix.

Table 4 shows the full and post-WW2 sample results of these experiments. As in Schularick and Taylor (2012), the credit variable is, in all specifications, positively related to a higher probability of a subsequent crisis. The model with credit growth as a single variable has an AUC of 0.68 in the full sample, and 0.75 in the post-WW2 sample, statistically different from the fixed effect null model. Including the three liability-side ratios provides

Table 4: *Multivariate logit models for systemic financial crises, lagged levels.*

	(1) Full	(2) Post	(3) Full	(4) Post	(5) Full	(6) Post	(7) Full	(8) Post
Δ Loans	20.09***	37.12***	22.68***	37.23***	12.91***	22.71***	21.00***	18.65***
	(4.23)	(6.68)	(4.90)	(7.09)	(4.91)	(6.77)	(5.27)	(6.57)
Cap Ratio			5.90***	13.18				
			(1.50)	(9.13)				
LtD Ratio					1.47***	2.86***		
					(0.48)	(0.88)		
Noncore							-0.36	11.01***
							(0.94)	(2.87)
Pseudo R^2	0.047	0.109	0.071	0.114	0.063	0.147	0.047	0.184
AUC	0.68	0.75	0.72	0.75	0.70	0.79	0.68	0.85
	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)
Observations	1767	1037	1767	1037	1742	1033	1763	1033

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy and the regressors are in one-period lagged levels. All models include country fixed effects. The null fixed-effects only model has AUC = 0.62 (0.03) in the full and AUC = 0.60 (0.06) in the post-WW2 sample. Clustered standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

no additional predictive power in the full sample. The coefficient on the capital ratio is positive and significant. The sign would be consistent with the notion that capital ratios are raised in response to higher risk-taking on the bank's loan-book prior to financial crises. The AUC improves from 0.68 to 0.72 but the difference is not statistically significant. The loan-to-deposits ratio has a more economically intuitive sign and is also significant. Alas the AUC only improves to 0.70 and is also not significantly different than the null model's. Lastly, the non-core ratio has an AUC equivalent to the null model in the full sample.

The post-WW2 results have a similar flavor with a few notable differences. The capital ratio still has a positive coefficient and adds no predictive value beyond that of credit growth. The loan-to-deposits ratio has a significant coefficient but the improvement in predictive ability is not significant. However, this time the non-core ratio comes in significantly, with the expected sign (more non traditional funding increasing crisis risk) and there is a measurable improvement in predictive ability (the AUC improves from 0.75 in the null model of column (1) to 0.85).

Table 5 presents results using 5-year average changes in our balance sheet variables instead of levels. The coefficient for changes in the capital ratio in the full sample is now negative, but still insignificant, and the change in capital ratios does not add any predictive power to the model as can be seen by comparing the AUCs in (1)and (3). In the post-WW2 sample the coefficient remains insignificant and adds no predictive power to the credit growth model. The 5-year average annual change of the LtD ratio is insignificant in the full

Table 5: *Multivariate logit models for systemic financial crises, 5-year changes.*

	(1) Full	(2) Post	(3) Full	(4) Post	(5) Full	(6) Post	(7) Full	(8) Post
Δ Loans	20.09***	37.14***	20.43***	37.05***	17.53***	31.57***	19.80***	35.59***
	(4.21)	(6.67)	(4.09)	(6.27)	(3.98)	(6.39)	(4.21)	(6.82)
Δ Cap Ratio			-23.63	100.76				
			(32.31)	(148.94)				
Δ LtD Ratio					3.59	8.80*		
					(3.62)	(5.08)		
Δ Noncore							2.22	20.94
							(5.95)	(12.83)
Pseudo R^2	0.048	0.109	0.049	0.114	0.050	0.118	0.048	0.117
AUC	0.68	0.75	0.68	0.76	0.68	0.75	0.68	0.75
	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)
Observations	1770	1039	1770	1039	1749	1039	1769	1038

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy. Results are shown using data on the largest banks and using aggregated data. All models include country fixed effects. The null fixed-effects only model has AUC = 0.62 (0.03) in the full and AUC = 0.60 (0.06) in the post-WW2 sample. Clustered standard errors in parentheses. See text. $^{*}p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

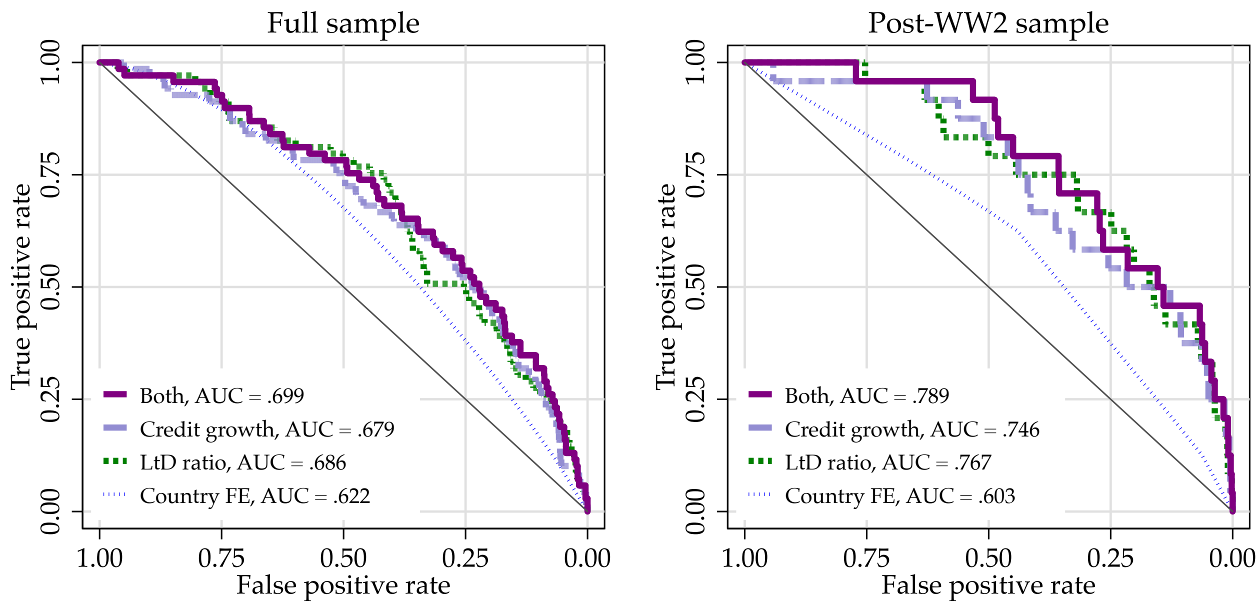
and weakly significant in the post-WW2 sample, while the relationship between the share of non-core ratio and crises remains insignificant in both specifications (7) and (8). None of the models adds predictive accurracy compared to the baseline credit growth models.

We can visualize our findings by plotting the correct classification frontiers (CCFs) for an array of models using 5-year average changes in credit and/or the balance sheet ratios. We can compare these CCFs with the null fixed-effects only model. These graphs offer a comprehensive way to assess the performance of the respective models. A model can be interpreted as performing better in crisis prediction the more the CCF is shifted towards the upper right corner of the unit square. We display the findings for the LtD and the non-core ratio as these were the only models with improved predictive power.

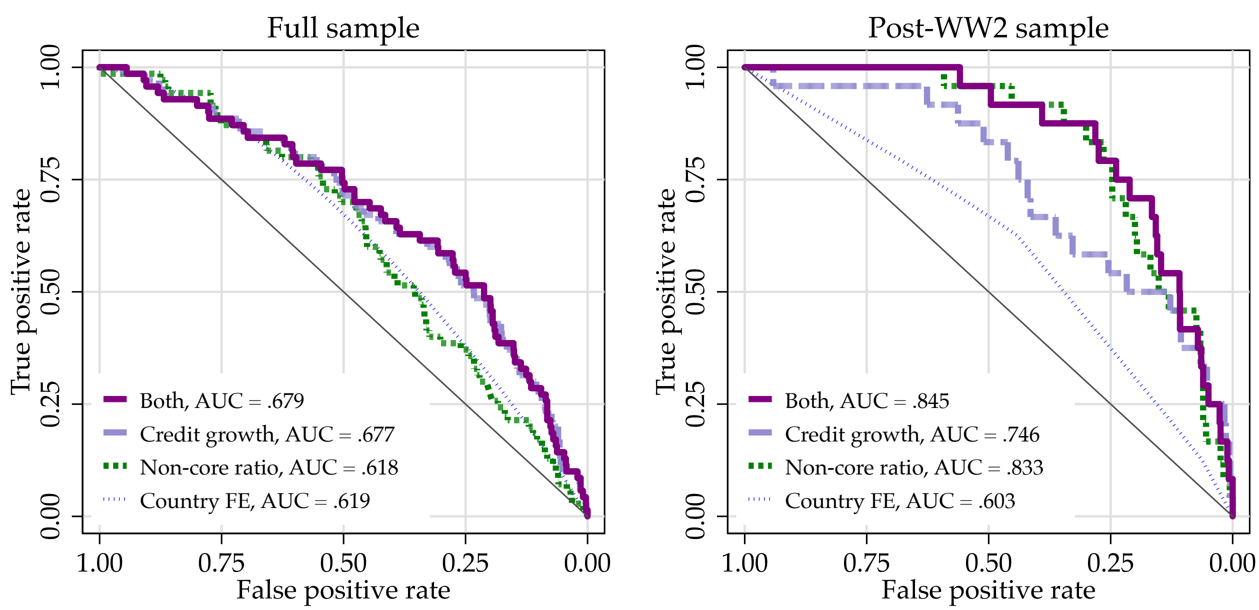
The left panel in Figure 8a now refers to the full sample results of the logit estimations with the LtD ratio added separately (short-dashed green), credit growth added separately (long-dashed blue) and using both variables added jointly (solid purple) in the logit model including fixed effects. We see that the lines are close for all three models, with the purple line being shifted a little higher than the blue one. The information in the LtD ratio does add a little power to the credit growth model. In Figure 8b we repeat the procedure for the non-core ratio. As a predictor, this ratio alone performs visibly worse in the full sample, but it significantly adds valuable information to the credit growth model in the post-WW2 subsample.

Figure 8: *Correct classification frontiers for systemic financial crises.*

(a) *Classification based on credit growth and LtD ratio*



(b) *Classification based on credit growth and non-core ratio*



Notes: Country FE refers to null fixed effects only model. Credit growth refers to a single variable model including smoothed 5-year average annual change of bank credit over GDP. Non-core ratio and LtD ratio refer to single variable models including one-period lagged levels in the respective variables. "Both" refers to models including credit growth and the respective balance sheet ratio as presented in Table 4. See text.

Summarizing, the loan-to-deposits ratio and the share of non-core debt liabilities point to financial vulnerabilities of the banking sector. In terms of predictive ability, they add some nuance to more parsimonious prediction models based on credit growth alone. That said, the single best indicator of impending financial instability still turns out to be credit growth. Capital ratios provide no help in crisis prediction.

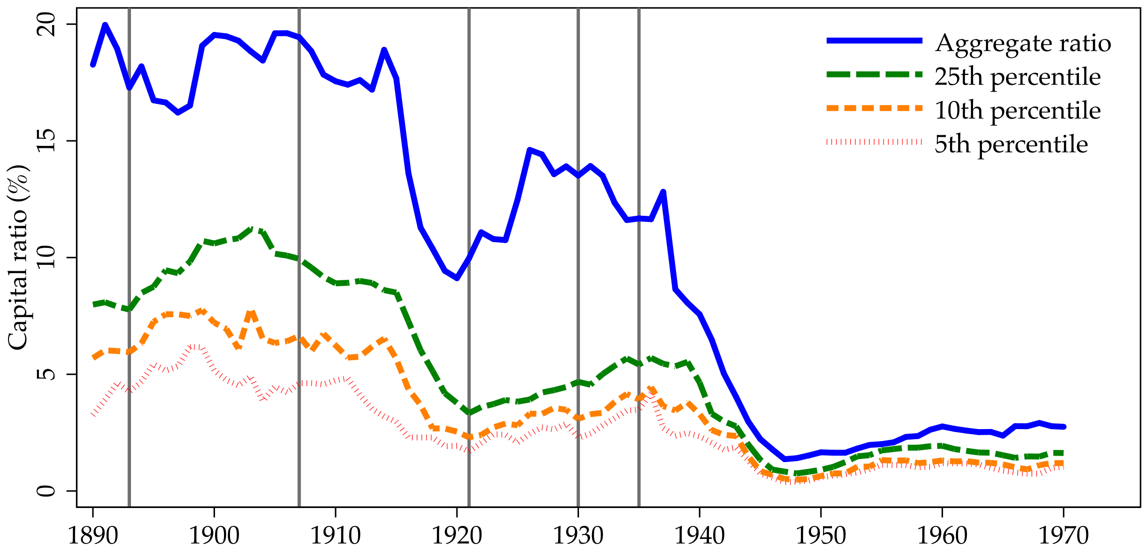
The Appendix shows that these findings are robust to excluding the global financial crisis. We also check for the fact that we do not observe the capital structure of shadow banking activities. The Appendix therefore provides specifications that exclude the UK and the US since these two countries have large shadow banking activities. We find similar results to those reported earlier. We also re-ran our logit models by including a number of additional control variables as well as including all balance sheet ratios jointly. These specifications did not change the sign of the capital ratio and the loan-to-deposits ratio coefficients in the full sample as well as leaving the non-core share in the post-WW2 sample as an important predictor. Finally, we also show tables where we start from the full model and drop one variable at a time to show that the capital ratio only improves predictive accuracy in the full sample, when the coefficient has a positive sign.

4.3. Concentration of risk

Aggregate capital ratios could mask substantial heterogeneity within banking systems and risks could be highly concentrated in a few, systemically important institutions or in a subset of banks with very low capital ratios. Our data do not have sufficient granularity for each country in our sample to subject these mechanisms to empirical tests. However, we want to analyze both mechanisms based on available data for subsamples. First, we check whether very low capital ratios of a few banks matter for the risk of experiencing a financial crisis. Here we provide evidence from Italy, where the historical archive of credit (Natoli *et al.* (2016)) contains micro-level balance sheet data for the near-universe of banks over more than 80 years, between 1890 and 1973. In a second step, we will look at the capitalization of the biggest banks as a correlate of crises.

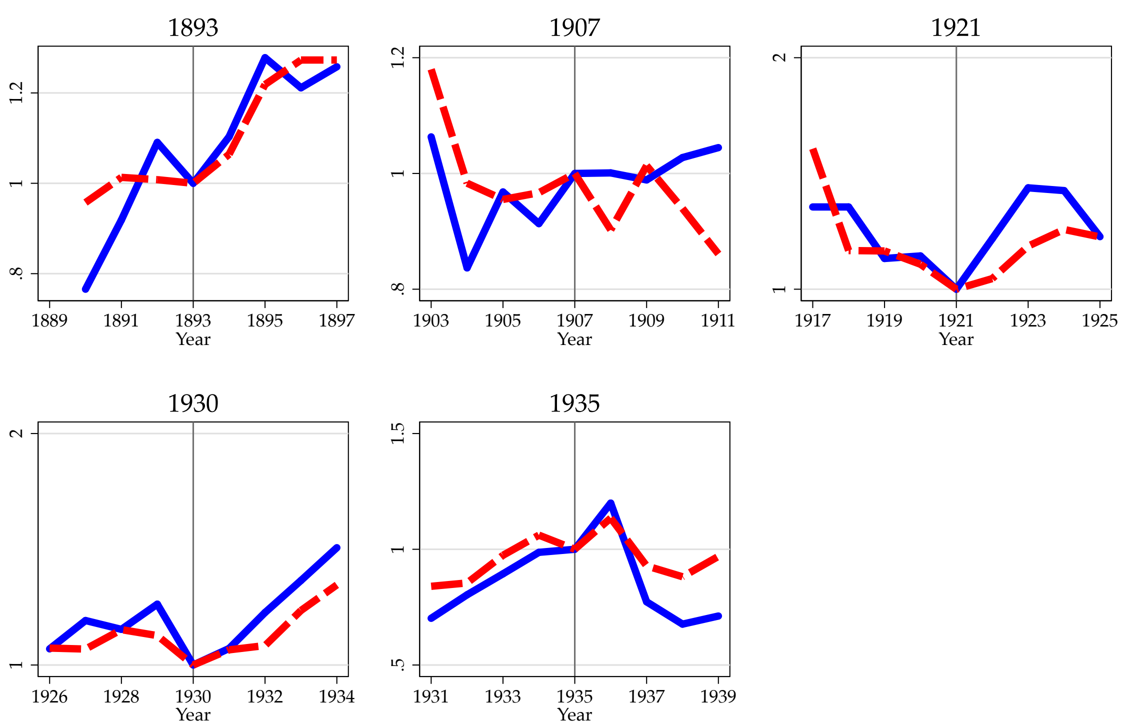
During this period Italy experienced five systemic banking crises: 1893, 1907, 1921, 1930, and 1935. For our analysis, we use all observations on joint-stock banks and savings banks that are present at least 5 years in the sample and have a market share larger than 0.1% in the respective year. We exclude cooperative banks as these were sampled only every 5 years. For all the remaining banks we observe the capital ratio yearly. In Figure 9 we present the evolution of different percentiles of the capital ratio distribution per year. The 5th (red dot), the 10th (orange dash), and the 25th percentiles (green long dash) of the distribution of capital ratios across banks display a similar time series pattern as the aggregate ratio (blue

Figure 9: *Capital ratio dispersion of banks in Italy.*



Notes: Percentiles of capital ratio in Italy, 1890–1973: the 5th percentile (red dot), the 10th percentile (orange dash), the 25th percentile (green long dash) and the aggregate ratio (blue solid). Vertical lines correspond to systemic financial crises. See text.

Figure 10: *Capital ratios around systemic financial crises in Italy.*



Notes: The red dashed line shows the capital ratio at the 10th percentile; the blue solid line shows the capital ratio at the 5th percentile. Values are scaled to equal 1 in the year of the respective financial crisis. Vertical lines correspond to systemic financial crises. See text.

Table 6: *Logit models for systemic financial crises in Italy, sample 1890–1973.*

	5th pctile	10th pctile	25th pctile	Aggregate
Capital ratio	33.07*	18.57	11.93	11.51*
	(18.59)	(13.35)	(9.75)	(6.27)
Pseudo R^2	0.036	0.024	0.020	0.061
AUC	0.68	0.65	0.64	0.71
	(0.09)	(0.09)	(0.09)	(0.11)
Observations	81	81	81	81

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy. Regressors are in one-period lagged levels. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

solid) used in our macro-level analysis. In addition, the distribution becomes less dispersed over time. Unlike today, it does not seem to be the case that the largest banks have the lowest capital ratios. The banks contained in the 10th percentile for example fluctuate between 6% and 10% of market share, measured by total assets, between 1890 and 1973.

In order to get a sense of any distributional effects on the likelihood of a crisis, Figure 10 plots the the 5th and 10th percentiles around systemic financial crises. In line with our previous results, there appears to be no systematic relationship between the distribution of capital ratios and the occurrence of financial crises. Capital ratios of those lower percentiles decrease prior to the crises in 1907 and 1921, but increase prior to the crises of 1893 and 1935. Table 6 confirms this first impression. Although the sample is very limited, we estimated a logit model with the financial crisis dummy as the dependent variable and the capital ratio measures as explanatory variables. Instead of only using the aggregate ratio, we additionally examine various percentiles of the capital ratio distribution.

The results reported are consistent with our findings analyzing the full sample aggregate capital ratios. The lagged level of the capital ratio is positively associated with financial instability. It is weakly significant for the 5th percentile, and insignificant otherwise. The aggregate measure has the highest AUC, but AUC differences across columns are insignificant. These findings were also confirmed when we re-estimated the specifications using the 5-year changes in capital ratios instead of lagged levels.

4.4. Capitalization of the largest banks

Another objection to our findings could be that it is the capitalization of the largest and systemically important banks that matters for financial crisis risks. As a matter of fact, current regulations contain capital surcharges for large and inter-connected institutions. To examine this proposition, we test whether low or falling capital ratios of the largest banks signals signal growing financial fragility.

This analysis builds on micro-data collected and kindly shared by Mazbouri *et al.* (2017) for the subset of the largest banks in Belgium, France, Germany, Italy, Switzerland and the UK for the period 1890 to 1970. We then extended the coverage of the data series using data for the same set of banks in France, Germany, Switzerland and the UK. Our additional data is based on balance sheets published in annual reports of the institutions (for Germany, excluding the hyperinflation years, and for France from 1872-1889), from the Swiss National Bank (after 1971), and from Braggion *et al.* (2017) for the identical set of banks in the UK from 1885 to 1889. From these data we construct a weighted capital ratio of the largest banks and rerun the empirical analysis by estimating logit classification models for systemic financial crises. As before, we include country fixed effects and 5-year lagged changes in the loans-to-GDP ratio.

The core results are presented in Table 7, where column (1) shows the baseline regression including the lagged capital ratio of the largest banks. Column (2) is based on the capital ratio from the aggregate series for a matched sample of country-year observations and therefore allows a comparison to previous results. Again, we find that a higher level of the capital ratio is positively related to the probability of a financial crisis. This is also true when we include credit growth in column (3). For the 5-year change in the capital ratio the mean coefficient estimate is negative but insignificant. In addition, all the AUCs show that the capital ratio measures do not have a significant effect on predictive accuracy. We also explored alternative specifications with only capital ratios as the predictor, for prewar and postwar subsamples and without fixed effects. All these regression confirmed our overall conclusion that there is no robust evidence in the long-run data that capital ratios are closely related to rising risks of financial instability.

5. Bank capital and the severity of financial crisis recessions

Is all the attention bank capital ratios have received from regulators and academics misguided? After all, there does not seem to be a connection with financial crisis risk. Not entirely. We show in this section that higher capital ratios are associated with milder recessions and swifter recoveries from financial crises. This finding echoes recent work by Cecchetti *et al.* (2011) and Berkmen *et al.* (2012) on the global financial crisis and adds nuance to the characterization of financial crisis recoveries reported by Jordà *et al.* (2013).

Our new data provide a unique laboratory to evaluate the merits of higher levels of capitalization. The long historical sample provides much greater heterogeneity in capital ratios than would be available with the post-WW2 samples commonly available, as Figures

Table 7: *Logit models for systemic financial crises. Largest banks.*

	(1) Largest	(2) Aggregate	(3) Largest	(4) Aggregate	(5) Largest	(6) Aggregate
Capital Ratio	3.55	7.80***	3.59	7.82**		
	(2.32)	(2.86)	(2.93)	(3.35)		
Δ Capital Ratio					-31.49	-32.00
					(20.51)	(34.38)
Loans-to-GDP 5-year change			22.51***	21.95***	20.24*	20.99**
			(7.22)	(7.45)	(10.74)	(9.98)
Pseudo R^2	0.033	0.052	0.050	0.068	0.049	0.042
AUC	0.64	0.69	0.67	0.71	0.70	0.67
	(0.08)	(0.08)	(0.10)	(0.09)	(0.08)	(0.09)
Observations	349	349	349	349	349	349

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy. The capital ratio is in one-period lagged levels. Changes in the capital ratio are 5-year average changes. All specifications include country fixed effects. The null fixed-effects model has AUC=0.65 (0.08). Data on capital ratios in (1), (3) and (5) is based only on the largest banks instead of the whole banking system. See text. Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1 and 2 show. The focus here is on comparing the aftermath of financial crises with a well capitalized banking sector relative to banking sectors with a diminished loss absorption capacity.

In order to study the variation in time series trajectories with different levels of bank capital we turn to local projection techniques (Jordà (2005)). We do this by focusing on recession episodes. We split these episodes into normal and financial recessions (those associated with a financial crisis in a ± 2 year window). Finally, we split financial recessions into two bins based on the one-period lagged capital ratio of the banking sector at the onset of the recession. Later, we extend the analysis by conditioning on covariates. We want to ensure that any differences we find for different levels of the capital ratio are not explained by alternative omitted factors for which we have data that we can include in the analysis. We also experimented with a split of normal recessions based on the capital ratio, but we do not find any significant differences between the two bins in normal recessions, a finding that is echoed in our later analysis.

More formally, the dependent variable is the difference in 100 times the log of real GDP per capita from the year when the recession starts $t(p)$, to h years later $t(p) + h$, and written as $\Delta_h y_{i,t(p)}$. The notation $t(p)$ refers to the calendar time period t where the business cycle peak p takes place. This definition of the dependent variable can be interpreted as the cumulative growth of real GDP per capita between the business cycle peak and year

$t(p) + h$. In order to account for country fixed effects and still be able to estimate a constant average path for the sample, we define the fixed effects in such a way that they add up to zero and implicitly define them in reference to a specific country as $D_{i,t(p)} = \mathbb{1}[i]/I$ for $i = 1, .., I - 1$ where I refers to the reference country, in this case, the U.S.

The indicator variable, $d_{i,t(p)}$, is used to distinguish normal from financial crisis recessions and is therefore 1 if the recession is a financial recession and zero otherwise. We define an indicator variable, $\delta_{i,t(p)}$, that is one if the capital ratio of the banking sector in country i at the start of the financial recession $t(p)$ is higher than the mean of capital ratios over all financial recessions.

Splitting observations with this indicator variable allows us to compare financial recessions based on whether the capital ratio at the start of the recession was relatively high or low. Using these auxiliary indicator variables, we begin by estimating panel local projections without covariates as follows:

$$\Delta_h y_{i,t(p)} = \sum_{i=1}^{I-1} \alpha_{i,h} D_{i,t(p)} + \mu_h + \gamma_h^{HI} d_{i,t(p)} \times \delta_{i,t(p)} + \gamma_h^{LO} d_{i,t(p)} \times (1 - \delta_{i,t(p)}) + \epsilon_{i,t(p)}\,, \quad (5)$$

for $h = 1, ..., 5$. We will be interested in characterizing the average path of the economy after a normal recession, that is, μ_h. The coefficients γ_h^{HI} (above-average capital) and γ_h^{LO} (below-average capital), modulate how the economy behaves after a financial crisis recession as a function of the level of the bank capital ratio at the start of the recession as explained earlier. Notice that the terms associated with these coefficients are the result of the interaction of the two auxiliary indicator variables defined earlier. Summarizing, the average path of output per capita after a financial recession with a below– (or, above–) average capitalized banking sector is given by $\mu_h + \gamma_h^{LO}$ (or, $\mu_h + \gamma_h^{HI}$), compared to μ_h for a normal recession.

Estimates reported in Table 8 are for the full sample of N = 252 recessions found based on the Bry and Boschan (1971) algorithm, as explained earlier. On average, financial recessions are worse than normal recessions, as the negative coefficients in the second and third rows of the table indicate. However. the economy seems to recover faster from a financial recession with a well capitalized banking sector. After 5 years, output per capita is more than three percentage points lower relative to a normal recession when the banking sector is poorly capitalized (-6.67) than otherwise (-3.19).

Table 8 reports the p-value of a test of the null that the coefficients for low and high bank capital ratios at the start of the crisis are equal. The tests show that the coefficients are generally statistically different from each other (with p-values below 0.10 except for year 2). However in economic rather than statistical terms, a high capital ratio in the banking

Table 8: *Normal versus financial recessions, with bank capital ratio bins and no controls, full sample.*

100 × log of real GDP per capita	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	-1.78***	0.18	2.52***	4.01***	5.43***	10.35***
	(0.14)	(0.26)	(0.27)	(0.34)	(0.28)	(1.13)
Financial, high capital ratio	-0.50	-2.25*	-2.72**	-2.54	-3.19*	-11.20*
	(0.49)	(1.24)	(1.23)	(1.68)	(1.62)	(5.46)
Financial, low capital ratio	-1.64**	-4.06***	-6.08***	-6.33***	-6.67***	-24.78***
	(0.59)	(0.97)	(1.28)	(1.45)	(1.12)	(4.70)
Controls	No	No	No	No	No	No
R^2	0.53	0.18	0.18	0.19	0.25	0.17
$H_0 : Hi = Lo$, p-value	0.05	0.13	0.08	0.08	0.08	0.05
Observations	252	252	252	252	252	252

Notes: Standard errors (clustered by country) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the cumulative change in real GDP per capita from the start of the recession. Financial recessions are binned depending on whether the capital ratio of the banking sector at the peak was above or below the historical mean. See text.

sector at the onset of a financial crisis coincides with considerably faster economic recovery. In sum, over the 5-year period after the peak of economic activity, the cumulative GDP costs of a financial crisis hitting a below-average capitalized banking sector amount, on average, to more than 13 percentage points lower GDP per capita compared to a financial crisis hitting an above-average capitalized banking sector, as reported in column (6) of the table (compare -24.78 with -11.20).

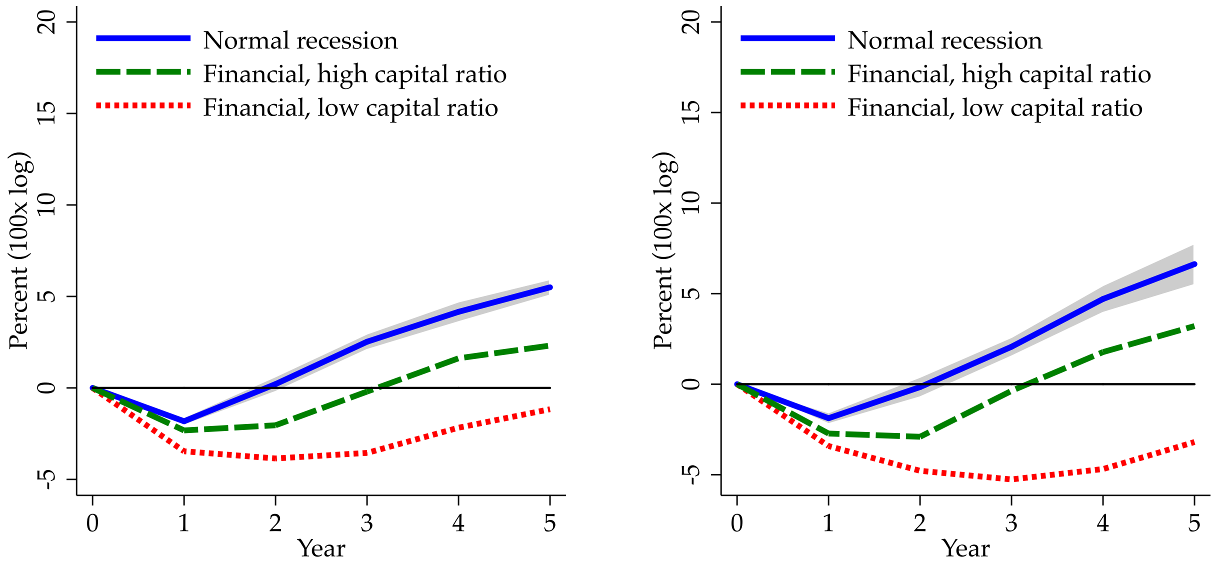
The left panel of Figure 11 displays the same results of the table in graphical form. The right panel shows the same results conditional on controls as discussed in the next section. Financial recessions tend to be worse than normal recessions in terms of the depth of output loss and the speed of economic recovery regardless of the bank capital ratio. However, while an economy with an above-average capitalized banking sector (green dashed line) recovers after year 2, and thereafter grows at a speed similar to that of a normal recession, an economy with a below-average capitalized banking sector (red dotted line) sees a more protracted slump and recovers more slowly.

5.1. Adding controls

Are the results we just reported an artifact of omitted macroeconomic aggregates that might be correlated with the bank capital structure and the economic recovery? In a second step, we include a number of control variables into the specification to account for observable characteristics. The controls include: the value at peak and the first lag of the growth rates

Figure 11: *Real GDP per capita: normal versus financial recessions by capital ratio bin*

(a) *No controls, full sample.* **(b)** *With controls, full sample.*



Notes: This figure displays the coefficients reported in Table 8 (left) and Table 9 (right). The average effect after a financial recession with an above- (or, below-) average capitalized banking sector is given by $\mu_h + \gamma_h^{LO}$ (or, $\mu_h + \gamma_h^{HI}$), compared to μ_h for a normal recession. These outcomes are shown by the green dashed, red dotted, and blue solid lines, respectively. The grey area is the 90% confidence region for the normal recession path. Full sample results: 1870-2013, excluding world wars and 5-year windows around them.

of real GDP per capita, real investment per capita, CPI inflation, short and long term interest rates, and the current account to GDP ratio. Let $X_{i,t(p)}$ denote the vector of these controls, and bank capital to modulate normal recessions as well as financial crisis recessions. Then our augmented local projection specification becomes:

$$\Delta_h y_{i,t(p)} = \sum_{i=1}^{I-1} \alpha_{i,h} D_{i,t(p)} + \mu_h + \gamma_h^{HI} d_{i,t(p)} \times \delta_{i,t(p)} + \gamma_h^{LO} d_{i,t(p)} \times (1 - \delta_{i,t(p)}) + \Theta X_{i,t(p)} + \epsilon_{i,t(p)}, \quad (6)$$

for $h = 1, ..., 5$. Due to data availability, the sample now comes down a bit to $N = 212$ recession observations.

The results of the estimating this augmented model are presented in Table 9 and are very similar to the earlier results without control variables. Once again, the coefficients for the two financial crisis recession bins separated by the level of banking sector capitalization are statistically not distinguishable until year 2, and then capitalization begins to matter from year 3 onwards. The paths are shown in the right panel of Figure 11, and the similarities with the earlier results are clear. Indeed, the path differences seem, if anything, even starker after controls are added.

Table 9: *Normal versus financial recessions, with bank capital ratio bins and with controls, full sample.*

100 × log of real GDP per capita

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	-1.87***	0.03	2.33***	4.91***	6.85***	12.24***
	(0.18)	(0.31)	(0.28)	(0.42)	(0.63)	(1.22)
Financial recession, high capital ratio	-0.85	-2.74**	-2.44*	-2.93**	-3.42**	-12.38**
	(0.65)	(1.07)	(1.18)	(1.37)	(1.45)	(4.78)
Financial recession, low capital ratio	-1.54**	-4.62***	-7.33***	-9.39***	-9.83***	-32.70***
	(0.60)	(0.95)	(1.35)	(1.52)	(1.41)	(4.98)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.573	0.310	0.338	0.332	0.400	0.333
$H_0 : Hi = Lo$, p-value	0.45	0.11	0.04	0.02	0.01	0.02
Observations	212	212	212	212	212	212

Notes: Standard errors (clustered by country) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the cumulative change in real GDP per capita from the start of the recession. Financial recessions are binned depending on whether the capital ratio of the banking sector at the peak was above or below the historical mean. See text.

5.2. Capital ratios as a continuous treatment

So far we have split financial recessions into two bins according to the capitalization of the banking sector, i.e., into those that occurred at times when the capital ratio was above or below the sample mean in financial recessions. We will now pursue a more ambitious specification to exploit the information in our continuous measure of bank capital ratios.

Instead of splitting the sample at the mean, we can now use a continuous measure of bank capital. In doing so, we will include the interaction of the type of recession $d_{i,t(p)}$ with the level of the capital ratio $w_{i,t(p)}$ at the respective peak, demeaned at the country i and bin (F, N) level, i.e., $(w_{i,t(p)} - \overline{w}_{i,N})$ and $(w_{i,t(p)} - \overline{w}_{i,F})$, where $\overline{w}_{i,N}$ refers to the mean capital ratio in country i in normal recessions and $\overline{w}_{i,F}$ to the mean in financial recessions. We compare the economic outcomes within a given country and type of recession, based on the capital ratio. We also include the 6 control variables from our baseline control specification. We then estimate the following set of local projections

$$\begin{aligned}\Delta_h y_{i,t(p)} \quad = \quad & \sum_{i=1}^{I-1} \alpha_{i,h} D_{i,t(p)} + \mu_h + \gamma_h d_{i,t(p)} + \beta_h^N (1 - d_{i,t(p)})(w_{i,t(p)} - \overline{w}_{i,N}) \\ & + \beta_h^F d_{i,t(p)} (w_{i,t(p)} - \overline{w}_{i,F}) + \Phi X_{i,t(p)} + \epsilon_{i,t(p)}\,, \qquad (7)\end{aligned}$$

for $h = 1, ..., 5$. As in previous specifications, μ_h is the average path after a recession peak,

Table 10: *Normal versus financial recessions and continuous capital ratios, controls included, full sample.*

100 × log real GDP per capita	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	-1.69***	0.11	2.59***	4.18***	5.61***	10.80***
	(0.15)	(0.27)	(0.27)	(0.33)	(0.28)	(1.11)
Financial recession	-1.37**	-4.03***	-5.71***	-6.36***	-6.46***	-23.92***
	(0.57)	(1.00)	(0.99)	(1.21)	(1.02)	(4.10)
Normal recession x capital ratio	-0.01	-0.03	0.03	-0.04	-0.04	-0.09
	(0.03)	(0.04)	(0.08)	(0.08)	(0.08)	(0.27)
Financial recession x capital ratio	-0.02	0.11***	0.24***	0.25**	0.26***	0.85***
	(0.03)	(0.03)	(0.08)	(0.09)	(0.08)	(0.29)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.576	0.299	0.320	0.307	0.377	0.312
$H_0 : N = F$, p-value	0.02	0.00	0.00	0.00	0.00	0.00
$H_0 : N.cap. = F.cap$, p-value	0.92	0.02	0.13	0.02	0.01	0.03
Observations	212	212	212	212	212	212

Notes: Standard errors (clustered by country) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the cumulative change in real GDP per capita from the peak. Normal and Financial refer to the average path after normal and financial recessions. Interaction terms refer to marginal effects of capital ratios after normal and financial recessions relative to the historical mean. Capital ratios have been multiplied by 100. See text.

$\mu_h + \gamma_h$ is the average path after a financial peak, and β_h^F and β_h^N are the marginal effects of the capital ratio at the begin of the recession. Again, all control variables are demeaned within each bin.

The results are presented in Table 10. The coefficient in the first row is the average path of real GDP per capita for a normal recession, and in the second row is the average difference from that path for a financial crisis recession. As we have seen before, financial recessions are deeper and more protracted. Furthermore, we also see in the fourth row that the interaction of the capital ratio with financial recessions has a significantly positive effect on the path of real GDP per capita: a higher capital ratio is associated with a higher path of real GDP per capita after the crisis. That is, financial recessions are less severe in their output costs after the crisis, the higher is the capital ratio of the banking sector at the onset. We see that the capitalization of the banking sector seems to matter even more the longer the horizon we analyze. Putting numbers to these impacts, a bank capital ratio 10% higher than the country-specific mean at the start of a financial recession is associated with a cumulative real GDP per capita that is higher in year 5 by 2.6% (and cumulatively higher by 8.5% over 5 years).

In contrast to this finding, bank capital ratios do not seem to matter for the recovery path after normal recessions as shown by the insignificant coefficient in the third row. We present p-values for two tests: First, we see that the coefficients for the average coefficients of financial and normal recessions differ significantly after year 2. Furthermore, we present the p-value of a test for equality of the coefficients of the capital ratio in normal and financial recessions. We see that the hypothesis of these two coefficients being equal is rejected at the 5% level for the cumulative effect in years 4 and 5. This distinction is consistent with models of amplification by leverage in which an initial shock to the banking sector propagates through highly leveraged banks.

5.3. Excluding the 2007/2008 crisis

Could our results be biased by the inclusion on our sample of the recent Global Financial Crisis and its aftermath? We saw that banking sectors had significantly higher leverage in the post-WW2 period and economic recovery after the recent crisis is slow relative to other recessions. A simple way to rule out that our results are driven only by the global financial crisis is to exclude those observations. The sample then falls in Table 11 and Figure 12a to $N = 195$ recession observations. However, the findings are unchanged and a higher capital ratio at the onset of a financial recession is still associated with a faster economic recovery.

As we have seen in the descriptive part of the paper, capital ratios have changed over our sample period. This might be a concern if financial recessions at the beginning of our sample were just different from financial recessions at later periods in our sample for reasons not captured by our control variables. We therefore additionally run Equation 6 on two subsamples, namely those observations before and those after WW2, where the capital ratio followed different patterns. This comes at the cost of small sample sizes and as a result the coefficients for our two types of banking crises are not statistically different from each other in the post-WW2 sample. Figure 12b shows the average paths when we exclude the global financial crisis for the full and the post-WW2 sample. Again, it is easy to see that economic recovery takes longer if the banking sector had less loss absorption capacity at the beginning of a financial crisis recession.

5.4. Historical performance of a 20% capital ratio

So far in this section we have shown that financial recessions have been more severe when banks were financed to a larger degree by debt, that is, they entered the recession with a lower capital ratio, all else equal. The results can be interpreted as being in favor of banks financing themselves with more capital, should the macroprudential goal be to limit the

Table 11: *Normal versus financial recessions binned by capital ratio, with controls, full sample excluding post-2006 (global financial crisis).*

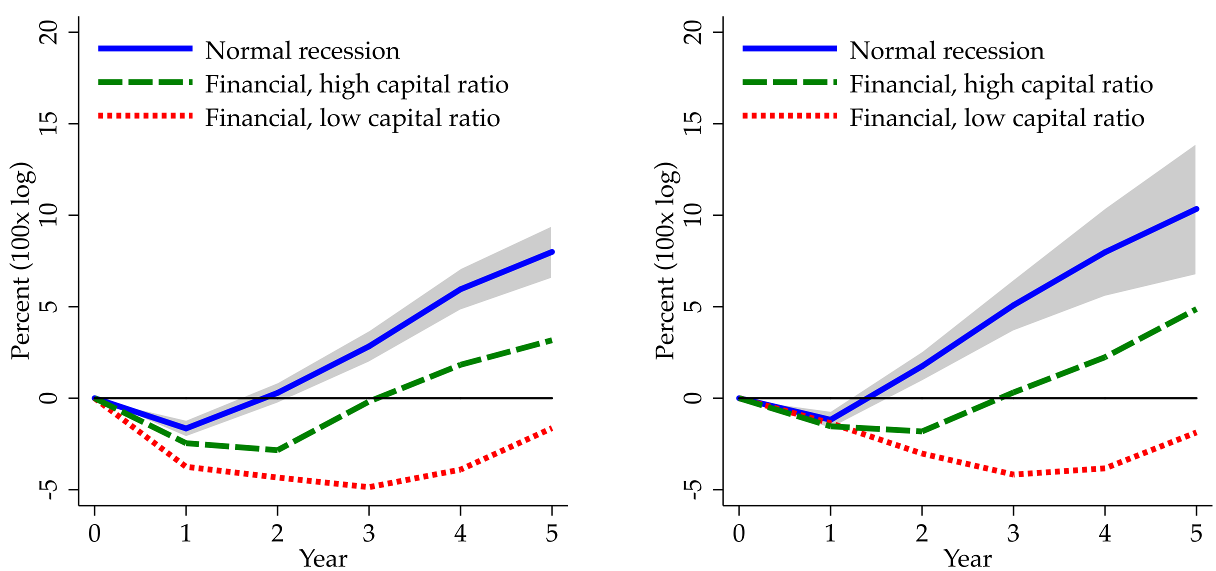
100 × log real GDP per capita

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	-1.72***	0.24	2.75***	5.77***	8.01***	15.05***
	(0.26)	(0.36)	(0.51)	(0.67)	(0.88)	(2.14)
Financial recession, high capital ratio	-0.33	-2.71*	-1.96	-2.66	-4.01*	-11.67*
	(0.49)	(1.28)	(1.58)	(1.55)	(2.16)	(6.09)
Financial recession, low capital ratio	-1.62**	-4.20***	-6.64***	-8.39***	-8.81***	-29.67***
	(0.68)	(1.24)	(1.60)	(1.85)	(1.71)	(6.20)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.591	0.282	0.351	0.352	0.423	0.346
$H_0 : F^{HI} = F^{LO}$, p-value	0.06	0.32	0.09	0.06	0.11	0.07
Observations	195	195	195	195	195	195

Notes: Standard errors (clustered by country) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the cumulative change in real GDP per capita from the start of the recession. Financial recessions are binned depending on whether the capital ratio of the banking sector at the peak was above or below the historical mean. See text.

Figure 12: *Real GDP per capita, normal vs. financial recessions binned by bank capital, controls included, full and post-WW2 samples excluding post-2006 (global financial crisis).*

(a) *Full sample.* **(b)** *Post-WW2.*



Notes: This figure displays the coefficients for estimating Equation 6 on samples excluding the global financial crisis, i.e., 1870–2006 (left) and 1946–2006 (right). The solid blue line reports the average path after normal recessions. The grey area corresponds to the 90% confidence region around the recession path. The green dashed line corresponds to the sum of the coefficients of the average recession path and the financial recession coefficient when the pre-crisis capital ratio was high. The dotted red line corresponds to the sum of the average recession coefficient and the financial recession coefficient when the pre-crisis capital ratio was low.

economic costs of financial crisis recessions.

Can we be more specific than this, and tune our empirical work to match current debates over appropriate policy parameters? Prevailing suggestions for the regulatory capital ratio for banks range somewhere between the Basel status quo level of 3% or 4.5% (for the leverage ratio which is closest to the definition presented in this paper) versus, at the other extreme, notable suggestions for a more aggressive capital ratio in the range of 20% to 30%, as forcefully advocated by Admati and Hellwig (2013). As we have remarked before, the latter ratio seems very high in the current context, but it is actually quite comparable to some of the observed historical levels in the long timespan covered by our new dataset.

While we have little to say on the optimality of these different proposals, we can let our historical data speak and compare the recovery paths of normal and financial crisis recessions, with the latter split into bins according to whether their *absolute* banking sector capital levels (i.e., raw, not country-demeaned) were above versus below the alternative 20% threshold. We then estimate local projections of the form

$$\begin{aligned}\Delta_h y_{i,t(p)} &= \sum_{i=1}^{I-1} \alpha_{i,h} D_{i,t(p)} + \mu_h + \gamma_h^{>20} d_{i,t(p)} \times \lambda_{i,t(p)} + \gamma_h^{<20} d_{i,t(p)} \times (1 - \lambda_{i,t(p)}) \\ &\quad + \Psi X_{i,t(p)} + \epsilon_{i,t(p)}\,, \end{aligned} \tag{8}$$

for $h = 1, ..., 5$, where we abstract from average country-level differences in capital ratios, for the moment, and sort historical financial crises into two categories according to whether the capital ratio was above ($\lambda_{i,t(p)} = 1$) or below 20% ($\lambda_{i,t(p)} = 0$) at the beginning of the financial recession. $X_{i,t(p)}$ is the vector of 6 control variables including the value at peak and the first lag of the growth rates of real GDP per capita, real investment per capita, CPI inflation, short and long term interest rates, and the current account to GDP ratio.

As can be seen in Table 12 the coefficients for the two types of financial recessions are significantly different from each other in almost all years as indicated by the presented p-value for the equality of the two coefficients. The coefficient for financial recessions with capital levels above 20% is negative but not statistically different from zero. This means that banking crises that occurred at capital ratios above 20% have historically not been associated with significant output losses relative to normal recessions, an important new finding for the bank capital debate.

5.5. The role of liquidity ratios

We have seen that bank capital plays a critical role in mitigating the social economic costs of financial recessions. Is the same true for liquidity ratios? After all, these ratios turned

Table 12: *Normal vs. financial recessions, capital ratio bins above and below 20%, controls included, full sample.*

100 × log real GDP per capita

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	-1.81***	0.19	2.21***	3.69***	5.24***	9.53***
	(0.14)	(0.33)	(0.38)	(0.33)	(0.52)	(1.33)
Financial recession, capital ratio above 20%	-0.06	-1.27	-0.99	-0.32	-1.73	-4.37
	(0.83)	(1.44)	(2.14)	(2.20)	(2.37)	(7.56)
Financial recession, capital ratio below 20%	-1.42**	-4.59***	-6.17***	-6.57***	-6.65***	-25.39***
	(0.60)	(1.00)	(1.06)	(0.92)	(0.85)	(3.75)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.576	0.324	0.339	0.323	0.383	0.330
$H_0 : F(> 20\%) = F(< 20\%)$, p-value	0.12	0.03	0.05	0.02	0.09	0.03
Observations	212	212	212	212	212	212

Notes: Standard errors (clustered by country) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the cumulative change in real GDP per capita from the start of the recession. Financial recessions are binned depending on whether capital ratios at the beginning of the recession are below or above 20%. See text.

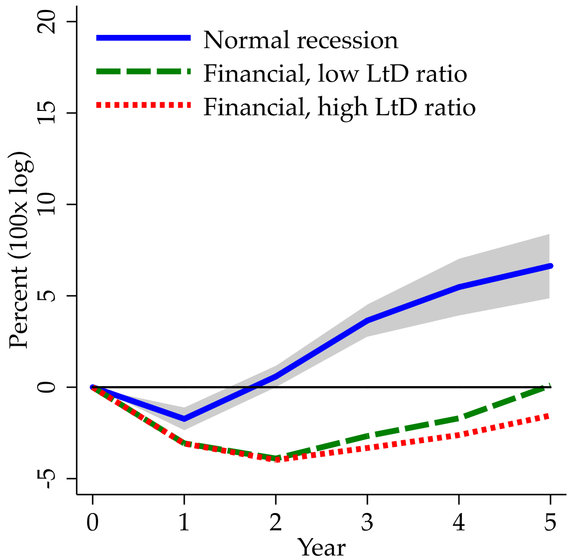
out to be more helpful than capital ratios in predicting financial crises. We therefore repeat the analysis presented above, studying how the levels of LtD and non-core ratios affect the path of recovery. We do not find significant differences between those financial recessions associated with high and those with low levels of these two liquidity ratios. In Figure 13 we present results of estimating Equation 6, where $\delta_{i,t(p)}$ refers to the LtD or non-core ratio instead of the capital ratio. In each graph, the dotted red path refers to a high LtD or non-core ratio at the onset of the financial recession, low ratios are displayed in green. As one would have expected, GDP is slightly lower for high LtD and non-core ratios, but the differences between those coefficients are not statistically significant.

5.6. Credit after crises

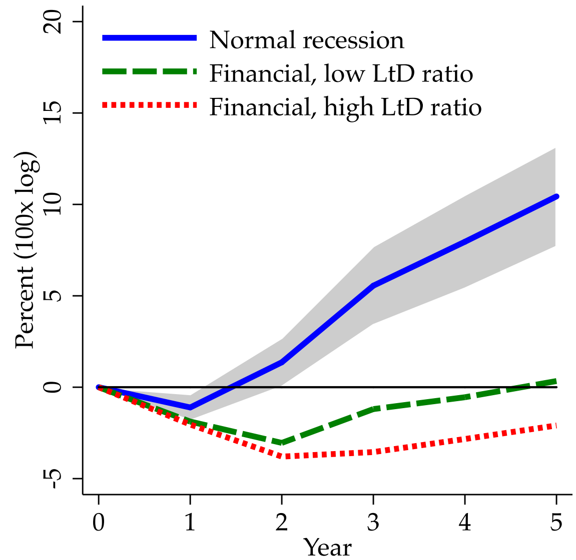
The previous section has shown that there is a robust relationship between the pre-crisis capital ratio and economic recovery several years into the crisis. This might be the case as a result of the inability of highly levered intermediaries to extend credit after an initial shock to their balance sheets. In order to test whether this mechanism could be at play, we run local projections with cumulative changes in real private credit per capita as the dependent variable and allow for differences in capital ratios before the financial peak. We use real private credit instead of normalizing credit by GDP in order to avoid measuring the relationship of bank capital with GDP that we have shown in the previous section.

Figure 13: *Real GDP per capita, normal vs. financial recessions binned by LtD and non-core ratio, controls included, full and post-WW2 samples.*

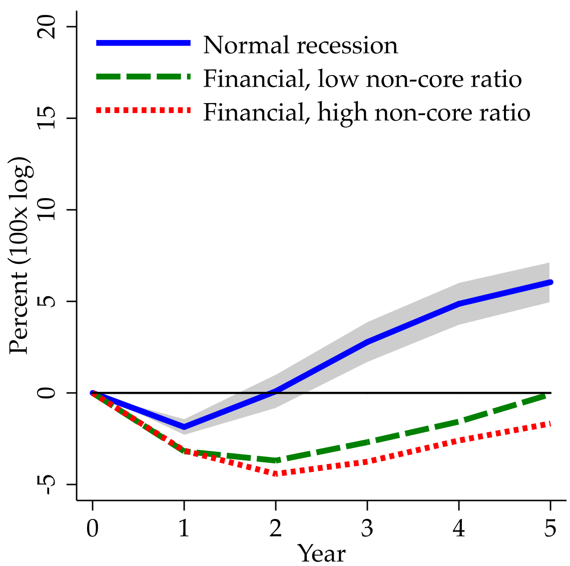
(a) *Full sample, LtD ratio.*



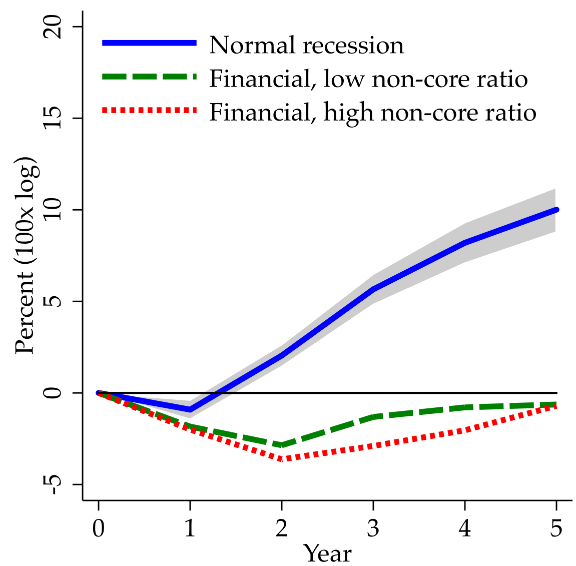
(b) *Post-WW2, LtD ratio.*



(c) *Full sample, non-core ratio.*



(d) *Post-WW2, non-core ratio.*



Notes: This figure displays the coefficients for estimating Equation 6 on full (left) and post-WW2 (right) samples. The solid blue line reports the average path after normal recessions. The grey area corresponds to the 90% confidence region around the recession path. The green dashed line corresponds to the sum of the coefficients of the average recession path and the financial recession coefficient when the pre-peak LtD and non-core ratio was low. The dotted red line corresponds to the sum of the average recession coefficient and the financial recession coefficient when the pre-peak LtD or non-core ratio was high.

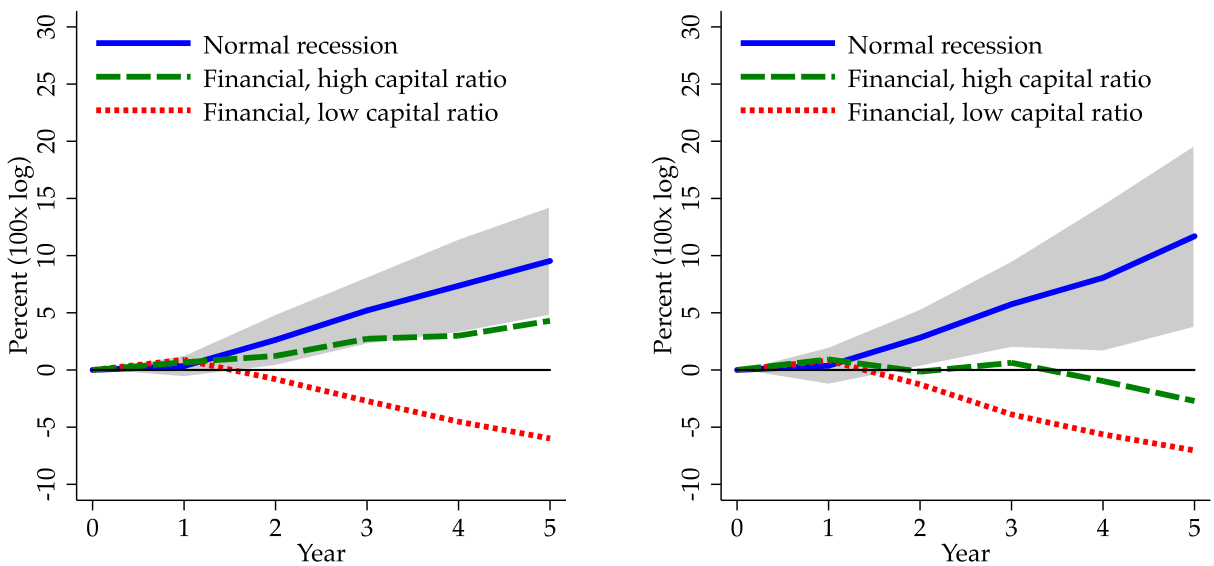
Hence, we estimate local projections with $\Delta_h y_{i,t(p)}$ referring now to the cumulative change in real private credit per capita extended by financial intermediaries.

The path of real private credit per capita after economic peaks is visualized in Figure 14.

As in the previous exercises, the solid blue line refers to the path after normal recessions, while the dotted red and dashed green line reflect financial recessions when banks were above (dashed) and below (dotted) the mean capital ratio of all financial recessions. We see first, that credit growth after financial peaks is on average lower than after a normal business cycle peak. Furthermore, capital matters. Similar to the dynamics of aggregate output, it seems that recovery is protracted and pre-crisis less capitalized banking systems extend less credit several years after a financial peak. These results are consistent with recent models of macroeconomic amplification through the balance sheets of levered financial intermediaries (e.g. Adrian and Boyarchenko (2012)).

Figure 14: *Real private credit per capita, normal vs. financial recessions binned by bank capital, controls included.*

(a) *Full sample.* **(b)** *Post-WW2.*



Notes: This figure displays the coefficients for estimating Equation 6 with real private credit as the dependent variable. The solid blue line reports the average path after normal recessions. The grey area corresponds to the 90% confidence region around the recession path. The green dashed line corresponds to the sum of the coefficients of the average recession path and the financial recession coefficient when the pre-crisis capital ratio was high. The dotted red line corresponds to the sum of the average recession coefficient and the financial recession coefficient when the pre-crisis capital ratio was low.

6. Conclusions

In this paper, we introduced a new dataset covering the composition of banking sector liabilities from 1870 to 2013 for a sample of 17 advanced economies. We showed that in most countries banking sector capital ratios have declined strongly before WW2, but thereafter the capital ratios have remained low but stable.

Over this long time span, our first main finding is that, perhaps counterintuitively, the capital ratio is not a good early-warning indicator, or predictor, of systemic financial crises. Rather, the evidence suggests that regulators should focus on credit booms as the best signal to watch—although some funding ratios like LtD may add some marginal additional information.

That said, in another major finding, we have also presented evidence that, conditional on being in a crisis, higher initial capital ratios are associated with significantly shallower recessions. From a social cost standpoint, in terms of GDP losses, the long record of macroeconomic experience shows that economies with better capitalized banking systems appear to weather financial storms more successfully than those with lower capital ratios.

So the evidence suggests that higher capital ratios in banking systems can bring about more resilience: not of the banks per se, but of the wider macroeconomy. In other words, history does indeed lend support for a precautionary approach to capital regulation. Its main role appears to lie not so much in eliminating the chances of systemic financial crises, but rather in mitigating their social and economic costs—a distinct but arguably more important benefit.

References

Admati, Anat R., and Hellwig, Martin. 2013. *The Bankers' New Clothes: What's Wrong With Banking and What to Do About It*. Princeton University Press, Princeton, N.J.

Admati, Anat R., DeMarzo, Peter M., Hellwig, Martin, and Pfleiderer, Paul. 2013. Fallacies, Irrelevant Facts, and Myths in the Discussion of Capital Regulation: Why Bank Equity is Not Socially Expensive. Rock Center for Corporate Governance, Stanford GSB, Working Paper Series 161.

Adrian, Tobias, and Boyarchenko, Nina. 2012. Intermediary Leverage Cycles and Financial Stability. FRBNY Staff Report 567.

Adrian, Tobias, Mönch, Emanuel, and Shin, Hyun S. 2014. Dynamic Leverage Asset Pricing. FRBNY Staff Report 625.

Basel Committee on Banking Supervision. 2011. Basel III: A Global Regulatory Framework for more Resilient Banks and Banking Systems - Revised Version June 2011. Bank for International Settlements, Basel.

Basel Committee on Banking Supervision. 2014. Basel III Leverage Ratio Framework and Disclosure Requirements. Bank for International Settlements, Basel.

Berkmen, Pelin S., Gelos, Gaston, Rennhack, Robert, and Walsh, James P. 2012. The Global Financial Crisis: Explaining Cross-Country Differences in the Output Impact. *Journal of International Money and Finance*, **31**(1), 42–59.

Braggion, Fabio, Dwarkasing, Narly, and Moore, Lyndon. 2017. Nothing Special about Banks: Competition and Bank Lending in Britain,1885-1925. *Review of Financial Studies*. Forthcoming.

Brunnermeier, Markus K., and Sannikov, Yuliy. 2014. A Macroeconomic Model with a Financial Sector. *American Economic Review*, **104**(2), 379–421.

Bry, Gerhard, and Boschan, Charlotte. 1971. *Cyclical Analysis of Times Series: Selected Procedures and Computer Programs*. National Bureau of Economic Research, New York.

Calomiris, Charles, Flandreau, Marc, and Laeven, Luc. 2016. Political Foundations of the Lender of Last Resort: A Global Historical Narrative. CEPR Discussion Paper 11448.

Cecchetti, Stephen G., King, Michael R., and Yetman, James. 2011. Weathering the Financial Crisis: Good Policy or Good Luck? BIS Working Paper 351.

Cerutti, Eugenio, Claessens, Stijn, and Laeven, Luc. 2015. The Use and Effectiveness of Macroprudential Policies: New Evidence. IMF Working Paper 15/61.

Dagher, Jihad, Dell'Ariccia, Giovanni, Laeven, Luc, Ratnovski, Lev, and Tong, Hui. 2016. Benefits and Costs of Bank Capital. IMF Staff Discussion Note 16/04.

Demirgüc-Kunt, Asli, Kane, Edward, and Laeven, Luc. 2014. Deposit Insurance Database. World Bank Policy Research Working Paper 6934.

Diamond, Douglas W., and Dybvig, Philip H. 1983. Bank Runs, Deposit Insurance, and Liquidity. *Journal of Political Economy*, **91**(3), 401–419.

Fahlenbrach, Rdiger, Prilmeier, Robert, and Stulz, Ren M. 2016. Why Does Fast Loan Growth Predict Poor Performance for Banks? NBER Working Paper 22089.

Farhi, Emmanuel, and Tirole, Jean. 2012. Collective Moral Hazard, Maturity Mismatch, and Systemic Bailouts. *American Economic Review*, **102**(1), 60–93.

Flannery, Mark J., and Rangan, Kasturi P. 2008. What Caused the Bank Capital Build-up of the 1990s? *Review of Finance*, **12**(2), 391–429.

Geanakoplos, John. 2010. The Leverage Cycle. *NBER Macroeconomics Annual 2009*, **24**, 1–65.

Grossman, Richard S. 2010. *Unsettled Account: The Evolution of Banking in the Industrialized World Since 1800*. Princeton University Press, Princeton, N.J.

Hahm, Joon-Ho, Shin, Hyun S., and Shin, Kwanho. 2013. Non-Core Bank Liabilities and Financial Vulnerability. *Journal of Money, Credit, and Banking*, **45**(1), 3–36.

Haldane, Andrew G. 2010. The $100 billion question. *BIS Review*, **40**.

Haldane, Andrew G. 2011. Capital Discipline. Remarks Based on a Speech Given at the American Economic Association, Denver, Colorado. January 9. (www.bis.org/review/r110325a.pdf).

He, Zhiguo, and Krishnamurthy, Arvind. 2013. Intermediary Asset Pricing. *American Economic Review*, **103**(2), 732–770.

Herrera, Helios, Ordonez, Guillermo, and Trebesch, Christoph. 2014. Political Booms, Financial Crises. NBER Working Paper 20346.

Jordà, Òscar. 2005. Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review*, **95**(1), 161–182.

Jordà, Òscar, Schularick, Moritz, and Taylor, Alan M. 2013. When Credit Bites Back. *Journal of Money, Credit and Banking*, **45**(2).

Jordà, Òscar, Schularick, Moritz, and Taylor, Alan M. 2015. Leveraged Bubbles. *Journal of Monetary Economics*, **76**, 1–20.

Jordà, Òscar, Schularick, Moritz, and Taylor, Alan M. 2016a. The Great Mortgaging: Housing Finance, Crises, and Business Cycles. *Economic Policy*, **31**(85), 107–152.

Jordà, Òscar, Schularick, Moritz, and Taylor, Alan M. 2016b. Sovereigns versus Banks: Credit, Crises, and Consequences. *Journal of the European Economic Association*, **14**(1), 45–79.

Jordà, Òscar, Schularick, Moritz, and Taylor, Alan M. 2017. Macrofinancial History and the New Business Cycle Facts. *NBER Macroeconomics Annual 2016.* Forthcoming.

Kiyotaki, Nobuhiro, and Moore, John. 1997. Credit Cycles. *Journal of Political Economy*, **105**(2), 211–248.

Kroszner, Randall. 1999. The Impact of Consolidation and Safety-Net Support on Canadian, US and UK Banks: 1893–1992: Comment. *Journal of Banking and Finance*, **23**(2), 572–577.

Laeven, Luc, and Valencia, Fabian. 2012. Systemic Banking Crises Database: An Update. IMF Working Paper 12/163.

Mazbouri, Malik, Guex, Sebastian, and Lopez, Rodrigo. 2017. University of Lausanne. Project – Swiss Data Bank of International Bank Data (1890-1970) . (http://www.unil.ch/hist/placefinanciere).

Mendoza, Enrique G., and Terrones, Marco E. 2012. An Anatomy of Credit Booms and their Demise. NBER Working Paper 18379.

Merton, Robert. 1974. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *Journal of Finance*, **29**, 449–70.

Merton, Robert C. 1995. Financial Innovation and the Management and Regulation of Financial Institutions. *Journal of Banking and Finance*, **19**(3), 461–481.

Miles, David, Yang, Jing, and Marcheggiano, Gilberto. 2013. Optimal Bank Capital. *Economic Journal*, **123**(567), 1–37.

Modigliani, Franco, and Miller, Merton H. 1958. The Cost of Capital, Corporation Finance, and the Theory of Investment. *American Economic Review*, **48**(3), 261–297.

Natoli, Sandra, Piselli, Paolo, Triglia, Ivan, and Vercelli, Francesco. 2016. Historical Archive of Credit in Italy. Bank of Italy Economic History Working Papers 36.

Organisation for Economic Co-operation and Development. 2010. OECD Banking Statistics, 1979–2009. (http://www.oecd-ilibrary.org/finance-and-investment/data/oecd-banking-statistics_bank-data-en).

Pennacchi, George. 2016. Banks, Taxes, and Nonbank Competition. Unpublished. University of Illinois.

Reinhart, Carmen M., and Rogoff, Kenneth S. 2009. *This Time is Different: Eight Centuries of Financial Folly*. Princeton University Press, Princeton, N.J.

Saunders, Anthony, and Wilson, Berry. 1999. The Impact of Consolidation and Safety-Net Support on Canadian, US and UK Banks: 1893–1992. *Journal of Banking and Finance*, **23**(2), 537–571.

Schularick, Moritz, and Taylor, Alan M. 2012. Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008. *American Economic Review*, **102**(2), 1029–61.

Appendices

A. Systemic banking crises

The crisis prediction classification models in the paper employ data on all systemic financial crises from 1870 to 2008. Dates of systemic financial crises are based on Jordà *et al.* (2017).

AUS:	1893, 1989.
BEL:	1870, 1885, 1925, 1931, 1934, 1939, 2008.
CAN:	1907.
CHE:	1870, 1910, 1931, 1991, 2008.
DEU:	1873, 1891, 1901, 1907, 1931, 2008.
DNK:	1877, 1885, 1908, 1921, 1931, 1987, 2008.
ESP:	1883, 1890, 1913, 1920, 1924, 1931, 1978, 2008.
FIN:	1878, 1900, 1921, 1931, 1991.
FRA:	1882, 1889, 1930, 2008.
GBR:	1890, 1974, 1991, 2007.
ITA:	1873, 1887, 1893, 1907, 1921, 1930, 1935, 1990, 2008.
JPN:	1871, 1890, 1907, 1920, 1927, 1997.
NLD:	1893, 1907, 1921, 1939, 2008.
NOR:	1899, 1922, 1931, 1988.
PRT:	1890, 1920, 1923, 1931, 2008.
SWE:	1878, 1907, 1922, 1931, 1991, 2008.
USA:	1873, 1893, 1907, 1929, 1984, 2007.

B. Business cycle peaks

The local projections empirical analysis in the paper employs business cycle peaks from 1870 to 2008, excluding windows around the two world wars, with projections out to five years ahead, with the annual panel sample data. The peak dates that are used are as shown in the table below, where "N" denotes a normal business cycle peak, and "F" denotes a peak associated with a systemic financial crisis (a crisis within ± 2 years of the peak). The dating method follows Jordà, Schularick, and Taylor (2011) and uses the Bry and Boschan (1971) algorithm. See text.

Table A.1: *Dates of normal (N) and financial (F) peaks*

AUS	N	1875	1878	1881	1883	1885	1887	1889	1896	1898	1900	1904
		1910	1913	1926	1938	1943	1951	1956	1961	1973	1976	1981
		2008										
	F	1891	1894	1989								
BEL	N	1872	1874	1887	1890	1900	1913	1916	1942	1951	1957	1974
		1980	1992									
	F	1870	1883	1926	1930	1937	2008					
CAN	N	1871	1874	1877	1882	1884	1888	1891	1894	1903	1913	1917
		1928	1944	1947	1953	1956	1981	1989	2008			
	F	1907										
CHE	N	1875	1880	1886	1890	1893	1899	1902	1906	1912	1916	1920
		1933	1939	1947	1951	1957	1974	1981	1994	2001		
	F	1871	1929	1990	2008							
DEU	N	1879	1898	1905	1913	1922	1943	1966	1974	1980	1992	2001
	F	1875	1890	1908	1928	2008						
DNK	N	1870	1880	1887	1911	1914	1916	1923	1939	1944	1950	1962
		1973	1979	1992								
	F	1872	1876	1883	1920	1931	1987	2008				
ESP	N	1873	1877	1892	1894	1901	1909	1911	1916	1927	1932	1935
		1940	1944	1947	1952	1958	1974	1980	1992			
	F	1883	1889	1913	1925	1929	1978	2007				
FIN	N	1870	1883	1890	1898	1907	1913	1916	1938	1941	1943	1952
		1957	1975	2008								
	F	1876	1900	1929	1989							
FRA	N	1872	1874	1892	1894	1896	1900	1905	1907	1909	1912	1916
		1920	1926	1933	1937	1939	1942	1974	1992			
	F	1882	1929	2007								
GBR	N	1871	1875	1877	1883	1896	1899	1902	1907	1918	1925	1929
		1938	1943	1951	1957	1979						
	F	1873	1889	1973	1990	2007						
ITA	N	1870	1883	1897	1918	1923	1925	1932	1939	1974	2002	2004
	F	1874	1887	1891	1929	1992	2007					
JPN	N	1875	1877	1880	1887	1890	1892	1895	1898	1903	1919	1921
		1929	1933	1940	1973	2001	2007					
	F	1882	1901	1907	1913	1925	1997					
NLD	N	1870	1873	1877	1889	1894	1899	1902	1913	1929	1957	1974
		1980	2001									
	F	1892	1906	1937	1939	2008						
NOR	N	1876	1881	1885	1893	1902	1916	1923	1939	1941	1957	1981
		2007										
	F	1897	1920	1930	1987							
PRT	N	1870	1873	1877	1888	1893	1900	1904	1907	1912	1914	1916
		1925	1927	1934	1937	1939	1941	1944	1947	1951	1973	1982
		1992	2002	2004								
	F	1890	1923	1929	2008							
SWE	N	1873	1876	1881	1883	1885	1888	1890	1899	1901	1904	1913
		1916	1924	1939	1976	1980						
	F	1879	1907	1920	1930	1990	2007					
USA	N	1875	1887	1889	1895	1901	1909	1913	1916	1918	1926	1937
		1944	1948	1953	1957	1969	1973	1979	1981	1990	2000	
	F	1873	1882	1892	1906	1929	2007					

Table A.2: *Logit models for systemic financial crises, full sample.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Capital ratio	13.32						3.15	
	(19.40)						(22.89)	
Capital ratio		4.62***						2.85**
		(0.95)						(1.27)
Δ LtD ratio			9.49***				9.40**	
			(3.20)				(3.77)	
LtD ratio				1.98***				1.70**
				(0.40)				(0.68)
Δ Non-core ratio					13.41**		-0.16	
					(6.64)		(8.70)	
Non-core ratio						0.53		-0.11
						(0.86)		(1.30)
Pseudo-R^2	0.024	0.043	0.036	0.055	0.026	0.022	0.036	0.063
AUC	0.62	0.68	0.66	0.69	0.63	0.62	0.66	0.71
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	1842	1854	1806	1813	1840	1849	1805	1813

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year average annual changes (Δ) or in one-period lagged levels. All models include country fixed effects. The null fixed-effects only model has AUC = 0.60 (0.03). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

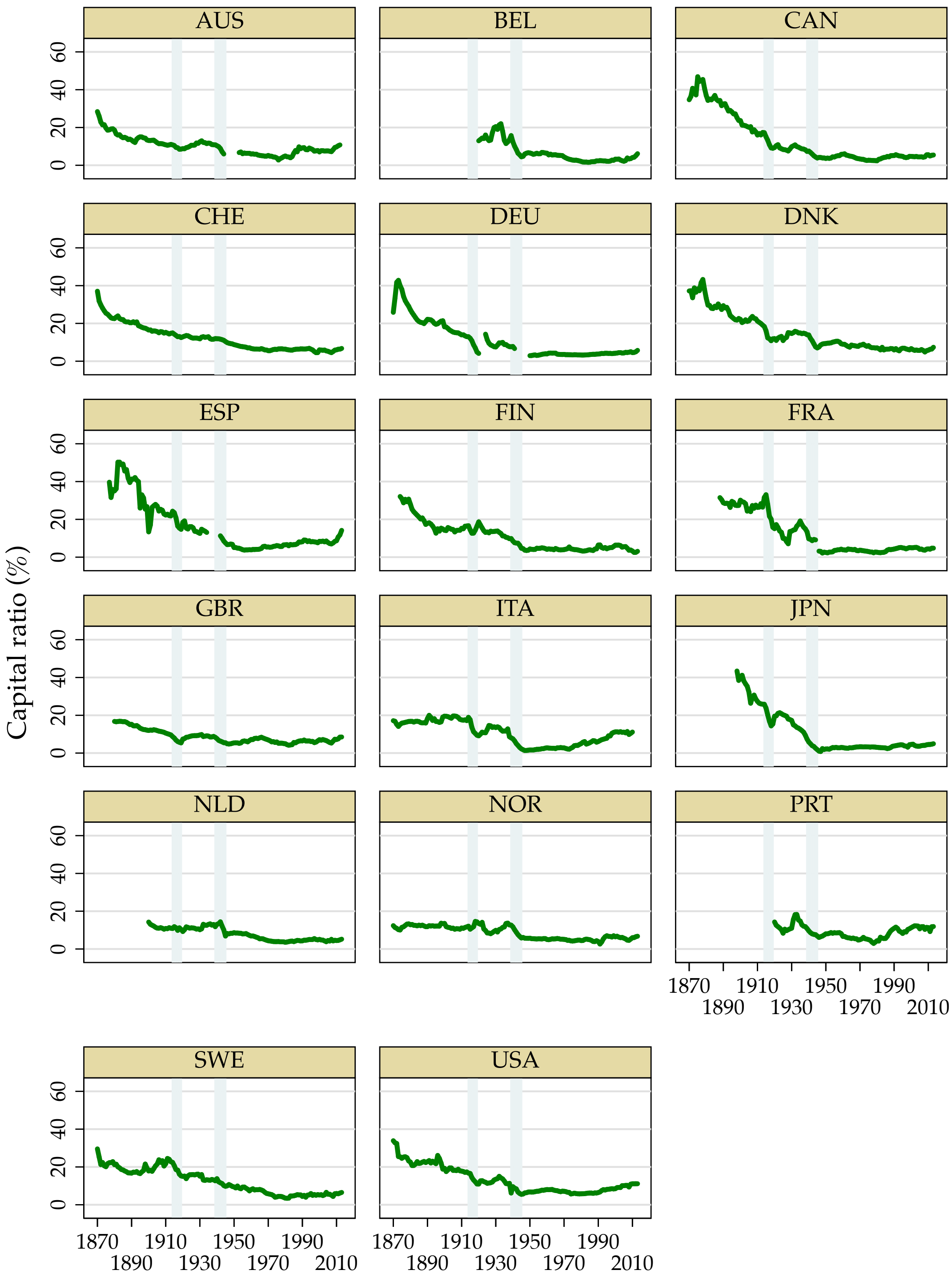
C. Baseline results without credit growth

Table A.2 presents the baseline results of estimating Equation 4 solely including balance sheet ratios in $X_{i,t}$. In columns (1) and (2) we explore if low levels of capital are associated with systemic financial instability. Given the regulatory focus on higher capital ratios one might be tempted to expect a significantly negative relationship between the two. All else equal, better capitalized banking systems should be less susceptible to financial crises and increases in capital ratios should, ceteris paribus, make banking systems safer. As in our main analysis, the positive coefficients reported in columns (1) and (2) are consistent with the reverse causality argument discussed in the introduction: riskier borrowing manifests in a demand for higher capital ratios. The first difference specification reported in column (1) has an AUC of 0.62, indistinguishable from the benchmark of 0.60 based on the fixed-effects only model. The specification in column (2) has an AUC of 0.68, a significant improvement over the 0.60 null, but only mildly so.

Columns (3) and (4) of the table refer to the predictive ability of the LtD ratio. If this ratio measures aggregate illiquidity and hence maturity mismatch, we would expect a positive relationship with financial crises. The historical data lend some support to these ideas. Both the five-year average annual changes and the lagged level of the LtD ratio turn out to be positively related to financial distress. Including the LtD ratio improves predictive accuracy somewhat in both specifications with AUC values of 0.66 and 0.69, respectively.

Columns (5) and (6) refer to the mix of debt and use the share of non-core liabilities as a measure of financial vulnerability, as suggested by Hahm *et al.* (2013). An increase in the non-core share can be a sign of a boom as the growth of retail deposits cannot keep pace with asset growth so that banks have to turn to other sources for funding. The results here show that little role for this ratio

Figure A.1: *Capital ratio by country, averages by year for 17 countries, full sample.*



Notes: This figure plots the capital ratio for all 17 sample countries from 1870 to 2013. Years of world wars are shown in shading.

Table A.3: *Logit models for systemic financial crises, post-WW2 sample.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Capital ratio	77.44						72.76	
	(117.47)						(122.10)	
Capital ratio		11.66						2.28
		(11.81)						(15.32)
Δ LtD ratio			17.81^{***}				14.91^{***}	
			(4.79)				(5.20)	
LtD ratio				4.22^{***}				1.10
				(0.85)				(1.09)
Δ Non-core ratio					30.92^{**}		13.30	
					(15.34)		(16.43)	
Non-core ratio						13.87^{***}		11.77^{***}
						(2.50)		(3.63)
Pseudo-R^2	0.020	0.021	0.061	0.122	0.035	0.166	0.065	0.169
AUC	0.63	0.63	0.69	0.77	0.64	0.83	0.69	0.84
	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.03)	(0.06)	(0.03)
Observations	1047	1045	1047	1041	1046	1041	1046	1041

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year average annual changes (Δ) or in one-period lagged levels. All models include country fixed effects. The null fixed-effects only model has AUC = 0.59 (0.06). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

with an AUC of 0.63 and 0.62, respectively. These values are not significantly different from the null fixed-effects only model.

Including all three measures simultaneously improves predictive ability only mildly, as columns (7) and (8) show. The levels specification in column (8) turns out to improve predictive accuracy more as the AUC goes up to 0.71. Furthermore, the levels of the capital and the LtD ratio remain significant.

The results in Table A.3 are based on the post-WW2 sample only. They offer a similar picture to the findings for the full sample, with some notable differences. Again, the capital ratio, the LtD ratio, and the non-core ratio are all positively related to financial crisis risk. While the capital ratio coefficients are unhelpful predictors, the LtD ratio and non-core share turn out to be very useful. Furthermore, the classification ability increases considerably in the levels specifications for the LtD ratio (AUC = 0.77) and non-core share (AUC = 0.83).

When used in combination, the LtD changes and the non-core share in the levels estimation remain highly important, as columns (7) and (8) in the table indicate. Comparing the AUC in columns (6) and (8) it seems that the non-core ratio already includes most of the information that might allow one to predict financial distress. The AUC improves from 0.83 to 0.84 only.

Table A.4 in the Appendix reports results for the pre-WW2 subsample. It turns out that our liability measures are not clearly related to financial stability in these early days of modern banking. It is only the change in non-core funding that is significant at the 5% level, while all models add some accuracy to the classification ability as indicated by the AUC statistics that lie between 0.66 (using the level of the capital ratio) and 0.69 (using the growth of LtD ratio). We also present in the appendix the results of pooled regressions, which are in line with the results obtained here.

D. Logit models for-pre WW2 era

Table A.4: *Multivariate logit models for systemic financial crises, pre-WW2 sample.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Cap Ratio	14.20						6.73	
	(10.17)						(14.10)	
Cap Ratio		-1.38						-5.28*
		(1.18)						(2.70)
Δ LtD Ratio			9.17*				6.57	
			(4.68)				(5.41)	
LtD Ratio				1.28*				2.70*
				(0.74)				(1.42)
Δ Noncore					18.41**		9.80	
					(8.31)		(10.41)	
Noncore						2.23		-0.73
						(2.02)		(2.88)
Pseudo R^2	0.058	0.051	0.066	0.058	0.062	0.053	0.068	0.068
AUC	0.67	0.67	0.70	0.69	0.69	0.67	0.69	0.71
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	729	743	693	706	728	742	693	706

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year annual average changes (Δ) or in one-period lagged levels. All specifications include a country fixed effect. The fixed effects only model has AUC=0.61(0.03). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E. Multivariate logit models without country fixed effects

Table A.5: *Logit models for systemic financial crises, full sample, no fixed effects.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Cap Ratio	15.97						3.15	
	(19.93)						(27.72)	
Cap Ratio		4.09^{***}						3.38^{***}
		(0.68)						(1.12)
Δ LtD Ratio			8.50^{***}				8.32^{**}	
			(3.13)				(3.73)	
LtD Ratio				0.84^{*}				0.62
				(0.44)				(0.54)
Δ Noncore					12.65^{**}		0.12	
					(6.29)		(8.39)	
Noncore						-0.13		-0.19
						(0.64)		(0.93)
Pseudo R^2	0.002	0.021	0.012	0.011	0.003	0.000	0.012	0.026
AUC	0.51	0.66	0.58	0.60	0.50	0.52	0.57	0.68
	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
Observations	1842	1854	1806	1813	1840	1849	1805	1813

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year average annual changes (Δ) or in one-period lagged levels. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: *Multivariate logit models for systemic financial crises, post-WW2 sample, no fixed effects.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Cap Ratio	74.35						73.95	
	(103.45)						(100.35)	
Cap Ratio		14.40**						18.43***
		(6.11)						(6.34)
Δ LtD Ratio			14.96***				11.95***	
			(3.27)				(3.77)	
LtD Ratio				2.33***				1.20**
				(0.51)				(0.57)
Δ Noncore					30.52**		13.88	
					(12.16)		(14.09)	
Noncore						3.45***		2.92***
						(0.88)		(0.99)
Pseudo R^2	0.003	0.011	0.037	0.059	0.019	0.052	0.042	0.086
AUC	0.51	0.59	0.62	0.69	0.57	0.70	0.61	0.74
	(0.06)	(0.05)	(0.07)	(0.05)	(0.06)	(0.06)	(0.07)	(0.05)
Observations	1113	1111	1113	1107	1112	1107	1112	1107

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year average annual changes (Δ) or in one-period lagged levels. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

F. Multivariate logit models including additional control variables

Table A.7: *Multivariate logit models for systemic financial crises, full sample.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Loans	29.49***	27.25***	32.13***	22.40***	17.09**	25.04***	18.99**
	(4.55)	(7.08)	(6.76)	(8.69)	(7.14)	(8.63)	(7.38)
Δ Cap Ratio		75.11					
		(59.82)					
Cap Ratio			11.57***				
			(3.86)				
Δ LtD Ratio				7.80			
				(6.06)			
LtD Ratio					1.95***		
					(0.49)		
Δ Noncore						7.76	
						(14.82)	
Noncore							2.36*
							(1.21)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.067	0.170	0.179	0.164	0.176	0.162	0.168
AUC	0.70	0.81	0.82	0.80	0.81	0.80	0.80
	(.04)	(.04)	(.03)	(.04)	(.03)	(.04)	(.04)
Observations	1197	1197	1197	1197	1197	1197	1197

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year annual average changes (Δ) or in one-period lagged levels. All models include country fixed effects. The fixed effects only model has AUC = 0.60 (0.03). All models include a set of control variables. These are the first two lags of the growth rates of GDP and investment per capita, CPI inflation, short and long term interest rates, and the current account to GDP ratio. Furthermore, controls include 5-year changes in real house and real stock prices and the share of liquid bank assets computed as 1 minus the share of loans in total assets. Standard errors (clustered by country) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: *Multivariate logit models for systemic financial crises, post-WW2 sample.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Loans	34.96***	29.86***	35.28***	25.65***	15.00	26.98***	1.58
	(7.53)	(9.69)	(11.80)	(9.73)	(9.56)	(9.13)	(9.76)
Δ Cap Ratio		31.25					
		(203.30)					
Cap Ratio			27.05				
			(22.57)				
Δ LtD Ratio				8.28			
				(7.29)			
LtD Ratio					4.52***		
					(1.47)		
Δ Noncore						16.92	
						(18.12)	
Noncore							17.19***
							(4.49)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.105	0.218	0.225	0.222	0.263	0.222	0.311
AUC	0.74	0.84	0.85	0.84	0.87	0.84	0.90
	(.05)	(.05)	(.05)	(.05)	(.04)	(.05)	(.04)
Observations	905	905	905	905	905	905	905

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year annual average changes (Δ) or in one-period lagged levels. All models include country fixed effects. The fixed effects only model has AUC = 0.59 (0.06). All models include a set of control variables. These are the first two lags of the growth rates of GDP and investment per capita, CPI inflation, short and long term interest rates, and the current account to GDP ratio. Furthermore, controls include 5-year changes in real house and real stock prices and the share of liquid bank assets computed as 1 minus the share of loans in total assets. Standard errors (clustered by country) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G. Logit models excluding the global financial crisis

Table A.9: *Multivariate logit models for systemic financial crises, full sample excluding the global financial crisis.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Cap Ratio	14.35						2.79	
	(23.42)						(24.50)	
Cap Ratio		5.62^{***}						2.00
		(1.20)						(1.95)
Δ LtD Ratio			10.55^{**}				10.68^{**}	
			(4.29)				(4.75)	
LtD Ratio				2.35^{***}				2.73^{***}
				(0.47)				(0.88)
Δ Noncore					13.97		-1.23	
					(11.90)		(13.22)	
Noncore						-0.50		-2.02
						(1.06)		(1.64)
Pseudo R^2	0.027	0.056	0.038	0.061	0.030	0.023	0.038	0.078
AUC	0.63	0.70	0.66	0.70	0.64	0.63	0.66	0.74
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	1706	1720	1613	1625	1704	1715	1612	1625

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year average annual changes (Δ) or in one-period lagged levels. All specifications include a country fixed effect. The fixed effects only model has AUC = 0.60 (0.03). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: *Multivariate logit models for systemic financial crises, post-WW2 sample excluding the global financial crisis.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Cap Ratio	252.67*						171.78	
	(143.87)						(111.60)	
Cap Ratio		5.03						-16.81
		(17.71)						(19.67)
Δ LtD Ratio			51.32***				44.95***	
			(15.09)				(14.95)	
LtD Ratio				6.45***				5.56
				(2.32)				(3.98)
Δ Noncore					57.78*		18.79	
					(33.53)		(29.26)	
Noncore						12.69***		5.05
						(3.89)		(5.67)
Pseudo R^2	0.040	0.006	0.203	0.160	0.073	0.132	0.223	0.172
AUC	0.62	0.52	0.82	0.82	0.69	0.80	0.82	0.82
	(0.08)	(0.10)	(0.06)	(0.05)	(0.09)	(0.06)	(0.06)	(0.05)
Observations	633	632	634	632	633	632	633	632

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year average annual changes (Δ) or in one-period lagged levels. All specifications include a country fixed effect. The fixed effects only model has AUC = 0.59 (0.06). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

H. Logit models excluding the US and the UK

Table A.11: *Multivariate logit models for systemic financial crises, full sample excluding the US and the UK.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Cap Ratio	14.76						5.80	
	(19.40)						(23.16)	
Cap Ratio		4.57^{***}						2.75^{*}
		(1.00)						(1.44)
Δ LtD Ratio			8.61^{**}				8.53^{**}	
			(3.42)				(4.18)	
LtD Ratio				1.80^{***}				1.58^{**}
				(0.43)				(0.72)
Δ Noncore					12.30		-0.71	
					(7.75)		(10.21)	
Noncore						-0.00		-0.43
						(0.99)		(1.67)
Pseudo R^2	0.027	0.047	0.038	0.054	0.028	0.023	0.038	0.063
AUC	0.63	0.69	0.66	0.69	0.64	0.62	0.66	0.71
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
Observations	1614	1624	1578	1583	1612	1619	1577	1583

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year annual average changes (Δ) or in one-period lagged levels. All specifications include a country fixed effect. The fixed effects only model has AUC = 0.60 (0.03). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: *Multivariate logit models for systemic financial crises, post-WW2 sample excluding the US and the UK.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Cap Ratio	122.30						104.56	
	(123.46)						(122.06)	
Cap Ratio		12.18						1.53
		(13.11)						(21.61)
Δ LtD Ratio			17.77***				13.40**	
			(5.10)				(5.26)	
LtD Ratio				4.23***				0.74
				(0.97)				(1.17)
Δ Noncore					43.62**		20.65	
					(21.43)		(22.79)	
Noncore						15.59***		14.07***
						(3.13)		(4.31)
Pseudo R^2	0.021	0.017	0.063	0.124	0.041	0.188	0.072	0.189
AUC	0.62	0.63	0.68	0.76	0.66	0.85	0.69	0.85
	(0.07)	(0.06)	(0.08)	(0.06)	(0.06)	(0.04)	(0.07)	(0.04)
Observations	915	913	915	909	914	909	914	909

Notes: The table shows logit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year annual average changes (Δ) or in one-period lagged levels. All specifications include a country fixed effect. The fixed effects only model has AUC = 0.61 (0.06). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

I. Comparing the AUC of different models

Table A.13: *AUC for multivariate logit models for systemic financial crises.*

	Full model	Excl. credit growth	Excl. capital ratio	Excl. loan-to-deposits	Excl. noncore ratio
Full sample					
AUC	0.727	0.713	0.715	0.726	0.727
$H_0 : AUC = AUC^{Full}$ p-value		0.375	0.273	0.903	0.776
N	1742	1742	1742	1742	1742
Pre-WW2 sample					
AUC	0.747	0.740	0.722	0.717	0.743
$H_0 : AUC = AUC^{Full}$ p-value		0.592	0.289	0.126	0.723
N	643	643	643	643	643
Post-WW2 sample					
AUC	0.843	0.835	0.845	0.843	0.791
$H_0 : AUC = AUC^{Full}$ p-value		0.460	0.536	0.658	0.102
N	1033	1033	1033	1033	1033

Notes: This table reports the AUC for different logit classification models. The full model includes the 5-year change in loans-to-GDP and the lagged capital ratio, loan-to-deposit ratio and noncore ratio as regressors. In columns (2)-(5) we drop one regressor at the time. For these specifications we report the p-value of a test of equality of the AUC with the AUC of the full model.

Table A.14: *AUCs from multivariate logit models for systemic financial crises.*

	(1) Full model	(2) Excl. credit growth	(3) Excl. capital ratio	(4) Excl. noncore ratio
Full sample				
AUC	0.723	0.705	0.679	0.719
$H_0 : AUC = AUC^{Full}$ p-value		0.419	0.009	0.504
N	1763	1763	1763	1763
Pre-WW2 sample				
AUC	0.718	0.696	0.709	0.718
$H_0 : AUC = AUC^{Full}$ p-value		0.338	0.467	0.886
N	664	664	664	664
Post-WW2 sample				
AUC	0.843	0.833	0.845	0.752
$H_0 : AUC = AUC^{Full}$ p-value		0.426	0.603	0.012
N	1033	1033	1033	1033

Notes: This table reports the AUC for different logit classification models. The full model includes the 5-year change in loans-to-GDP and the lagged capital ratio and noncore ratio as regressors. In columns (2)-(4) we drop one regressor at the time. For these specifications we report the p-value of a test of equality of the AUC with the AUC of the full model.