Bank Capital Redux: Solvency, Liquidity, and Crisis*

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Abstract

What is the relationship between bank capital, the risk of a financial crisis, and its severity? This paper introduces the first comprehensive analysis of the long-run evolution of the capital structure of modern banking using newly constructed data for banks' balance sheets in 17 countries since 1870. In addition to establishing stylized facts on the changing funding mix of banks, we study the nexus between capital structure and financial instability. We find no association between higher capital and lower risk of banking crisis. However, economies with better capitalized banking systems recover faster from financial crises as credit begins to flow back more readily.

Keywords: financial crises, risk taking, crisis prediction, local projections, bank liabilities, capital ratio, macroprudential regulation.

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

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1. Introduction

Systemic banking crises are a recurring phenomenon in modern economic history. Recent macro-finance research points to a general pattern where buoyant conditions in credit markets, measured by increases in the quantity of credit (Schularick and Taylor 2012; Jordà, Schularick, and Taylor 2013; Mian, Sufi, and Verner 2017), or by low expected returns on credit assets (Krishnamurthy and Muir 2016), presage banking crises and severe downturns. A key question for macroprudential regulators is whether higher capital ratios are associated with lower crisis risks, or at least alleviate their economic fallout. Their instinct is to increase the loss-absorption capacity of banks, at least in recent years. However as we will show, financial crises have overwhelmed even the highest of defenses.

Bankers have an incentive to take excessive risks if the payouts from their bets are asymmetric and creditors do not monitor banks closely (Merton 1977). A remedy might be to increase equity capital: more *skin in the game* should induce more prudent behavior and thereby reduce the probability that financial institutions will face large losses that put their existence at risk (Holmstrom and Tirole 1997; Mehran and Thakor 2011). But this view has not gone unchallenged. Rajan (2018) raised fundamental doubts whether equity governance is able to discipline banks *ex ante*. The regulatory response to the global financial crisis has, by and large, embraced higher capital buffers and regulation of bank leverage. This is not the first time that capital ratios have been raised in response to a systemic banking crisis, as Grossman (2010) reports. But despite all regulatory efforts, crises have not gone away.

A competing explanation for why financial crises happen starts from the observation that when credit booms are underway, neither financial markets nor the bankers themselves are necessarily aware that the risks on the balance sheets are rising. Recent research by Baron and Xiong (2017), Fahlenbrach, Prilmeier, and Stulz (2017), as well as Cheng, Raina, and Xiong (2014) documents evidence of overoptimism by insiders and market-wide neglect of crash risk during credit booms. These findings mesh well with the older insights of Kindleberger (1978), Minsky (1977, 1986), and Shiller (2000) where, time and again, financial markets have become overly exuberant only to be disappointed later. They also echo the ideas proposed in recent theoretical work by Bordalo, Gennaioli, and Shleifer (2018), Simsek (2013), as well as Greenwood, Hanson, and Jin (2018). In line with the empirical evidence on overoptimism and neglected crash risk, in these models excessive credit booms are the product of behavioral biases—such as extrapolative belief formation—and not due to incentive problems of rational agents. In this context, higher capital will do little to moderate such overoptimism during the buildup of risks, although it may still act as a buffer for losses once optimism wanes.

How then is capital structure related to banking crisis risk and severity? Ultimately this is an empirical question, and we answer it by turning to 150 years of modern financial history across 17 advanced economies. Our paper belongs to a growing literature in macrofinance that relies on long-run and cross-country perspectives to produce new knowledge about rare crisis events and the role of financial factors in the business cycle (Reinhart and Rogoff 2009; Schularick and Taylor 2012; Jordà, Schularick, and Taylor 2013; Krishnamurthy and Muir 2016; Romer and Romer 2017).

The backbone of our study is a newly constructed aggregate data set for the advanced economies over the 1870–2015 period which covers three core categories of the funding mix of financial intermediaries: capital, deposits, and other (non-deposit) debt instruments. The new panel data complement prior work on the asset side of banking systems, and bank credit in particular (see Jordà, Schularick, and Taylor 2017). Looking ahead, we expect that the new data we release here will become an important resource for future research, over and above their contribution to this study.

We make three main contributions, corresponding to three parts of the paper. First, we establish new stylized facts on the long-run evolution of the capital structure of banking systems in advanced economies. Importantly, we correct the widely held view that capital ratios decreased substantially in the decades preceding the 2007–08 crisis. On the contrary, even unweighted (i.e., not risk-adjusted) capital ratios have remained remarkably stable over the entire post-WW2 period. Capital-to-asset ratios fell from around 30% in the late 19th century to about 5%–10% in 1950 (see Figure 1 below). Since then they have remained in a tight range across all the countries in our sample.

Such stability in capital ratios is quite striking compared to the "hockey stick pattern" seen in many other financial variables in advanced economies, such as aggregate balance sheets and mortgage lending (Jordà, Schularick, and Taylor 2017). Instead, the most notable long-run change in banks' funding structures occurred in the composition of debt liabilities. For example, in 1950, bank debt funding consisted almost entirely of deposits. The share of non-deposit debt liabilities increased rapidly starting in the 1970s. On the eve of the 2007–08 crisis, the deposit share of debt funding had shrunk to 50% of total debt liabilities. In short, the important development in the capital structure of banks was not a decline in equity capital, but rather the banks' increasing reliance on non-deposit and potentially "runnable" debt funding.

In the second part of the paper, we study the relationship between the capital structure of banks and *systemic* banking crises. We establish stylized correlations by comparing the predictive ability of capital ratios, as a measure of "skin in the game", to that of credit expansions and the two liquidity measures: the loans-to-deposits ratio and the share of non-deposit liabilities to debt. In line with the recent literature, we identify systemic banking crises narratively as periods when significant parts of the banking system fail or have to be rescued by government intervention (Schularick and Taylor 2012; Laeven and Valencia 2012; Jordà, Schularick, and Taylor 2017). Our results are robust to other chronologies, as we will show.

We find scant evidence that bank capital ratios are predictive of systemic banking crises *ex ante*. This is true whether we focus on the long-term variation in the levels of capital ratios, or whether we focus on short-term variation by looking at 5-year changes in capitalization. Lower capital ratios do not predict elevated crisis probabilities in either our full sample, or focusing on the post-WW2 period. This is true even after controlling for a wide range of macroeconomic indicators as well as indicators of asset risk and the equity market's perception of bank riskiness. The substantial variation of capital in our data allows us to show that, historically, banking systems have been overwhelmed by financial crises even with the highest of capital buffers.

Other parts of the funding structure could be related to crisis risk. The loan-to-deposit ratio is a measure of aggregate maturity mismatch or banking system illiquidity, often linked to financial instability (Farhi and Tirole 2012; Diamond and Dybvig 1983) and indeed this is what we find in the data. The same applies to the share of non-deposit liabilities to debt—what we call the "non-core ratio:" an increasing reliance on wholesale funding is also a predictor of financial distress. However, the non-core ratio matters as a predictor only once deposits are insured and non-core liabilities are more run-prone than insured deposits. That said, the predictive power of these alternative funding measures is limited compared to credit growth, which remains the single best predictor of crisis risk (Schularick and Taylor 2012).

We also show that bank capital, when viewed as a proxy of the "skin in the game" hypothesis, does not predict future bank stock returns. Instead, quantity-based measures—credit expansions in particular—perform much better, in line with the results on overoptimism during the boom in Baron and Xiong (2017). Increases in loans-to-deposits are associated with significantly lower subsequent returns, but this relationship weakens once we condition on credit growth. From this perspective too, one can question the wisdom of a regulatory framework that is focused on bank capital and other liability indicators instead of focusing on the asset side.

In the third and last part of the paper, we examine the shock absorbing role of bank equity. We ask how bank capital affects the intensity of banking crises and their economic costs *ex post*. Seminal contributions on banking distress in the Great Depression (Bernanke 1983), the role of financial intermediary health in Japan's 1990s downturn and the Great

Recession (Peek and Rosengren 2000; Khwaja and Mian 2008; Jordà, Schularick, and Taylor 2013), and recent work in macro-finance (Muir 2017; He and Krishnamurthy 2013; Geanakoplos 2010; Kiyotaki and Moore 1997; Brunnermeier and Sannikov 2014; Adrian, Mönch, and Shin 2014) all emphasize that financial intermediary balance sheets and leverage drive macroeconomic dynamics and asset prices. If intermediary health plays such an important role for economic outcomes, it is natural to suspect that equity capital likely affects post-crisis economic outcomes.

This is precisely what we find: bank capital limits the economic fallout of financial crises. A more weakly capitalized financial sector going into the crisis is associated with a deeper recession and a slower recovery. The differences in social costs are economically sizable. Using a simple stratification around the mean, we find a 4 percentage point difference in real GDP per capita over 5 years after the start of the recession (see Table 8). Our long-run data thus confirm that the cross-country findings in Cecchetti, King, and Yetman (2011) and Berkmen, Gelos, Rennhack, and Walsh (2012) for the 2007–08 crisis and its aftermath, carry over to other systemic events. We also find that in better capitalized banking systems, credit grows much faster in the recovery, a potential channel that might explain this difference in outcomes.

Overall, the central finding is that our current regulatory system is built on an indicator that is unrelated to the incidence of systemic banking crises across modern economic history. Our results on the predictability of crises and returns do not prove, but are consistent with the view that the causes of financial crises are rooted in collective failures to understand and adequately price risks. In this view, crises occur when overly exuberant expectations are adjusted and the prices of leveraged assets fall rapidly, thus putting lenders' solvency in doubt (Baron and Xiong 2017; Krishnamurthy and Muir 2016; Bordalo, Gennaioli, and Shleifer 2018).[1] This view also implies that capital requirements have little bite during the buildup of risks in a boom.

Once the crisis materializes, capital buffers play a role in limiting damage to the economy; but substantial losses are baked in, and this is only partial mitigation. The case for bank capital regulation is intact. At the same time, these findings caution against being lulled into a false sense of security by rising capital ratios. Higher capital ratios are no shortcut to evaluate and achieve financial stability. Instead, reducing crisis risk may depend on quite different actions, e.g. targeting credit growth and maturity mismatch more directly.[2]

[1] Baron and Xiong (2017) show that higher crash risk of bank equity during a credit boom is not adequately priced. Krishnamurthy and Muir (2016) find that credit spreads are too low prior to financial crises. Bordalo, Gennaioli, and Shleifer (2018) show that these empirical findings are consistent with extrapolative expectations, where agents over-weigh incoming information when building expectations about the future.

[2] A similar concern has recently been voiced by Sarin and Summers (2016).

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

	Total	Capital	Deposits	Other (non-core)
Australia	1870–1945	1870–1945	1870–1945	1870–1945
	1950–2015	1951–2015	1950–2015	1950–2015
Belgium	1920–2015	1920–2015	1920–2015	1920–2015
Canada	1870–2015	1870–2015	1870–2015	1870–2015
Denmark	1870–2015	1870–2015	1870–2015	1870–2015
Finland	1873–2015	1873–2015	1873–2015	1873–2015
France	1890–2015	1890–2015	1946–2015	1946–2015
Germany	1870–1920	1870–1920	1870–1920	1870–1920
	1924–1940	1924–1940	1924–1940	1924–1940
	1950–2015	1950–2015	1950–2015	1950–2015
Great Britain	1880–2015	1880–2015	1945–2015	1945–2015
Italy	1870–2015	1870–2015	1870–2015	1870–2015
Japan	1893–2015	1893–2015	1893–2015	1893–2015
Netherlands	1900–2015	1900–2015	1900–2015	1900–2015
Norway	1870–2015	1870–2015	1870–2015	1870–2015
Portugal	1920–2015	1920–2015	1920–2015	1920–2015
Spain	1874–1935	1874–1935	1874–1935	1874–1935
	1942–2015	1942–2015	1942–2015	1942–2015
Sweden	1870–2015	1870–2015	1871–2015	1871–2015
Switzerland	1870–2015	1870–2015	1870–2015	1870–2015
United States	1870–2015	1870–2015	1870–2015	1870–2015

2. New data

The new dataset introduced here includes balance sheet liabilities of financial institutions on an annual basis from 1870 to 2015 for 17 advanced economies. Moreover, we disaggregate bank liabilities into capital, deposits, and other (non-core) liabilities. Schularick and Taylor (2012), and the updates in Jordà, Schularick, and Taylor (2017), focused on the asset side of bank balance sheets (and on macroeconomic aggregates). The new data cover the liability side of the bank balance sheets, thus completing the picture.

Table 1 describes the coverage of the new data. Except for a few countries, we were able to locate data for the entire 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 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 emphasize the within-country consistency of our data series.[3]

We take *book values* from banking sector balance sheets and we aggregate the capital structure into three broad categories: capital, deposits, and other debt liabilities. Table 2 displays, in simplified form, the typical structure of aggregate banking-sector balance sheets, displaying data for 1929 and 2007 for the United States as an example. The table already reveals a big change in the funding mix of banks over time, as we will show: non-core liabilities have become a much more important source of funding, rising here from under one-tenth to almost one-third of liabilities even as capital has remained largely unchanged.

2.1. Capital

Bank *capital* corresponds to the Basel III definition of Common Equity Tier 1 capital, i.e., shareholders' funds that allow banks to absorb losses on an ongoing basis. These are normally common stock (paid-up capital), reserves, and retained earnings.[4] Since our focus is on within-country consistency of our series, we choose a broader definition in some countries based on availability.[5] Dividing the resulting measure of capital by total assets yields an unweighted capital ratio akin to the "leverage ratio" in Basel III (Basel Committee on Banking Supervision 2014). Our definition of total assets differs 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 for off-balance sheet exposures.[6]

Paid-up capital, retained earnings, and reserves have been reported in almost all cases throughout the entire period. We chose this specific definition of a capital ratio, as other 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, DeMarzo, Hellwig, and Pfleiderer (2013). Furthermore, in contrast to

[3]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).

[4]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. 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."

[5]Furthermore, our series for the United Kingdom are adjusted for reserves hidden in bank balance sheets until 1968 based on the data provided by Billings and Capie (2007). Similarly, we adjust for hidden reserves in Sweden as suggested by Hortlund (2005).

[6]Basel Committee on Banking Supervision (2011) outlines how to adjust total assets in order to arrive at the total exposure measure.

Table 2: *Snapshots of a banking system balance sheet: United States in 1929 and 2007*

(a) End of year 1929			
Cash/liquid	17 %	Deposits	79 %
Loans	56 %	Non-core	9 %
Securities	22 %		
Other	5 %	Capital	11 %
Total assets	100 %	Total liabilities and capital	100 %
(b) End of year 2007			
Cash/liquid	4 %	Deposits	65 %
Loans	59 %	Non-core	27 %
Securities	14 %		
Other	22 %	Capital	8 %
Total assets	100 %	Total liabilities and capital	100 %

Sources: Federal Deposit Insurance Corporation (2007), chain linked with Historical Statistics of the United States (1929).

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. We will, however, verify our results later with market measures of bank capital as a robustness check.

Finally, note that our capital ratios cannot account for contingent shareholder liability, such as double or unlimited liability. Such buffers were not uncommon in the US, Canada, and the UK in the early 20th century. Double-liability meant that shareholders were also personally liable (to debt holders) for the par value of their investment; hence, they could lose up to twice their original investment. Such provisions were phased out in the 1930s. The capital ratios reported here for these countries may therefore be biased downwards in the early years; still, if anything, this would reinforce our main findings.

2.2. Deposits and debt instruments

We include in *deposits* both term and sight deposits, and both checking and savings accounts by residents. Whenever possible we exclude interbank deposits and deposits by foreigners, as we aim to calculate total domestic deposits by non-financial resident entities. 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*. Balance sheet items picked up by this category have changed over the course of time, but they mainly consist of bonds, repos, and interbank loans. By convention, we will also refer to other liabilities as *non-core liabilities*.

2.3. Balance sheet ratios

Several key balance-sheet ratios of financial intermediaries are central to the analysis, starting with the *capital ratio* defined like today's Basel III "leverage ratio," that is, the ratio of capital over total assets given by

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

Next we compute the ratio of *loans to deposits*, which is often considered a measure of banking sector illiquidity or vulnerability (Cecchetti, King, and Yetman 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 renewed significance since 2007. Recent studies have argued that large inflows of non-core funds can destabilize the banking system (Hahm, Shin, and Shin 2013).

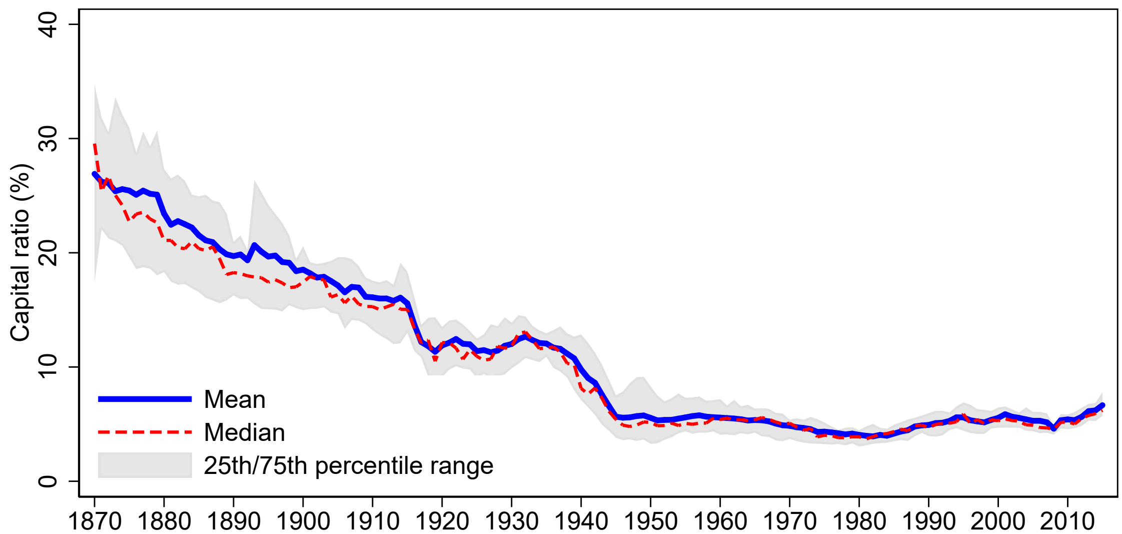
3. Key trends

In most countries, capital ratios decreased substantially from 1870 up to WW2 and have remained relatively stable thereafter. 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, as shown in Figure 1. The cross-country average aggregate capital ratio *decreased* steadily from around 30% to less than 10% right after WW2, before fluctuating in the range 5%–10% over subsequent decades up to the present. A similar picture emerges at the country level as we show in Figures A.1 and A.2 in the Appendix. This is consistent with the work of Saunders and

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 2015. The red line refers to the median of the sample countries. The grey area is the interquartile range for the 17 countries in our sample.

Wilson (1999), who studied the decline of capital ratios in Canada, the US, and the UK. It also dovetails with Grossman (2010), who documented a decreasing capital ratio between 1840 and 1940 for a subsample of our countries; it also mirrors developments discussed by banking historians for many smaller sub-periods at the individual country level. Our new data show that similar patterns hold across a broader set of advanced economies.

What explains these historical developments? Grossman (2010) argues that the observed decline in capital ratios over time 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, and the informational frictions and risks were high. As a result, 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.

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, the ongoing diversification and consolidation in banking systems may have reduced the size of equity buffers required to cope with risk (Saunders and Wilson 1999).

A second—not mutually exclusive—explanation rests on political and institutional changes that have 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. Over time, 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, Flandreau, and Laeven 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 1977). Deposit insurance today is the norm in almost all countries around the world (Demirgüc-Kunt, Kane, and Laeven 2014).

A last and arguably more recent extension of guarantees 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.[7]

Since scaling issues can make it difficult to track developments after 1945, we separately present these trends in Figure A.2. In the years preceding the financial crisis, capital ratios increased slightly in many countries although they are generally stable over this sample. Table 3, shows for each country in our sample the year with the lowest capital ratio until the year before the recent crisis. These dates are spread out over the 60 years between the end of WW2 and the financial crisis of 2007–08. 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 late 1980s, having been particularly low at the end of the 1970s.

3.2. Debt structure

In Figure 2 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

[7] A recent estimate by Haldane (2010) puts the annual too-big-to-fail 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 (2019). 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.

Table 3: *Lowest sample capital ratio by country*

Country	Year	Capital ratio in %	Country	Year	Capital ratio in %
Australia	1976	2.8	UK	1984	3.9
Belgium	1984	1.9	Italy	1952	1.4
Canada	1980	2.4	Japan	1952	2.0
Switzerland	1998	4.1	Netherlands	1981	3.7
Germany	1951	3.0	Norway	1991	2.6
Denmark	1993	5.5	Portugal	1983	1.8
Spain	1962	4.0	Sweden	1981	3.4
Finland	1981	3.2	USA	1974	3.9
France	1951	2.3			

Notes: This table displays the country-year observation with the lowest capital ratio between 1870 and 2006 for each country, excluding war years and 5 year windows around wars.

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.

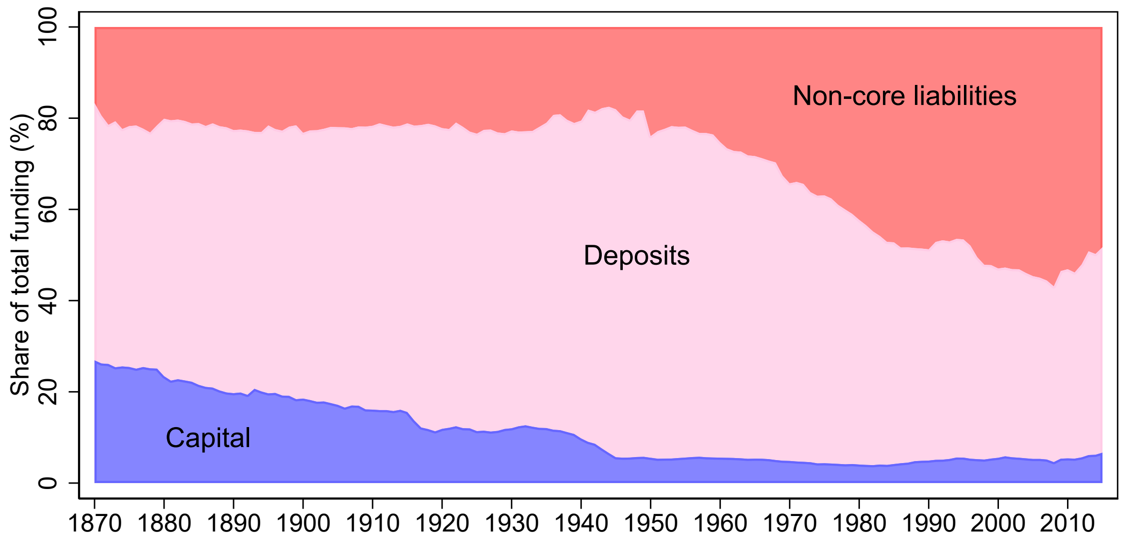
By the early 2000s, the share of deposits had fallen to around 50%. This illustrates the increasing importance in recent decades of non-core (e.g., wholesale) funding sources, which is central to the growing separation of money and credit in the post-WW2 period discussed by Schularick and Taylor (2012) as well as Jordà, Schularick, and Taylor (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. Figure A.3 shows the evolution of the 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 2007–08.

3.3. Liquidity

Banks intermediate funds between borrowers and savers. This intermediation model entails a maturity transformation since banks borrow short and lend 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 would typically find it more difficult to withstand large deposit outflows. Table 1 in Cecchetti, King, and Yetman (2011) shows large heterogeneity in this ratio across banking systems in the world today.

Figure 3 shows the mean LtD ratio for all 17 countries in the full sample. There is 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, a side-effect of war-time government finance policies

Figure 2: *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%).

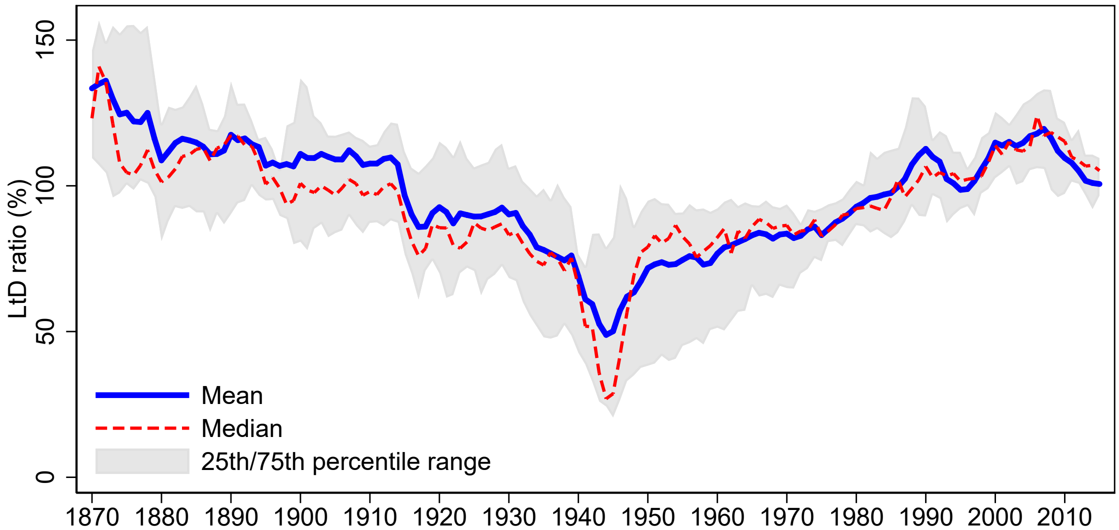
rather than a market outcome. Hand in hand with the increase of deposits as a source of funds, the average LtD ratio declined from above 100% in 1870 until 1945. It then increased, from 75% in the 1950s to more than 100% before the global financial crisis. After the crisis, the LtD ratio has decreased as banks have deleveraged and reduced non-core funding. Figure A.4 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.

3.4. Bank capital structure around financial crises

We conclude our exposition of key trends by describing the dynamics of banking sector balance sheet ratios around financial crises. Crises are identified narratively as periods when significant parts of the banking system fail or have to be rescued by government intervention (Laeven and Valencia 2012; Jordà, Schularick, and Taylor 2017; Schularick and Taylor 2012). The exact crisis dates are listed in the Appendix.

Consider the first two panels in Figure 4, which examine the LtD and capital ratios around financial crises. These ratios are shown relative to their value in the year of the crisis, year 0, which is normalized to 1. The solid blue line corresponds to the median of the corresponding ratio across all financial crises, and the grey area marks the interquartile range. We also split the data into a high- and a low-bank capital regimes. The dashed/dotted green/red lines plot the behavior of the median for financial crises when the lagged level of the capital ratio was above/below the median.

Figure 3: *LtD ratio, averages by year for 17 countries, full sample.*



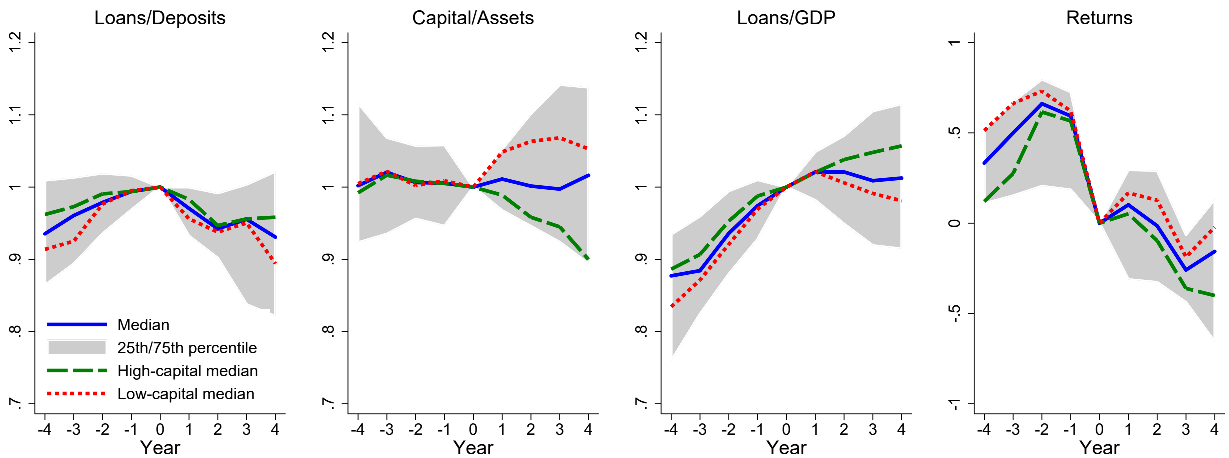
Notes: The blue line plots the mean of LtD ratios in the sample countries between 1870 and 2015. The red line refers to the median of the sample countries. The grey area is the interquartile range for the 17 countries in our sample.

The left panel of Figure 4 shows that the LtD ratio increases prior to financial crises and decreases afterwards. The patterns are less clear for the equity capital ratio, shown in the second panel of Figure 4. Before a financial crisis, book capital ratios do not change meaningfully. This is true at both high (dashed, green) and low (dotted, red) levels of capitalization. However, following a financial crisis the trajectory of capital ratios differs substantially depending on the initial level of capitalization. When capital is relatively low before the crisis, banks will tend to increase capital following the crisis. One possible explanation is that creditors probably penalize banks with low levels of capital. Moreover, changes in the regulatory environment following the crisis likely target banks whose capital buffers were deemed inadequate. When capital buffers are initially on the high side, they provide loss absorption capacity for banks following the crisis. As a result equity falls.

Another way to look at the data from the first two panels in Figure 4 is provided in Figure 5. These bin-scatter plots show that large credit expansions before a crisis are typically financed with a surge in non-deposit funding (the upward sloping cloud of points). These non-deposit funds then dry up after the crisis, at a time when credit growth is low or negative. In contrast, capital ratios remain stable (the flat cloud of points) in the lead up to the crisis, so that loss-absorption capacity does not appear to buildup concurrently, matching the patterns we described in Figure 4.

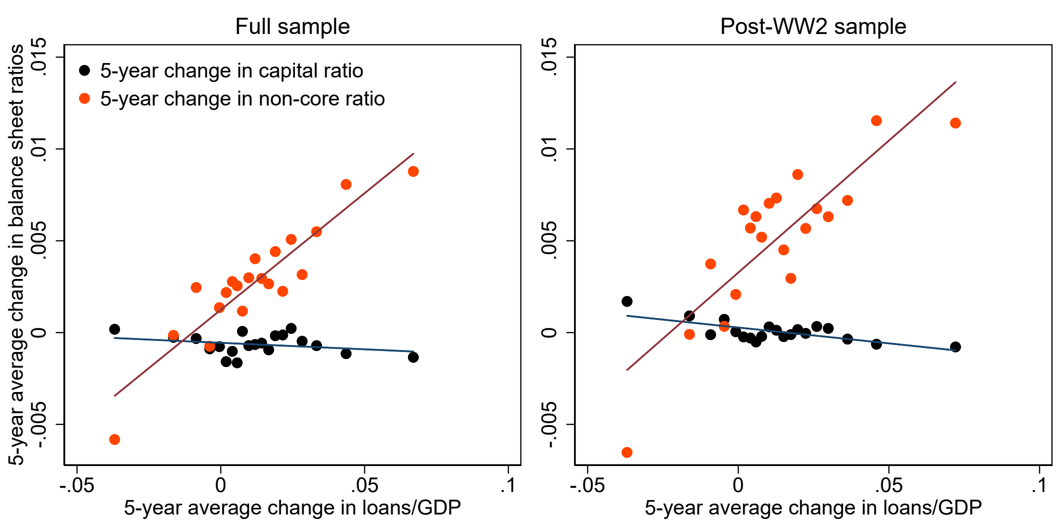
These two pieces of evidence speak of a weak connection between bank capital and crisis risk, a finding that is further corroborated in Figure 6. The graph shows the frequency of banking crises in five equal-sized bins, where observations are sorted into the bins according

Figure 4: *Event study of key variables centered on the crisis year.*



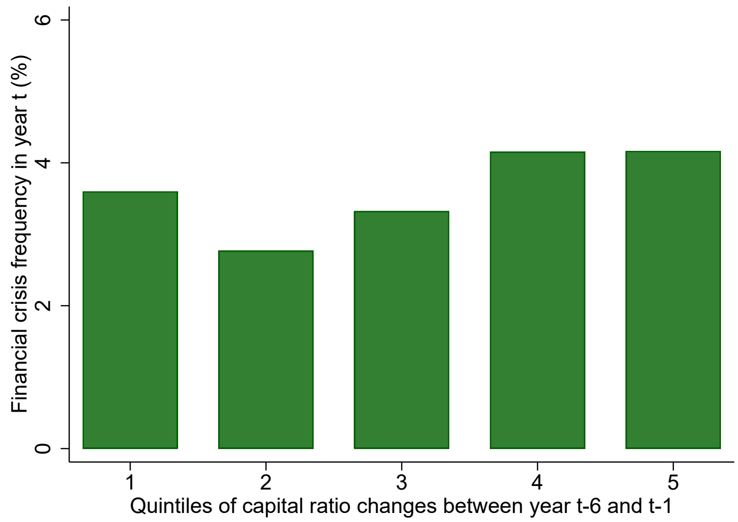
Notes: This figure presents the path of key variables around financial crises. Year 0 corresponds to a systemic financial crisis. The values of the respective ratio are scaled to equal 1 in year 0 in the first three panels. The fourth panel shows cumulative log excess returns on the bank index relative to year 0 (set to 0). The solid blue line corresponds to the median over all financial crises and the grey bands to the interquartile range. The dotted red/dashed green line shows the median for financial crises when the lagged level of the capital ratio was below/above the median of all financial crisis observations.

Figure 5: *Booms and liability composition.*



Notes: The graph shows binned scatterplots for the relationship between 5-year average changes in loans/GDP and changes in liability composition.

Figure 6: *Capital ratio changes and crisis frequency*



Notes: The figure shows the relationship between changes in capital ratios and financial crisis frequencies. Observations are sorted into five equal-sized bins according to the change in the capital ratio over the years $t-6$ to $t-1$. Vertical bars indicate the frequency of financial crises in year t for each of the bins.

to 5-year averages of changes in capital ratios. Banking crisis risks appear unrelated to capital ratio changes since the frequency of crises is almost the same in the lowest and highest bins of average 5-year capital ratio changes.[8]

Turning from asset and liability composition to the growth of balance sheets, the third panel of Figure 4 presents the well-known result that crises are preceded by a credit boom, which is clearly visible in the event windows. This pattern does not depend on the capitalization of the banking sector, the red dotted and the green dashed lines are essentially on top of each other. However, capitalization seems to play a role in the aftermath of financial crises, a pattern we explore in more detail later.

Finally, the fourth panel of Figure 4 shows cumulative log excess returns of bank shareholders relative to year 0. Returns are high during the boom, but shareholders make significant losses in the year of the crisis, mirroring the pattern reported in Baron and Xiong (2017). Even when bank capital ratios are above the median (the green dashed line), returns do increase prior to systemic banking crises, only for shareholders to be systematically disappointed in the following years. As argued by Baron and Xiong (2017) bank equity rallies during credit booms and before crisis events suggest that bank shareholders are not aware of the impending crisis. The right panel in Figure 4 suggests that bank equity prices do not seem to reflect risks more accurately when bank capital is above the median.

[8]Tables A.4 and A.5 report lagged levels and 5-year average changes of the capital ratio for crisis and no-crisis subsamples to get a sense of the variation of bank capital measures prior to financial crises.

4. Capital structure and crisis risk

How is capital structure related to bank risk-taking and the likelihood of financial crises? The previous section provided some suggestive evidence that we explore more formally in this section. Before that, it is useful to review what competing theories tell us about the role of capital. An influential view argues that "more skin in the game" would reduce bankers' risk-taking incentives. Bankers have an incentive to take risks since the payouts from their bets are asymmetric (Merton 1977). Thus, more skin in the game could lead to more prudent behavior, improve screening and monitoring incentives for banks, and thereby reduce the probability that financial institutions face large and life-threatening losses (Holmstrom and Tirole 1997; Mehran and Thakor 2011). Incentives to engage in risk shifting or asset substitution arise because of limited liability (Jensen and Meckling 1976) or to exploit mispriced deposit insurance (Merton 1977). In this view, higher capital ratios serve as a remedy for agency frictions at the heart of financial crisis dynamics.[9]

Another view puts overoptimism and neglect of tail risk at the center of the credit boom–crisis nexus. In recent credit cycle models (Bordalo, Gennaioli, and Shleifer 2018; Greenwood, Hanson, and Jin 2018) positive news during good times are extrapolated into the future and create overoptimism. Non-rational expectations of market participants allow financial crisis risks to remain largely unnoticed, until beliefs are suddenly corrected during a predictable reversal. In this view, bank capital is orthogonal to the buildup of crisis risks and only plays a buffer role once the reversal occurs.

In sum, theory offers no clear guidance whether higher capital is associated with lower crisis risk, and better empirical evidence is needed. Some studies have used contemporary data to study the performance of a leverage ratio as a crisis predictor and found no clear evidence.[10] Our long-run dataset on the liability composition of the banking sector allows

[9]Empirically, some studies report evidence consistent with the risk-shifting hypothesis (e.g., Esty 1997; Gan 2004; Landier, Sraer, and Thesmar 2011) while others have found little empirical support (e.g., Gropp, Hakenes, and Schnabel 2011 for banks and Gilje 2016 for non-financial firms). The disciplining role of equity capital has also been challenged theoretically. One strand of the literature argues that leverage can be beneficial because uninsured short-term creditors monitor and discipline bankers more effectively (Calomiris and Kahn 1991; Diamond and Rajan 2001) than equity holders. Other studies argue that imposing higher capital requirements may perversely increase bank risk (Kim and Santomero 1988; Rochet 1992; Blum 1999; Gale 2010). This will be especially the case, when banks have to meet profitability targets. Adrian, Friedman, and Muir (2015) show that return-on-equity targeting is indeed a widespread industry practice. Berger and Bouwman (2013) present emprical evidence that capital protects especially small banks individually against default, but Jiménez, Ongena, Peydró, and Saurina (2017) find evidence that higher regulatory capital buffers even increased risk-taking among Spanish banks during the boom in the early 2000's.

[10]Cihak and Schaeck (2010) and Detken, Weeken, Alessi, Bonfim, Boucinha, Castro, Frontczak, Giordana, Giese, Jahn, Kakes, Klaus, and Jan (2014) find no relationship between capital ratios and crisis risks, while Behn, Detken, Peltonen, and Schudel (2013) find a link between low capitalization and crisis risks. Barth, Caprio, and Levine (2006) find no relationship between bank capital regulation and crisis risks.

us to study the relationship between capital, risk-taking, and crises systematically, exploiting the within country variation in capital ratios over time.

We now turn to a formal econometric model to investigate financial crises and the predictive ability of our three key balance sheet measures, namely the capital ratio, the LtD ratio, and the non-core ratio. We will estimate probit regressions and assume, as is standard in the literature, that the probability of a crisis conditional on observables $\boldsymbol{X}_{i,t}$ can be represented in terms of the normal cumulative distribution function,

$$Pr[S_{i,t} = 1 \mid \alpha_i, \boldsymbol{X}_{i,t}] = \Phi(\alpha_i + \boldsymbol{\beta}\boldsymbol{X}_{i,t}) \,, \tag{4}$$

for all years t and countries i in the sample, where $S_{i,t}$ is an indicator variable for the start of a systemic financial crisis.

The vector $\boldsymbol{X}_{i,t}$ includes the average annual change of the ratio of credit to GDP over the previous 5-year window (denoted Δ_5 Loans/GDP), following Schularick and Taylor (2012). We then evaluate the additional predictive power coming from the lagged level of each of the three balance-sheet ratios and 5-year average annual changes in capital ratios, one at a time. The coefficients reported in all the tables correspond to the marginal effect of the covariate evaluated at its sample mean. To soak up cross-country heterogeneity, we include a country fixed effect, α_i. We exclude 5-year windows after the two world wars to avoid measuring the effects of wartime financing on banks' balance sheets as discussed earlier. Pooled models and a variety of other robustness checks are reported in the appendix.

To evaluate crisis predictive ability, we focus on the AUC statistic, the area under the ROC curve. This standard classification statistic measures the ability of a model to correctly sort the data into crisis and no-crisis bins. The AUC uses the variation of true and false positive rates as a function of the entire range of probability cutoffs. The AUC is close to 0.5 for models that have little ability to sort observations correctly, and it approaches 1 for models that perfectly sort the data. The advantage of the AUC over other standard measures of fit is that it is agnostic with respect to the analyst's preferences over true positives and true negatives. The better the prediction technology, the higher these true classification rates will be. In addition, it is less sensitive to settings where events (in this case, crises) are relatively rare.

The central question we address is whether capital ratios improve crisis prediction. We use as a benchmark null a model that only includes country-fixed effects. This benchmark has an AUC = 0.62 in the full sample, and an $AUC = 0.60$ in the post-WW2 sample. Since some countries are more prone to financial crises than others, 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.

Table 4: *Multivariate probit models for systemic financial crises.*

	(1) Full	(2) Post	(3) Full	(4) Post	(5) Full	(6) Post	(7) Full	(8) Post
Δ_5 Loans/GDP	0.85^{***}	0.62^{***}	0.84^{***}	0.64^{***}	0.59^{***}	0.26^{***}	0.84^{***}	0.17^{*}
	(0.11)	(0.07)	(0.11)	(0.07)	(0.12)	(0.09)	(0.12)	(0.10)
Capital ratio	0.17^{***}	0.06						
	(0.03)	(0.23)						
Δ_5 Capital ratio			-0.07	1.29				
			(1.09)	(1.90)				
LtD ratio					0.04^{**}	0.05^{***}		
					(0.02)	(0.01)		
Non-core ratio							-0.01	0.09^{***}
							(0.02)	(0.01)
AUC	0.75	0.74	0.71	0.75	0.72	0.80	0.71	0.84
	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)
Observations	1735	1004	1721	998	1713	1004	1671	1004

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

Table 4 shows the full and post-WW2 sample results for the specifications with covariates. As in Schularick and Taylor (2012), the credit variable is positively related to a higher probability of a crisis in all specifications. The model with 5-year annual average changes in credit/GDP as a single predictor variable (not reported) has an AUC = 0.70 in the full sample, and an AUC = 0.74 in the post-WW2 sample, statistically different from the fixed effect null model (with AUC = 0.62 or 0.60). In column (1), for example, the coefficient of 0.85 means that a 2 percentage point increase (about 1 standard deviation) in the average annual loans to GDP ratio would increase the probability of a crisis by 1.7 percentage points, all else equal. Note that crises happen about 5% of the time in the full sample, so this is a considerable boost in crisis risk.

We see that models that include the unweighted capital ratio typically have the "wrong" sign. Higher capital is associated with *higher* crisis risk. The effects are economically small. A 2 percentage point boost to capital (an oft discussed figure for countercyclical buffers) raises the crisis probability by 0.34 percentage points in the full sample, for the specification in column (1).

The coefficient on the loan-to-deposits ratio in column (5) is more intuitive and statistically significant though economically small. A 10 percentage point increase in this ratio (about 1 standard deviation) boosts crisis risk by 0.4 percentage points. Lastly, the model based on the non-core ratio and displayed in column (7) has an AUC = 0.71, almost equivalent to the credit-only null model in the full sample.

The post-WW2 results have a similar flavor but with a few notable differences. The levels and changes of the capital ratio now both have a positive coefficient and add no meaningful predictive value. The coefficient on the loan-to-deposits ratio is highly significant and yields some improvement in predictive ability: AUC rises from 0.74 in the credit-only model, to 0.80 using the LtD ratio in column (6). For the post-WW2 sample, the non-core ratio also enters significantly, with the expected sign (more non-traditional funding predicts crisis risk), and with further improvement in predictive ability, as the AUC increases to 0.84 in column (8). These results reiterate that, in the post-WW2 era, it was credit expansion and the debt funding structure of banks, not capital ratios, that best predicted crisis risk.

4.1. Additional controls, market-based capital, and subsamples

Why is there no visible association between bank capital and crisis risk? One explanation may be that the markets force banks to adjust capital endogenously if the riskiness of assets changes. Variations in the simple capital ratio might then not properly proxy for changes in the underlying risk-adjusted capital ratio. Controlling for asset and macroeconomic risks will thus be an important task, but not the only one. We will also study the capital-crisis nexus replacing the book value of capital with a market-based measure. We also explore the stability of our core results across a variety of additional specifications described briefly here and in more detail in the appendix.

However, all these checks reinforce the central message from Table 4: there is very little evidence linking capital, as a measure of skin in the game, and subsequent crises. This is a statement about the absence of predictive ability of the capital ratio, but it has interesting implications on its own. It means that our current system of global banking regulation is based on a variable that is not correlated with the outcomes that we care the most about—namely, reducing the incidence of financial crises.

4.2. Controlling for asset risk

Table 5 includes controls for macroeconomic risks, asset prices, and the market's perception of the riskiness of banks' balance sheets. For the latter we use the bank equity risk premiums constructed by Baron and Xiong (2017).[11] In addition to risk premiums, we control for house price booms, proxied by 5-year average changes in real house prices, and the volatility

[11] When data on bank index excess returns is not available, we use excess returns on the broad stock market index from Jordà, Knoll, Kuvshinov, Schularick, and Taylor (2019) instead.

Table 5: *Multivariate probit models for systemic financial crises, controlling for asset risk.*

	(1) Full	(2) Full	(3) Post	(4) Post	(5) Full	(6) Full	(7) Post	(8) Post
Δ_5 Loans/GDP	0.93***	0.70***	0.40***	0.26*	0.94***	0.71***	0.41***	0.27*
	(0.10)	(0.10)	(0.13)	(0.14)	(0.11)	(0.11)	(0.13)	(0.16)
Capital ratio	0.16***	0.16***	0.09	0.01				
	(0.05)	(0.06)	(0.18)	(0.19)				
Δ_5 Capital ratio					0.33	0.71	0.72	1.07
					(1.22)	(1.14)	(1.67)	(1.66)
Macrocontrols	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Asset prices	No	Yes	No	Yes	No	Yes	No	Yes
AUC	0.74	0.80	0.80	0.83	0.72	0.79	0.80	0.83
	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Observations	1582	1277	988	887	1570	1274	984	884

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy. All models include country fixed effects. Coefficients are marginal effects. Macrocontrols include volatilities of real GDP per capita, inflation, loans-to-GDP and short-term interest rates as well as averaged real GDP per capita growth, inflation, and short term interest rates over the previous five years. Asset risks include average changes of real house prices and the volatility of house price growth over the previous five years and three lags of log excess returns on the bank index if available, on the general index otherwise. See text. Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of house price growth over the preceding 5-year window. Interest rate or inflation volatility, as well as other macroeconomic risks could also affect the riskiness of banks' balance sheets. We control for these factors by including the volatilities of GDP growth, inflation, short-term interest rates, and loans-to-GDP changes over the preceding 5-year window, as well as GDP per capita growth, inflation, and short-term interest rates.

We first add these macroeconomic controls to the respective baseline model using long- and short-run variation in capital ratios in the full and post-WW2 sample in Table 5, in the odd-numbered columns. As for the asset price controls, the house price variables and bank equity risk premiums are only available for a subset of observations, so these regressors are added subsequently, in the even-numbered columns.

Summing up, all specifications in this table result in marginal effects nearly identical to those reported in Table 4. This is true after controlling for a wide range of financial and macroeconomic risk factors and it holds when analyzing long-term variation using levels of the capital ratio (columns 1 to 4) or whether focusing on short-term variation using 5-year average annual changes in capital ratios instead (columns 5 to 8). The coefficient on bank capital always enters with the "wrong" sign: more capital predicts a higher, not lower risk of crisis.

Table 6: *Multivariate probit models for systemic financial crises, market-based capital ratio, controlling for asset risk.*

	(1)	(2)	(3)	(4)
Δ_5 Loans/GDP	0.85***	0.14	0.98***	0.11
	(0.23)	(0.21)	(0.29)	(0.19)
Market-based capital ratio	0.03	-0.16		
	(0.12)	(0.12)		
Δ_5 Market-based capital ratio			0.62	0.24
			(0.88)	(0.53)
Macrocontrols	No	Yes	No	Yes
House Price Changes	No	Yes	No	Yes
AUC	0.68	0.77	0.68	0.83
	(0.07)	(0.06)	(0.07)	(0.04)
Observations	413	410	348	348

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy. All models include country fixed effects. Coefficients are marginal effects. Macrocontrols include volatilities of real GDP per capita, inflation, loans-to-GDP and short-term interest rates as well as averaged real GDP per capita growth, inflation, and short term interest rates over the previous five years. House price variables include average growth of real house prices and the volatility of house price growth over the previous five years. See text. Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3. Market value of capital

So far, our results suggest that accounting-based capital ratios have little predictive power for financial distress. Haldane (2011) reports a similar finding, and proposes using market-based capitalization indicators in addition to accounting data. While we included market returns as controls above, we now focus on a direct measure of market-based capitalization. On the right hand side of Table 6 we replace the book value of bank capital as a predictor with a market valuation-based capital ratio. We use data from Datastream on the price-to-book ratios for country level bank indices to compute this measure. Including this data causes our sample size to change substantially as the price-to-book ratio is only available for 14 of our 17 sample countries starting in 1973 or later.[12]

Based on the price-to-book ratio and our balance sheet data, we compute market leverage as:[13]

$$\text{Market Leverage} \equiv \frac{\text{Market Value of Equity}}{\text{Book Value of Assets}} = \text{Price-to-book Ratio} \times \text{Capital Ratio}\,. \tag{5}$$

[12]There is insufficient data on price-to-book ratios for bank indices in Finland, Norway and Sweden.

[13]Note that the price-to-book ratio is market value divided by book value of equity and our capital ratio was defined as book value of capital divided by total assets. The price-to-book measure is only available for listed banks contained in the bank index. Hence, we have to assume that this ratio is representative for the entire banking sector.

Column (1) of Table 6 shows that, even with this measure, there is still no systematic relationship between bank capital and banking crises. Moreover, measured by the *AUC*, the market capital measure does not add any predictive power. In column (2) we additionally control for macroeconomic risks and house price changes and their volatility. We do not include bank risk premiums here, as bank equity risk premiums are closely related to changes in market capitalization. The coefficient on capital turns negative (the "right" sign), but remains insignificant, in just this one specification. Columns (3) and (4) confirm that short-run variation in this measure is unrelated to crisis risk. In short, the results are in line with our previous findings.

4.4. Other robustness checks

The appendix presents a large battery of additional robustness tests, briefly described here.

Clustering In Table A.6 and Table A.7 we repeat our two main specifications additionally clustering standard errors on the year dimension to deal with possible cross-sectional correlation, but the results remain unchanged.

Deposit insurance Deposit insurance could affect the link between capital and crisis risk. Hence, we explore the stability of our results, and in Table A.8 we estimate our baseline specification separately for country-year observations with and without a deposit insurance scheme in place. The coefficients for the capital ratio remain insignificant and do not improve predictive ability.

Heterogeneity within banking systems Aggregate capital ratios could mask substantial heterogeneity within banking systems. Risks could be concentrated in a few, systemically important institutions or in a subset of banks with very low capital ratios. We employ more granular data in Table A.9 and Table A.10 to study whether the performance of the capital ratio as a crisis predictor improves when we focus on the largest banks in each country or when we focus on the distribution within a banking system based on a case study of the Italian banking sector. In both cases, capital ratios remain poor predictors of crisis risks.

Booms split by the preceding level of capital If more skin in the game induces prudent behavior by banks, we would expect to find in the data that credit booms starting at high levels of bank equity are less likely to end in a crisis than credit booms financed with less equity. In Table A.11, however, we find no difference between high and low capital booms.

Split samples by period In Tables A.12 and A.13 we present unconditional correlations from probit specifications including only fixed effects in the full and post-WW2 samples. Table A.14 shows that there is no systematic relationship between capital ratios and financial crises in a pre-1914 sample with little or no bank regulation in many countries.[14]

Saturated model Table A.15 shows results where we start from a full model including the change in credit-to-GDP, the capital ratio, and the non-core ratio. We then drop one variable at a time. The resulting decline in predictive accuracy from dropping the capital ratio is small relative to dropping the other variables, and the coefficient has the "wrong" positive sign in the full sample.

Further subsamples and crisis chronologies We then exclude the 2007–08 financial crisis (Table A.18), and repeat the analysis excluding the UK and the US. (Table A.19) since these two countries have historically the largest share of shadow banking activities. Additionally, we test robustness to the inclusion of country-decade fixed effects into the probit specifications (Table A.21) to control for unobservable long-run changes across countries. Table A.22 employs a different crisis chronology that is based on crashes in the bank equity index (Baron, Verner, and Xiong 2018), but capital ratios are also unrelated to these crashes.

IV estimate Many results here, and in the appendix, show that higher capital is weakly, but positively associated with higher crisis risk. As discussed above, one explanation could be that bank capital is endogenously determined. Specifically, our controls for asset risk may not entirely pick up the reality (or perception) that a bank with risky positions may hold or be forced to hold more capital. How much could endogeneity bias still matter here?

Ideally, an instrumental variable would be needed to capture exogenous variation in capital—a tall order. Given data availability, the best we can devise is past return on assets, a common source of voluntary capital expansions (Appendix U). The first stage shows this candidate IV is strong, but as always the exclusion restriction cannot be formally evaluated. Assuming that, and controlling for credit growth and risk premiums, changes in return on assets are otherwise unrelated to crisis risk, and it can serve as an instrument for bank capital. Subject to these caveats, Table A.23 shows Conditional IV estimates. Here, capital ratios are still not associated with crisis risk: the point estimate is negative, but is economically (and statistically) very weak. This exercise goes to show that the purported strong negative association between capital and crisis risk is hard to find.

[14] For completeness, Tables A.16 and A.17 repeat the estimates of Tables A.12 and A.13, but without fixed effects to account for the possibility that the fixed effects capture cross-country differences in capital ratios and their effects on crisis risks.

The results of all these tests confirm our findings: credit growth, the LtD ratio and the non-core ratio are significant predictors of financial crisis, but the capital ratio exhibits a weak or non-existent predictive relationship with crisis risk.

5. Capital ratios and bank stock returns

A different approach to analyzing the role of bank capital is by examining its relation to the returns on bank stocks. In recent work, Baron and Xiong (2017) show that loan growth predicts lower subsequent returns to bank equity—there is little evidence that investors ask for compensation for rising risks during credit booms. In line with behavioral theories of credit cycles, the equity market does not appear to price the risks stemming from rapid credit expansions. Current regulation builds on bank capital as indicator of bank risk. So is this reflected in stock returns? Does the capital ratio help predict stock returns going forward and signal rising risks in the way that asset-side quantities do?

Predicted bank stock returns To test this, we ask whether balance sheet ratios are correlated with future returns on bank stocks. This is a useful check of whether capital ratios contain valuable information for regulators. We follow Baron and Xiong (2017) and regress bank index excess returns on bank balance sheet ratios using credit growth and equity index dividends as controls using the following specification:

$$r^{bank}_{i,t+h} - r^{f}_{i,t+h} = \alpha_{h,i} + \boldsymbol{\beta} \boldsymbol{X}_{i,t} + \epsilon_{i,h} \,, \tag{6}$$

where $r^{bank}_{i,t+h}$ is the horizon-h cumulative log-return on bank equity, and $r^{f}_{i,t+h}$ the corresponding log-return using the safe rate.

Table 7 reports the estimates of this regression for each balance sheet variable of interest. Note that we standardize all explanatory variables at the country level and use only past observations to avoid any look-ahead bias. Table A.27 shows the results where these controls are omitted for completeness. The results are very similar.

Columns (1)–(3) in Panel A in Table 7 are the baseline results with only $\Delta_3 Loans/GDP$ and bank equity index dividend yield as regressors. Columns (1)–(3) confirm the core result from Baron and Xiong (2017) showing that an increase in the credit-to-GDP ratio over a three-year window is associated with lower bank equity returns going forward.

Next, Panel B looks at the additional explanatory power of the capital ratio measured two ways: first, in levels (columns (1)–(3)); and, second, over a three-year period (columns (4)–(6)). In both cases, higher capital ratios signal lower returns, but the standard errors are large and the fit is almost the same as the baseline regression in panel A.

Table 7: *Balance sheet measures and mean returns on the bank equity index.*

Cumulative returns	(1) 1-year	(2) 2-year	(3) 3-year	(4) 1-year	(5) 2-year	(6) 3-year
Panel A	RHS: Δ_3 Loans/GDP			RHS: Δ_3 Assets/GDP		
See column header	-0.042***	-0.083***	-0.108***	-0.006	-0.007	-0.021
	(0.005)	(0.011)	(0.017)	(0.008)	(0.015)	(0.026)
R^2	0.034	0.049	0.060	0.035	0.050	0.062
Observations	885	859	832	885	859	832
Panel B	RHS: Capital ratio			RHS: Δ_3 Capital ratio		
See column header	-0.050	-0.101	-0.145	-0.032	-0.036	-0.007
	(0.047)	(0.083)	(0.116)	(0.022)	(0.043)	(0.064)
R^2	0.037	0.054	0.066	0.037	0.051	0.060
Observations	885	859	832	885	859	832
Panel C	RHS: Δ_3 LtD ratio			RHS: Δ_3 Non-core ratio		
See column header	-0.014*	-0.026*	-0.025	0.005	0.009	-0.004
	(0.008)	(0.015)	(0.020)	(0.007)	(0.011)	(0.015)
R^2	0.034	0.049	0.058	0.033	0.047	0.057
Observations	873	847	820	859	833	806

Notes: The dependent variable is the log excess return on the bank equity index from Baron and Xiong (2017) cumulated over h years, where h is specified in the column header. All specifications include Δ_3 Loans/GDP and bank equity index dividend yield as control variables (with the exception of Δ_3 Loans/GDP in the first three columns of Panel A these results are nor reported). All RHS variables are standardized at the country level using past data to avoid look-ahead bias. All specifications include country fixed effects. Standard errors in parentheses are computed using the Driscoll-Kraay method accounting for autocorrelation of up to 17 lags (the mean of results using the automatic bandwidth selection in individual country time series regressions). *, **, *** indicate significance at the 0.1, 0.05, 0.01 level, respectively.

Finally, Panel C examines the two liquidity ratios we discussed earlier. We find that increasing loan-to-deposit ratios (columns (1)–(3)) are somewhat informative and are associated with lower returns to bank shareholders, but the effect is very mild (the effects are larger in the univariate analysis reported in Table A.27 not surprisingly).

Unlike quantity measures of asset growth, and insofar as one can interpret the capital ratio as a proxy for incentive-driven risk taking, we find that the capital ratio is *not* associated with future banking sector risks. Liquidity ratios contain some information, but in line with the idea of belief-driven credit cycles, asset-side quantity measures—such as loan growth—signal impending risks more effectively. In sum, the evidence on return predictability is also consistent with the view that risk-taking in credit booms is not closely linked to "skin in the game" explanations based on capital.

Discussion The evidence presented above does not suggest that capital ratios play an important role in signaling imminent crisis risk or future declines in bank stock returns. Our analysis, based on long-run cross-country data, confirms the results of studies that rely on shorter samples with fewer countries (see, e.g., Cihak and Schaeck 2010; Barth, Caprio, and Levine 2006). Historically, credit booms—and the repricing of risk that often follows them—appear to have overwhelmed even the highest of capital buffers. Credit booms are equally dangerous whether levels of bank capital are high or low.

Rather, the evidence suggests that the disciplining effects of bank capital are absent when they presumably matter most: during credit booms (Jiménez et al. 2017). This finding is consistent with work that points to the overoptimism of insiders and market-wide neglect of crash risk during credit booms (Kindleberger 1978; Minsky 1986; Shiller 2000; Bordalo, Gennaioli, and Shleifer 2018). This core result is robust to a whole battery of controls for asset and macroeconomic risk factors. Moreover, we find that the association between bank capital and crisis risk is weak across a wide range of regulatory and economic environments.

Capital ratios typically do not change much during the credit boom run-up to banking crises. Figure 5 has shown that changes in the liability composition observed during credit booms are mostly in the mix between deposits and non-core liabilities, and not in the mix between capital and debt. Moreover, the market value of equity capital is endogenous and often surges during the boom. He and Krishnamurthy (2013) therefore argue that intermediary leverage is counter-cyclical. From a historical perspective, given our new data, this seems quite plausible.

Market-based capital ratios do not outperform book measures of capital as crisis predictors. Equity investors typically fail to spot the risks that build up during credit booms, as Baron and Xiong (2017) have argued and our return predictability results also show. Our findings suggest that this failure is more closely related to the risks associated with quantity-based measures than with the debt-capital mix and its incentive effects.

However, liquidity matters. Rising loan-to-deposit ratios and non-deposit funding presage banking crises. Growing maturity mismatch and exposure to uninsured short-term debt pose a measurable threat to financial stability, in line with the seminal insights offered by Diamond and Dybvig (1983).

6. Bank capital and the severity of financial crisis recessions

Although modern financial history provides little evidence that higher levels of bank capital are associated with safer financial systems, could they facilitate the recovery from a crisis? This is the question we investigate in this section. Higher capital ratios are indeed associated with milder recessions and swifter recoveries from financial crises. This finding echoes recent empirical work by Cecchetti, King, and Yetman (2011) and Berkmen, Gelos, Rennhack, and Walsh (2012) on the 2007–08 financial crisis and adds nuance to the characterization of financial crisis recoveries reported by Jordà, Schularick, and Taylor (2013). The results are consistent with recent models of macroeconomic amplification through the balance sheets of levered financial intermediaries (e.g., Adrian and Boyarchenko 2012). Furthermore, they add an aggregate dimension to empirical results on the real effects of shocks to financial intermediaries (e.g., Peek and Rosengren 2000; Khwaja and Mian 2008; Jiménez et al. 2017). These results also show that the variation in leverage ratios that we measure do capture fluctuations in the risk exposure of banks, linking the first and the second part of the paper.

The experiments that we conduct are straightforward. We take bank capital at its pre-treatment level. Crises, by virtue of being largely unpredictable with respect to capital, act as a quasi-random assignment mechanism that permits us a direct comparison of their aftermath for different levels of capital. We use local projections to conduct this type of experiment (Jordà 2005) to allow for appropriate control.

In particular, we focus on recession episodes and split these into *financial* recessions (recessions associated with a financial crisis in a ± 2 year window), and *normal* recessions (all others), as in Jordà, Schularick, and Taylor (2013). We further split financial recessions into two bins depending on whether the one-period lagged capital ratio of the banking sector at the onset of the recession is above or below the historical average.

This simple setup provides a clean benchmark that is easy to grasp. Later, we extend the analysis by conditioning on a rich set of controls. We want to ensure that any differences we find for different levels of the capital ratio are not explained by alternative omitted observable factors. Though not reported here, we also experimented with a split of normal recessions based on the capital ratio. However, we do not find any significant differences between them, a finding that is echoed in subsequent analysis.

The dependent variable is defined as 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. We use the Bry and Boschan (1971) algorithm to determine $t(p)$. At yearly frequency, this algorithm exactly matches the NBER peak dating for the US. The definition of the dependent variable can be interpreted as the cumulative growth of real GDP per capita between the business cycle peak and h years later. The specification includes country fixed effects.

We define an 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

Table 8: *Normal versus financial recessions, real GDP per capita by capital ratio, no controls, full sample.*

Dependent variable: change in 100 × log real GDP per capita relative to Year 0

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	-1.91***	-0.00	2.34***	3.99***	5.40***	9.82***
	(0.15)	(0.28)	(0.28)	(0.37)	(0.28)	(1.18)
Financial recession, high capital ratio	-1.34*	-2.61**	-3.00***	-2.33	-3.09*	-12.37**
	(0.72)	(1.02)	(0.94)	(1.51)	(1.49)	(4.53)
Financial recession, low capital ratio	-1.14*	-3.90***	-6.20***	-6.52***	-7.16***	-24.91***
	(0.55)	(1.08)	(1.42)	(1.62)	(1.17)	(5.25)
R^2	0.532	0.191	0.184	0.191	0.257	0.178
H_0: financial high = low, p-value	0.79	0.19	0.07	0.04	0.04	0.05
Observations	248	248	248	248	248	248

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.

define an indicator variable, $\delta_{i,t(p)}$, that is one if the one-period lagged capital ratio of the banking sector in country i at the start of the financial recession $t(p)$ is higher than the mean of one-period lagged capital ratios over all financial recessions.

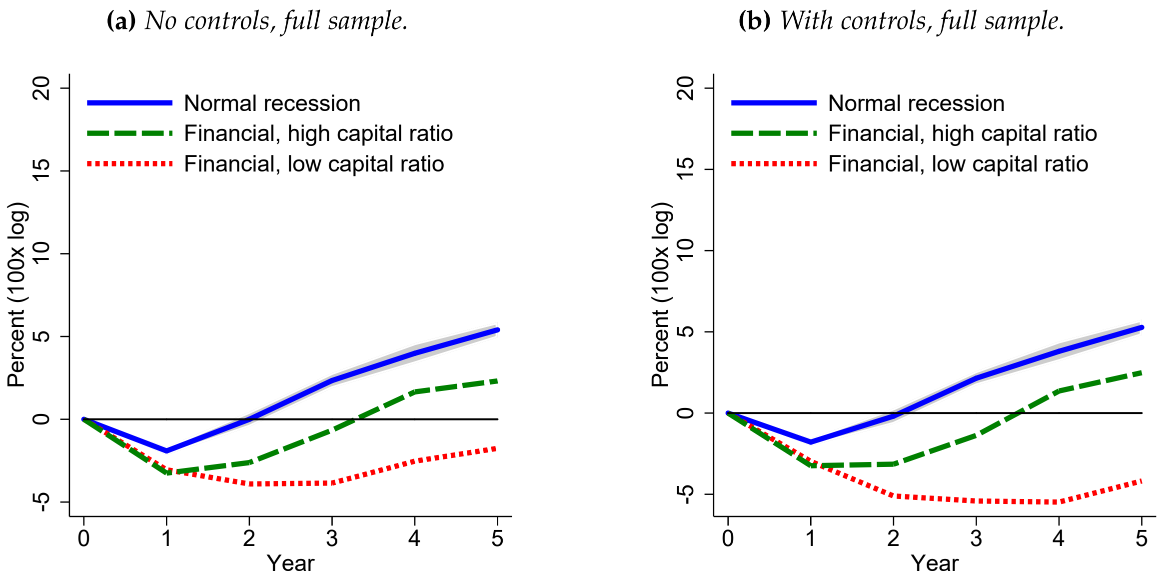
Using these indicators, we first estimate panel local projections without covariates,

$$\Delta_h y_{i,t(p)} = \sum_{i=1}^{I-1} \alpha_{i,h} D_{i,t(p)} + \mu_h + \gamma_h^{HI} d_{i,t(p)} \times \delta_{i,t(p)} + \gamma_h^{LO} d_{i,t(p)} \times (1 - \delta_{i,t(p)}) + \epsilon_{i,t(p)} \,, \quad (7)$$

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. With this setup, 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, $\mu_h + \gamma_h^{HI}$), which can then be compared to μ_h for a normal recession.

Estimates in Table 8 are for the full sample of N = 248 recessions. On average, financial recessions are worse than normal recessions, as shown by the negative coefficients in the second and third rows. However, though the path is still much worse than normal, the economy recovers faster from a financial recession with a well-capitalized banking sector. After 5 years, output per capita is more than four percentage points lower relative to a normal recession when the banking sector is poorly capitalized (-7.16%) than otherwise

Figure 7: *Normal versus financial recessions, real GDP per capita by capital ratio*



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.

(-3.09%). In our sample of financial recessions, the mean capital ratio of the banking system in the year prior to the start of a recession is 13.7%. The average capital ratio in the poorly-capitalized *LO* bin is 8.3%, while it is 22.7% in the better-capitalized *HI* bin.

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 1 and year 2). However, economically speaking, higher bank capital at the onset of a financial crisis coincides with a considerably faster economic recovery. Over the 5-year period considered, the relative cumulative GDP costs of a financial crisis with a below-average capitalized banking sector amount, on average, to a loss of more than 12 percentage points of cumulative GDP as reported in column (6) of the table (compare -24.91% with -12.37%).

The left panel in Figure 7 displays the results in Table 8 graphically. The right panel repeats the analysis by adding controls as discussed in the next section. Financial recessions are worse than normal recessions regardless of the bank capital ratio. However, while an economy with a well 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 poorly capitalized banking sector (red dotted line) sees a more protracted slump and recovers more slowly. Figure A.9 in the appendix shows very similar patterns when we sort financial crisis recessions into four quartlies according to lagged capital ratios.

Table 9: *Normal versus financial recessions, real GDP per capita by capital ratio, with controls, full sample.*

Dependent variable: change in 100 × log real GDP per capita relative to Year 0

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	-1.79***	-0.19	2.15***	3.80***	5.27***	9.24***
	(0.14)	(0.29)	(0.27)	(0.37)	(0.29)	(1.20)
Financial recession, high capital ratio	-1.45*	-2.96**	-3.52***	-2.44*	-2.79**	-13.16***
	(0.73)	(1.03)	(0.95)	(1.30)	(1.25)	(4.04)
Financial recession, low capital ratio	-1.19*	-4.92***	-7.56***	-9.28***	-9.45***	-32.40***
	(0.60)	(1.08)	(1.45)	(1.64)	(1.20)	(5.43)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.560	0.336	0.336	0.325	0.394	0.328
H_0: financial high = low, p-value	0.71	0.08	0.04	0.00	0.00	0.01
Observations	210	210	210	210	210	210

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.

6.1. Adding controls

Are the results just reported an artifact of omitted macroeconomic aggregates that might be correlated with bank capital structure and the economic recovery? In a second step, we add a vector of control variables $\boldsymbol{X}_{i,t(p)}$ to the specification of Equation 7. These are: 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.

The estimates of this augmented model appear in Table 9 and are very similar to the earlier results without control variables. Once again, the coefficients for the two crisis recession bins separated by the level of banking sector capitalization are statistically not distinguishable in year 1, but capitalization begins to matter from year 2 onwards. The paths are shown in the right panel of Figure 7, and the similarities with earlier results are clear. Indeed, the path differences seem, if anything, even starker after controls are added.

6.2. Capital ratios as a continuous treatment

So far we have split financial recessions into two bins according to the capitalization of the banking sector. 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, that is, $(w_{i,t(p)} - \overline{w}_{i,N})$ 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 six control variables from our baseline control specification above. We then estimate the following set of local projections

$$\begin{aligned}\Delta_h y_{i,t(p)} \quad = \quad & \sum_{i=1}^{I-1} \alpha_{i,h} D_{i,t(p)} + \mu_h + \gamma_h d_{i,t(p)} + \beta_h^N (1 - d_{i,t(p)})(w_{i,t(p)} - \overline{w}_{i,N}) \\ & + \beta_h^F d_{i,t(p)}(w_{i,t(p)} - \overline{w}_{i,F}) + \boldsymbol{\Phi} \boldsymbol{X}_{i,t(p)} + \epsilon_{i,t(p)} \,, \end{aligned} \tag{8}$$

for $h = 1, ..., 5$. Here, μ_h is the average path after a recession peak, $\mu_h + \gamma_h$ 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 percentage points higher than the country-specific mean at the start of financial recessions is associated with a cumulative real GDP per capita that is higher in year 5 by 3.1% (and cumulatively higher by 8.6% 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 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.

Table 10: *Normal versus financial recessions, real GDP per capita with continuous capital ratios, with controls, full sample.*

Dependent variable: change in 100 × log real GDP per capita relative to Year 0

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Normal recession	-1.76***	-0.19	2.07***	3.75***	5.23***	9.10***
	(0.14)	(0.28)	(0.22)	(0.33)	(0.26)	(1.03)
Financial recession	-1.31**	-4.05***	-5.76***	-6.25***	-6.50***	-23.88***
	(0.56)	(0.91)	(0.81)	(1.15)	(0.87)	(3.66)
Normal recession × capital ratio	-0.03	-0.06	0.05	-0.04	-0.06	-0.14
	(0.03)	(0.05)	(0.09)	(0.10)	(0.11)	(0.33)
Financial recession × capital ratio	-0.05	0.11*	0.21*	0.28**	0.31**	0.86**
	(0.04)	(0.05)	(0.11)	(0.12)	(0.11)	(0.40)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.565	0.339	0.327	0.301	0.383	0.313
H_0: normal = financial, p-value	0.52	0.00	0.00	0.00	0.00	0.00
H_0: normal × capital = financial × capital, p-value	0.63	0.02	0.27	0.04	0.01	0.05
Observations	210	210	210	210	210	210

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.

6.3. Accounting for long-run changes in capital ratios

Could our results be biased by the inclusion in our sample of the recent 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 to $N = 193$ recession observations (Table A.26). 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.

It is also possible that the speed of economic recovery after recessions changed over our long-run sample. In Table 11 we add more fixed effects to account for decade specific variations in the speed of economic recovery; these are defined in the same way as described for the country fixed effects, in order to estimate a constant average path.[15] The results, displayed in Table 11 are reassuring. A high capital ratio predicts a speedier recovery

[15] Hence, decade fixed effects add up to one and we omit the first decade of the twenty-first century.

Table 11: *Normal versus financial recessions, real GDP per capita binned by capital ratio, with controls, full sample including decade fixed effects.*

Dependent variable: change in 100 × log real GDP per capita relative to Year 0

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	-1.85***	0.24	2.89***	4.48***	6.18***	11.95***
	(0.15)	(0.30)	(0.27)	(0.63)	(0.66)	(1.77)
Financial recession, high capital ratio	-1.01	-2.06*	-2.90**	-0.32	-0.64	-6.93
	(0.70)	(0.99)	(1.35)	(2.14)	(2.35)	(6.26)
Financial recession, low capital ratio	-1.27	-4.36***	-6.45***	-7.60***	-7.30***	-26.97***
	(0.90)	(1.34)	(1.75)	(2.12)	(1.65)	(7.15)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Decade fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.599	0.422	0.451	0.465	0.518	0.471
H_0: financial high = low, p-value	0.81	0.12	0.09	0.02	0.03	0.03
Observations	210	210	210	210	210	210

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.

from a financial crisis recession, with the average path being close to the path in normal recessions. Low capital ratios are associated with slower recovery and lower output several years after the crisis.

Both approaches, excluding the recent crisis and including decade fixed effects, are depicted in Figure 8. The left panel shows average path estimates when we exclude the crisis from our data. The right panel shows the estimates when we include decadal fixed effects. In both cases, 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.

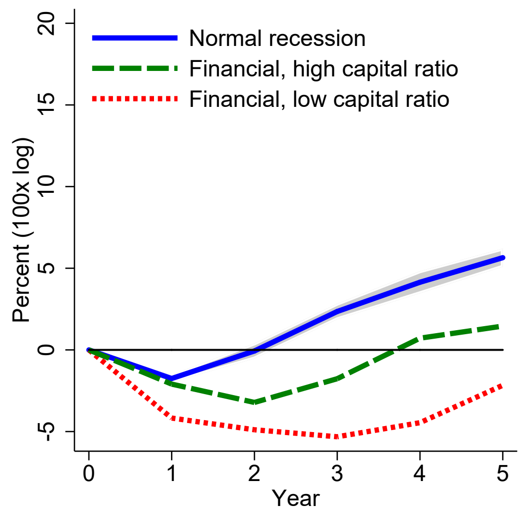
6.4. Inspecting the mechanism: the credit channel

Previous sections have shown that pre-recession capital ratios and economic recovery following the crisis are strongly related. It could be that highly levered intermediaries cannot extend credit after an initial shock to their balance sheets in line with recent research (Peek and Rosengren 2000; Khwaja and Mian 2008; Chodorow-Reich 2014).

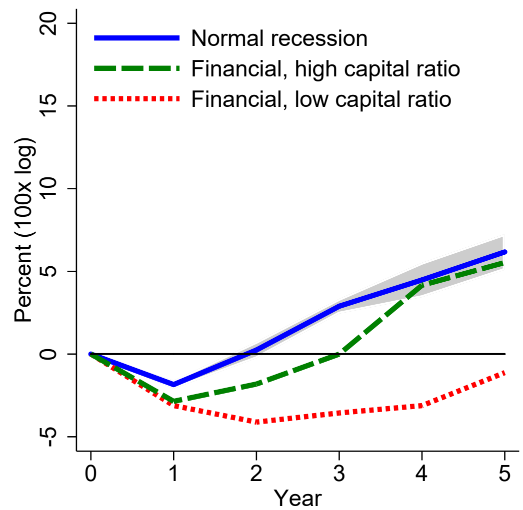
We test this proposition by estimating local projections with cumulative changes in real private credit per capita as the dependent variable, and by allowing for differences in capital ratios before the financial peak. We use real private credit instead of normalizing

Figure 8: *Normal versus financial recessions, real GDP per capita binned by bank capital, controls included, alternative estimates.*

(a) *Full sample excluding post-2006.*



(b) *Full sample including decade fixed effects.*



Notes: This figure displays the coefficient estimates on a sample excluding the global financial crisis, i.e., 1870–2006 (left) and on the full sample including decade fixed effects (right, Table 11). 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.

credit by GDP to avoid measuring the relationship of bank capital with GDP examined in previous subsections. Hence, $\Delta_h y_{i,t(p)}$ now refers to the cumulative change in real private credit per capita extended by financial intermediaries.

In Table 12 and Figure 9 we show results of this specification. We compare the path of real private credit per capita after normal and financial peaks and bin financial recessions by capital ratios. As in previous exercises, the solid blue line refers to the path after normal recessions, while the dotted red and dashed green lines reflect financial recessions when banks were above (dashed) and below (dotted) the mean capital ratio of all such recessions.

We see first that, after a peak, credit growth in a typical financial crisis recession is on average lower than in a normal recession. Furthermore, capital matters. Similar to the dynamics of output, below-average capitalized banking systems extend much less credit for several years in a financial crisis recession. These results therefore complement recent micro-evidence on the role of capital for lending (Peek and Rosengren 2000; Carlson, Shan, and Warusawitharana 2013; Gambacorta and Marques-Ibanez 2011; Jiménez, Ongena, Peydró, and Saurina 2017) and they are consistent with the idea that impairments to credit creation could be an important vector from low bank capital ratios to the slow pace of post-crisis economic recovery.

Table 12: *Normal versus financial recessions, real private credit per capita binned by capital ratio, controls included, full sample.*

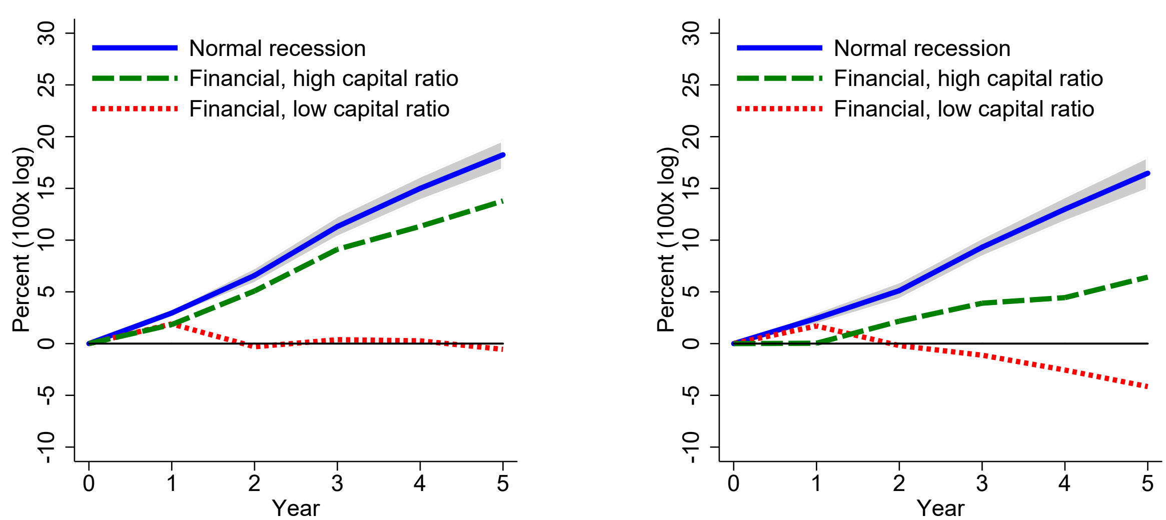
Dependent variable: change in 100 × log real private credit per capita relative to Year 0

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
Recession	2.44***	5.12***	9.31***	12.99***	16.47***
	(0.40)	(0.55)	(0.60)	(0.77)	(1.00)
Financial recession, high capital ratio	-2.41*	-2.95	-5.41**	-8.55**	-10.04*
	(1.28)	(1.95)	(2.24)	(3.14)	(4.78)
Financial recession, low capital ratio	-0.74	-5.31**	-10.43***	-15.55***	-20.62***
	(1.06)	(1.94)	(2.56)	(3.25)	(4.07)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes
R^2	0.256	0.335	0.440	0.451	0.458
H_0: financial high = low, p-value	0.27	0.29	0.12	0.13	0.10
Observations	199	199	199	199	199

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 private credit 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.

Figure 9: *Normal versus financial recessions, real private credit per capita binned by bank capital.*

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



Notes: This figure displays the coefficients for estimating Equation 7 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.

7. Conclusions

We present several hitherto unknown trends and stylized facts on the financial structure of banking systems by introducing a new dataset covering the composition of banking sector liabilities from 1870 to 2015 for a sample of 17 advanced economies. In most countries, banking sector capital ratios declined rapidly before WW2, but have remained low and stable since; yet other funding measures associated with banking fragility, like loan-to-deposit ratios and non-core ratios, have risen markedly.

Over this long time span, our first main finding is that, perhaps counterintuitively, there is no association between capital ratios and the likelihood of a systemic financial crisis. This non-finding is robust to subsample changes, to adding macroeconomic and risk controls and to replacing book capital with market valuations. Capital might protect banks individually against idiosyncratic shocks, but not collectively against systemic events.

However, we do find that loan-to-deposit ratios are a strong predictor of vulnerability, as some theories predict. And non-core liabilities have emerged in recent decades as a risk factor in a departure from the preceding century of modern finance. All that said, the evidence shows that the best crisis predictor for macroprudential regulators to monitor is still aggregate credit growth. This conclusion is supported by return predictability exercises that confirm a more important role for quantity-based measures as compared to balance sheet ratios.

Nonetheless our second main finding suggests that, even if capital ratios are not predictive of crisis incidence, well capitalized banking systems allow the economy to recover faster following a financial crisis and thus result in significantly shallower recessions. One reason appears to be that the recovery of credit is greatly facilitated by boosting the loss absorption capacity of lenders as a whole rather than individually—higher capital ratios in banking systems can bring about more resilience.

Of course, the key caveat is that such resilience is incomplete, in the sense that even with high capital, financial crisis recessions are still much more painful than normal recessions, and high capital is not associated with a lower risk of ending up in a financial crisis event. For that, other policy measures focusing on asset growth and liquidity may be needed.

Overall, history lends support to a more nuanced perspective on bank capital. It plays its main role not so much in reducing the risks of systemic financial crises, but rather in somewhat mitigating their social and economic costs—a distinct but still important benefit.

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Appendices

A. Deposit insurance timing

The dating of deposit insurance is based on the variable "Date of inception of explicit DGS" in Demirgüc-Kunt, Kane, and Laeven (2014). The dates for our sample are shown in the table below.

AUS:	2008	GBR:	1982
BEL:	1974	ITA:	1987
CAN:	1967	JPN:	1971
CHE:	1984	NLD:	1978
DEU:	1998	NOR:	1961
DNK:	1987	PRT:	1992
ESP:	1977	SWE:	1996
FIN:	1969	USA:	1933
FRA:	1980		

B. Systemic banking crisis timing

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, Schularick, and Taylor (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, 1977, 2008.
FIN:	1877, 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.

C. Business cycle peak timing

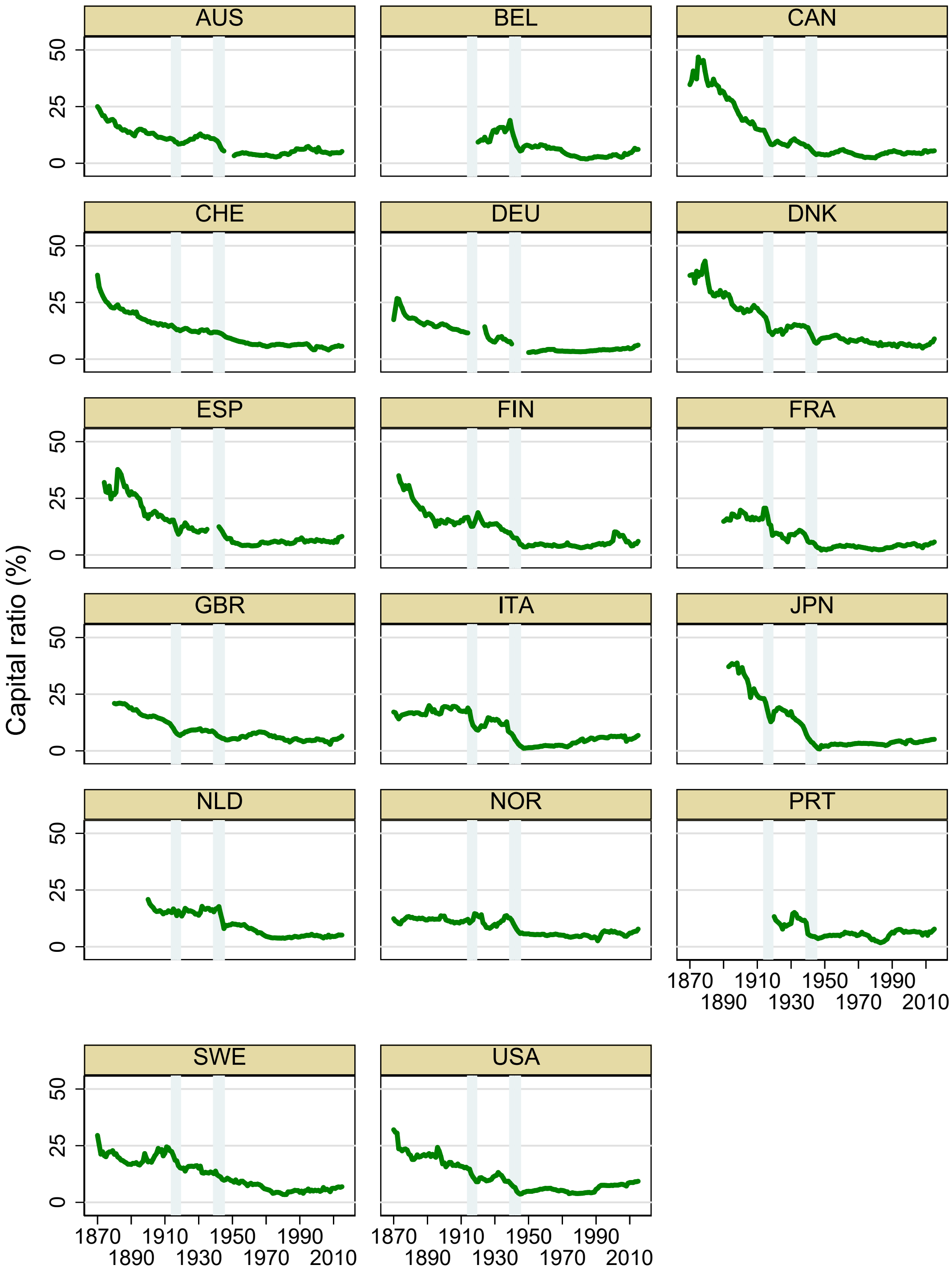
The local projections empirical analysis in the paper employs business cycle peaks from 1870 to 2008, excluding windows around the two world wars, with projections out to five years ahead, with the annual panel sample data. The peak dates that are used are as shown in the table below, where "N" denotes 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 uses the Bry and Boschan (1971) algorithm. See text.

Table A.1: *Dates of normal (N) and financial crisis (F) recession 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	2007					
CAN	N	1871	1874	1877	1882	1884	1888	1891	1894	1903	1913	1917
		1928	1944	1947	1953	1956	1981	1989	2007			
	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	1980	1992				
	F	1884	1888	1913	1925	1929	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	
	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									
	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	1882	1887	1889	1895	1901	1909	1913	1916	1918	1926
		1937	1944	1948	1953	1957	1969	1973	1979	1981	1990	2000
	F	1873	1892	1906	1929	2007						

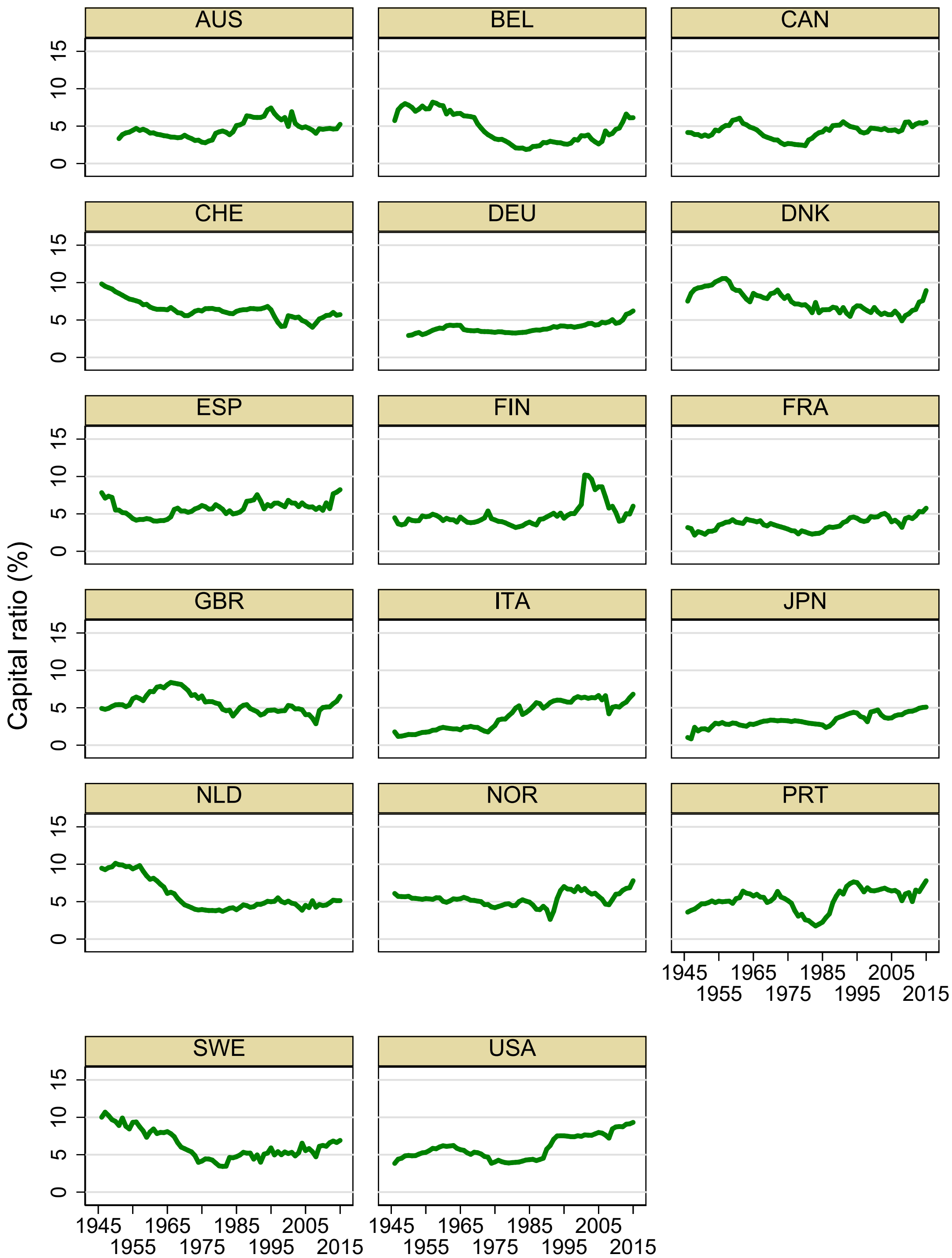
D. Capital ratio series by country

Figure A.1: *Capital ratio by country, full sample.*



Notes: This figure plots the capital ratio for all 17 sample countries from 1870 to 2015. Years of world wars are shown in shading.

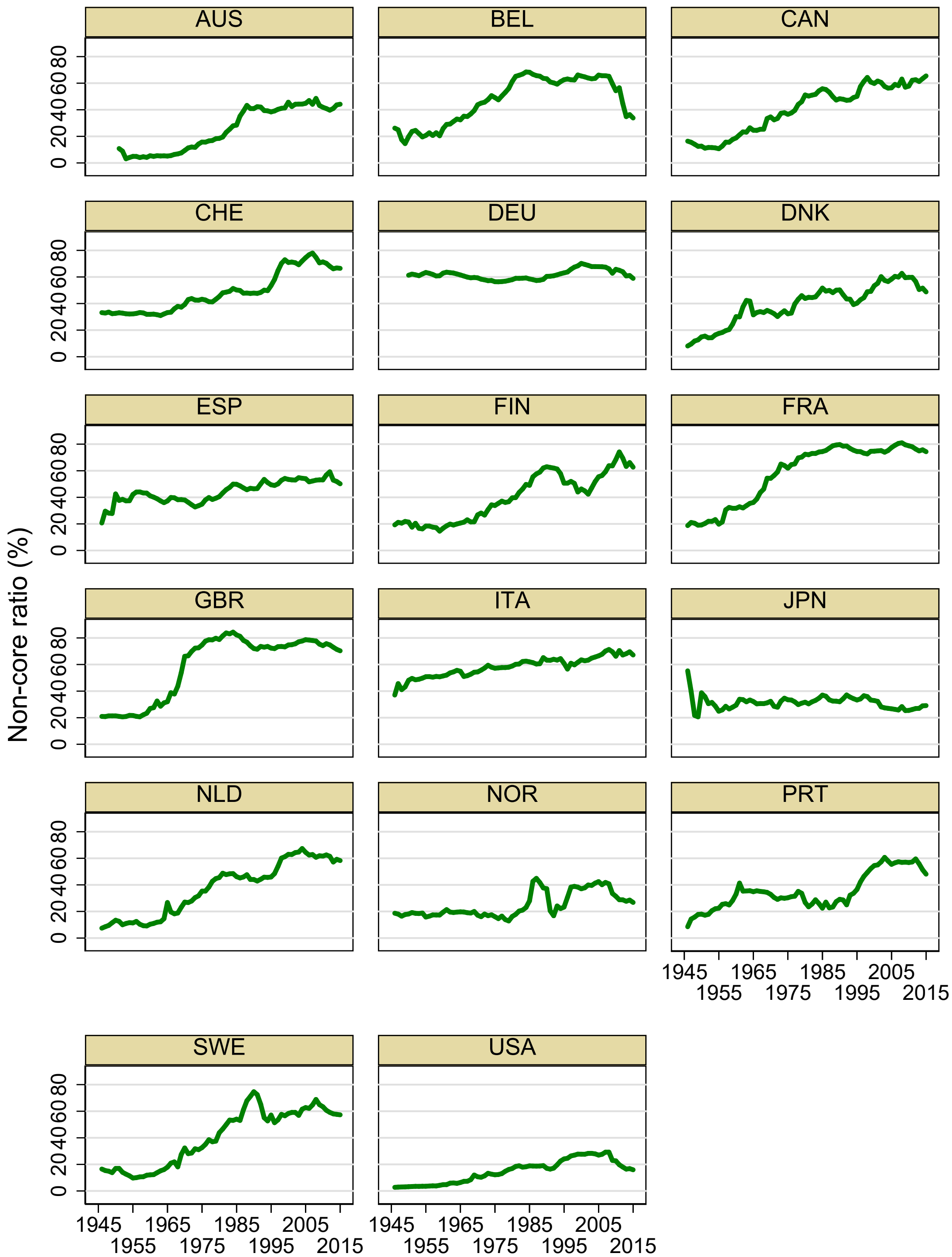
Figure A.2: *Capital ratio, 17 countries, post-WW2 sample.*



Notes: This figure plots the capital ratio for all sample countries for the period between 1945 and 2015. See text.

E. Non-core ratio series by country

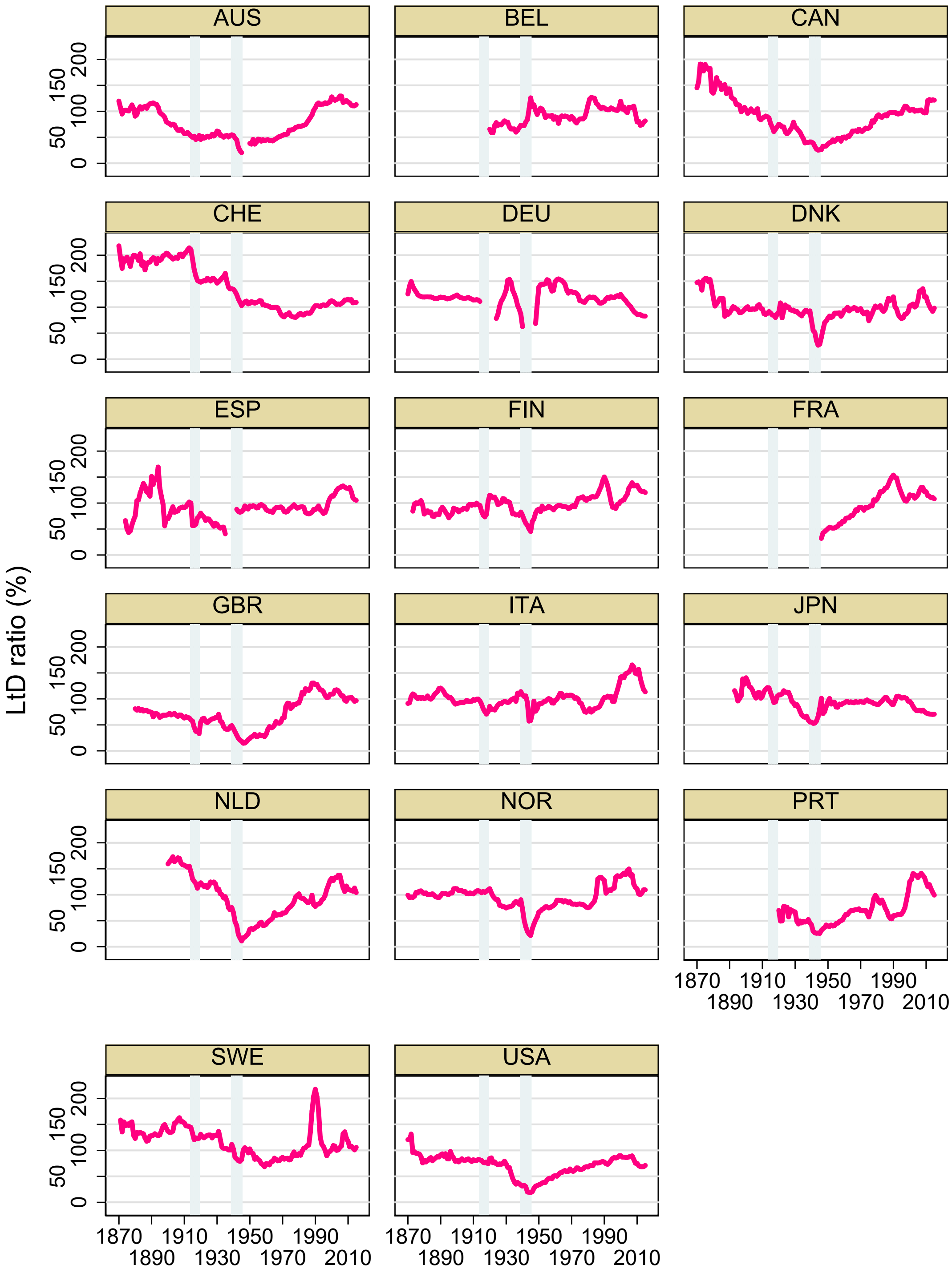
Figure A.3: *Non-core ratio by country, averages by year for 17 countries, post-WW2 sample.*



Notes: This figure plots the non-core ratio for all countries from 1945 to 2015. See text.

F. Loan-to-deposits ratio by country

Figure A.4: *LtD ratio by country, averages by year for 17 countries, full sample.*



Notes: Years of World Wars are shown in shading.

G. Summary statistics

Table A.2: *Full sample: summary statistics*

	Mean	Min.	Max.	S.D.	Obs.
Capital ratio	10.34	0.85	46.86	7.76	2018
Δ_5 Capital ratio	-0.07	-3.05	2.44	0.42	1773
LtD ratio	97.75	15.10	218.16	31.65	1978
Non-core ratio	35.84	2.35	84.37	20.14	1923

Table A.3: *Post-WW2 sample: summary statistics*

	Mean	Min.	Max.	S.D.	Obs.
Capital ratio	5.11	0.85	10.68	1.76	1149
Δ_5 Capital ratio	0.01	-0.92	1.08	0.21	1064
LtD ratio	93.04	15.10	217.52	27.34	1152
Non-core ratio	41.68	2.91	84.37	19.98	1149

Table A.4: *Capital ratio summary statistics split by crises, full sample*

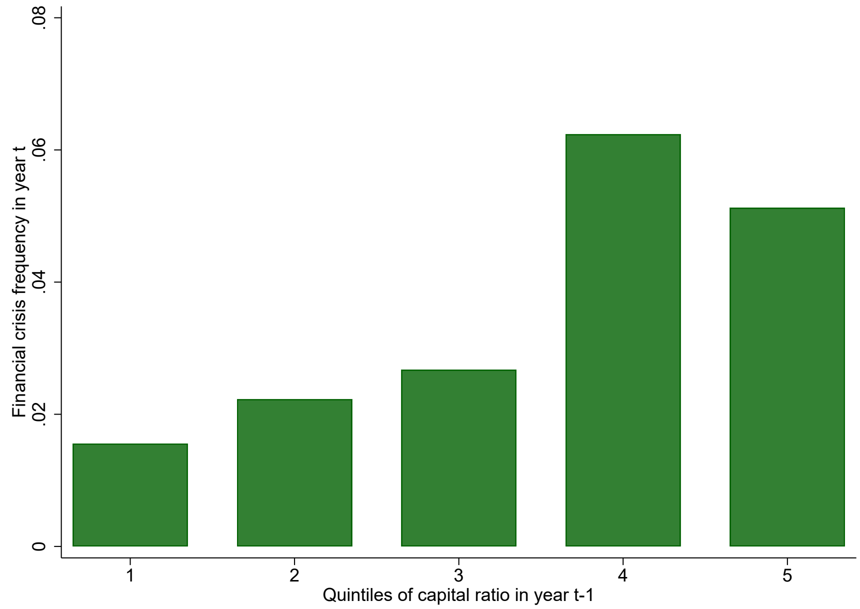
	No crisis observations					Crisis observations (one-period lagged)				
	Mean	Min.	Max.	S.D.	Obs.	Mean	Min.	Max.	S.D.	Obs.
Capital ratio	10.22	0.85	46.86	7.73	1940	13.27	3.81	38.29	7.82	78
Δ_5 Capital ratio	-0.07	-2.41	2.44	0.41	1710	-0.07	-3.05	1.46	0.68	63

Table A.5: *Capital ratio summary statistics, post-WW2 sample*

	No crisis observations					Crisis observations (one-period lagged)				
	Mean	Min.	Max.	S.D.	Obs.	Mean	Min.	Max.	S.D.	Obs.
Capital ratio	5.11	0.85	10.68	1.77	1125	5.27	3.81	7.89	1.14	24
Δ_5 Capital ratio	0.01	-0.92	1.08	0.21	1040	-0.00	-0.29	0.50	0.17	24

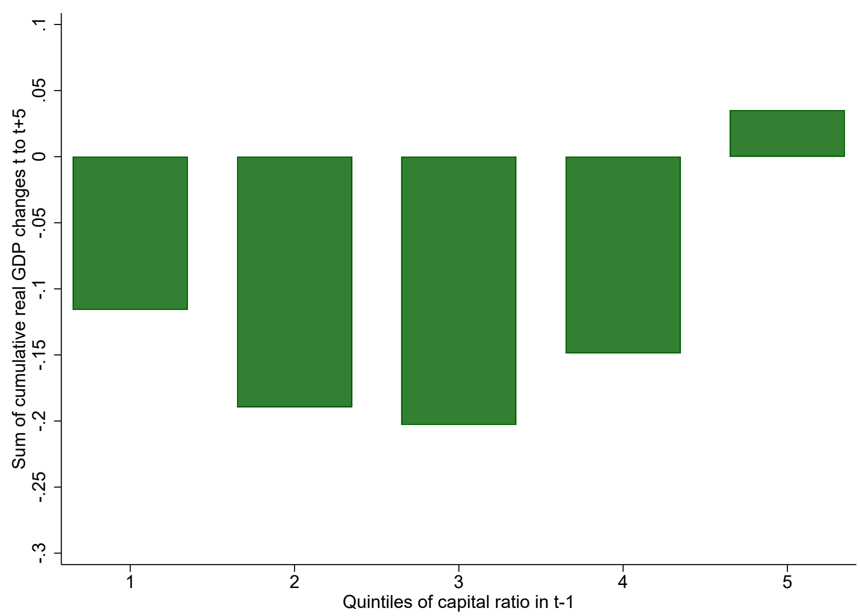
H. Binned barcharts

Figure A.5: *Capital ratio levels and crisis frequency*



Notes: This figure shows the relationship between levels in capital ratios and financial crisis frequencies. Observations are sorted into five equal-sized bins according to the capital ratioin $t-1$. Vertical bars indicate the frequency of financial crises in year t for each of the bins.

Figure A.6: *Capital ratio levels and crisis outcomes*



This figure shows the sum of cumulative growth in real GDP over the 5-years following a financial recession peak for different quintiles of the capital ratio sorted from 1 (lowest capital) to 5 (highest capital).

I. Crisis prediction with standard errors clustered on country and year

Table A.6: *Multivariate probit models for systemic financial crises, standard errors clustered by country and year.*

	(1) Full	(2) Full	(3) Post	(4) Post	(5) Full	(6) Full	(7) Post	(8) Post
Δ_5 Loans/GDP	14.33***	15.37***	13.12***	15.70***	9.50***	7.80***	13.02***	9.51**
	(2.48)	(3.41)	(2.27)	(3.48)	(1.85)	(1.84)	(2.08)	(3.70)
Capital ratio	2.87***	1.49						
	(1.06)	(3.23)						
Δ_5 Capital ratio			-1.08	31.77				
			(15.58)	(41.65)				
LtD ratio					0.60**	1.47***		
					(0.30)	(0.36)		
Non-core ratio							-0.15	4.82**
							(0.69)	(2.10)
Observations	1735	1004	1721	998	1713	1004	1671	1004

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy and the regressors are lagged by one period. All models include country fixed effects. The table corresponds to results in Table 4 in the main text. Here, we do not show marginal effects, but standard errors are clustered by country and year. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: *Multivariate probit models for systemic financial crises, controlling for asset risk, standard errors clustered by country and year.*

	(1) Full	(2) Full	(3) Post	(4) Post	(5) Full	(6) Full	(7) Post	(8) Post
Δ_5 Loans/GDP	15.12***	14.93***	13.78***	8.84*	14.97***	14.48***	13.99***	9.54*
	(2.27)	(3.40)	(4.71)	(4.81)	(2.20)	(3.24)	(4.59)	(4.94)
Capital ratio	2.55*	3.44	3.19	0.24				
	(1.50)	(2.13)	(3.67)	(4.76)				
Δ_5 Capital ratio					5.23	14.54	24.28	37.36
					(18.24)	(20.25)	(47.18)	(47.53)
Macrocontrols	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Asset risk	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1582	1277	988	887	1570	1274	984	884

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy. All models include country fixed effects. Macrocontrols include volatilities of real GDP per capita, inflation, loans-to-GDP and short-term interest rates as well as averaged real GDP per capita growth, inflation, and short term interest rates over the previous five years. Asset risks include average changes of real house prices and the volatility of house price growth over the previous five years and three lags of log excess returns on the bank index if available, on the general index otherwise. The table corresponds to results in Table 5 in the main text. Here, we do not show marginal effects, but standard errors are clustered by country and year. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

J. Deposit insurance

The presence or absence of deposit insurance could affect the link between capital structure and crisis risk. Without deposit insurance, short-term debtors have incentives to monitor banks and force them to endogenously increase capital when they take more risk. When deposit insurance is in place, debtor control is weakened and risk-shifting incentives emerge more strongly. In Table A.8 we repeat the analysis from Table 5, but split the sample depending on whether a deposit insurance scheme is in place or not. We estimate separate models for the two subsamples consisting of observations with deposit insurance (DI), and without (No-DI). Unsurprisingly, the number of observations is higher in the No-DI sample, as deposit insurance was introduced in the mid to late 20th century in most countries. We include changes in credit/GDP, plus country fixed effects, along with risk and macroeconomic controls. With deposit insurance, capital ratios are no longer positively correlated with crisis risk. The coefficient estimate turns negative, but remains statistically weak. A similar pattern emerges for 5-year average annual changes in capital ratios. Once more, we find little evidence that lower capital predicts excessive risk taking by banks. Interestingly, it is only after the introduction of deposit insurance, that the non-core ratio—representing the remaining runnable debt on bank balance sheets—begins to play an important role (see column (8)).

Table A.8: *Multivariate probit models for systemic financial crises, samples split by existence of deposit insurance scheme.*

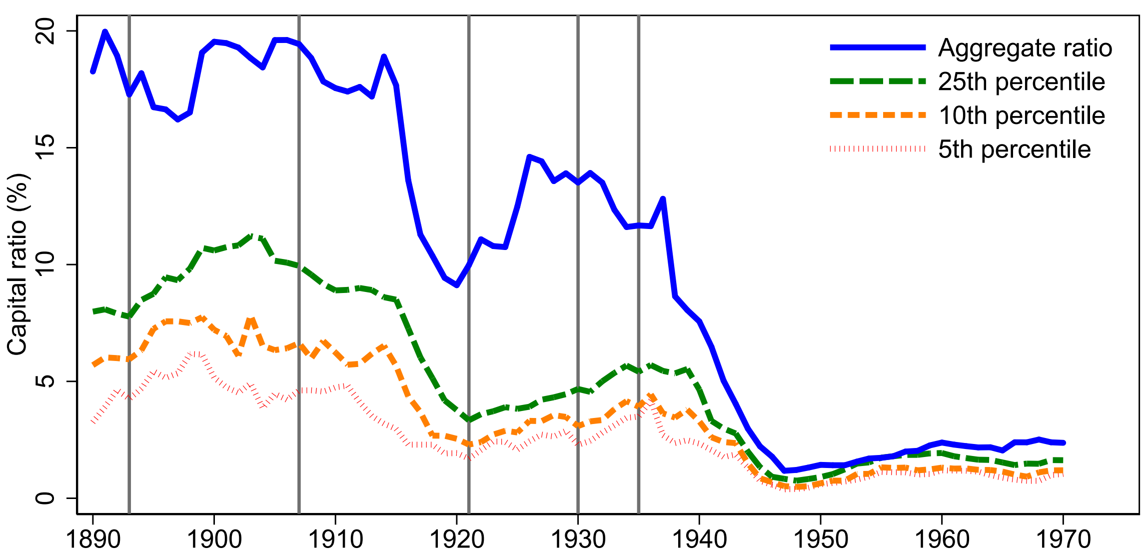
	(1) No-DI	(2) DI	(3) No-DI	(4) DI	(5) No-DI	(6) DI	(7) No-DI	(8) DI
Δ_5 Loans/GDP	0.78^{***}	0.22^{**}	0.94^{***}	0.21^{*}	0.39^{***}	0.11	0.79^{***}	0.13^{**}
	(0.13)	(0.11)	(0.15)	(0.13)	(0.14)	(0.11)	(0.17)	(0.06)
Capital ratio	0.21^{***}	-0.22						
	(0.07)	(0.18)						
Δ_5 Capital ratio			0.73	-0.87				
			(1.15)	(1.13)				
LtD ratio					0.05^{***}	0.03^{*}		
					(0.01)	(0.02)		
Non-core ratio							0.02	0.08^{*}
							(0.05)	(0.05)
Macrocontrols	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Asset risks	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AUC	0.86	0.86	0.83	0.86	0.86	0.86	0.83	0.88
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)
Observations	721	536	718	536	673	536	650	536

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy. Samples are split by the existence of a deposit insurance scheme (DI). All models include country fixed effects. Coefficients are marginal effects. Macrocontrols includes volatilities of real GDP per capita, inflation and short-term interest rates as well as averaged real GDP per capita growth, inflation, and short term interest rates over the previous five years. Asset risks include average changes of real house prices and the volatility of house price growth over the previous five years and three lags of log excess returns on the bank index if available, on the general index otherwise. Clustered standard errors in parentheses. Deposit insurance dates are in the appendix. See text. Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

K. 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 to subject these mechanisms to empirical tests. However, we can analyze these mechanisms based on available data for various subsamples. We turn to this now. First, we study whether capital ratios at the most highly levered banks helps predict a financial crisis. Here we rely on evidence from Italy, where the Historical Archive of Credit (Natoli, Piselli, Triglia, and Vercelli 2016) contains micro-level balance sheet data for the near-universe of banks over more than 80 years, from 1890 to 1973. In a second step, we focus on the capital at the biggest banks, where we have data for a few countries.

Figure A.7: *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.

Table A.9: *Probit models for systemic financial crises in Italy, sample 1890–1973.*

	5th pctile	10th pctile	25th pctile	Aggregate
Capital Ratio	1.93	1.21	0.79	0.65*
	(1.41)	(0.99)	(0.70)	(0.37)
AUC	0.68	0.65	0.64	0.71
	(0.09)	(0.09)	(0.09)	(0.11)
Observations	66	66	66	66

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

During the period for which we have data, 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 A.7 we present the evolution of different percentiles of the capital ratio distribution per year. The paths of 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 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.

Table A.9 confirms this impression. We again estimate a probit model with the crisis dummy as the dependent variable and the capital ratio as an explanatory variable, excluding war years from the sample. Yet instead of only using the aggregate capital ratio, we also use various percentiles of the capital ratio distribution.

The results reported are consistent with our previous findings. The lagged level of the capital ratio is positively associated with financial instability. The coefficients are insignificant, but similar to the one for the aggregate measure in the same sample. 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.

L. Capitalization of the largest banks

The capitalization of the largest and systemically important banks could be key to understanding financial crisis risks. In fact, current regulations often contain capital surcharges for large and inter-connected institutions. Hence, we test whether low or falling capital ratios of the largest banks signal growing financial fragility.

The analysis in this section builds on micro-data collected and kindly shared by Mazbouri, Guex, and Lopez (2017) for a subset of the largest banks in Belgium, France, Germany, Italy, Switzerland, and the UK for the period 1890 to 1970. We extended the coverage using data for the same set of banks in France, Germany, Switzerland, and the UK. We also added recent data from statistics for large commercial banks from the OECD Banking Statistics. In addition, we collected additional data from Denmark, Italy, the Netherlands, Norway, Sweden, and the US. The capital ratio measure used here is now an asset-weighted capital ratio of the largest banks.

The core results are presented in Table A.10. Column (1) shows the baseline regression including the lagged capital ratio of the largest banks for the full sample. Column (2) includes our control variables. Columns (3) and (4) repeat these these specifications in post-WW2 data. The results are similar to our previous findings. As in the aggregated data, the coefficient estimates are positive and significant in the full sample. They turn negative, but insignificant, when estimated on a post-WW2 sample. In columns (5) to (8) we look at short-run variation and use 5-year changes instead of the capital ratio levels. The coefficients are negative, but insignificant and without adding predictive power as measured by the AUCs.

Table A.10: *Probit models for systemic financial crises. Largest banks.*

	(1) Full	(2) Full	(3) Post	(4) Post	(5) Full	(6) Full	(7) Post	(8) Post
Δ_5 Loans/GDP	1.25***	1.08***	0.82**	0.10	1.41***	1.20***	0.98***	0.00
	(0.19)	(0.24)	(0.37)	(0.13)	(0.22)	(0.32)	(0.37)	(0.19)
Capital ratio large banks	0.09**	0.10	-0.28	-0.30				
	(0.04)	(0.07)	(0.49)	(0.19)				
Δ_5 Capital ratio large banks					-0.49	-0.51	-2.91	-1.55
					(1.37)	(1.30)	(5.33)	(1.57)
Macro controls	No	Yes	No	Yes	No	Yes	No	Yes
House price changes	No	Yes	No	Yes	No	Yes	No	Yes
Excess stock returns	No	Yes	No	Yes	No	Yes	No	Yes
AUC	0.72	0.77	0.72	0.86	0.74	0.79	0.73	0.88
	(0.05)	(0.04)	(0.07)	(0.04)	(0.04)	(0.04)	(0.08)	(0.04)
Observations	855	673	432	398	771	611	382	352

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy and the regressors are one-period lagged. Data on capital ratios is from the largest banks in a country only (see text). All models include country fixed effects. Coefficients shown are marginal effects. Macrocontrols includes volatilities of real GDP per capita, inflation and short-term interest rates as well as averaged real GDP per capita growth, inflation, and short term interest rates over the previous five years. Asset risks include average changes of real house prices and the volatility of house price growth over the previous five years and three lags of log excess returns on the bank index if available, on the general index otherwise. Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

M. Credit boom and capital ratio interactions

Table A.11: *Probit models for systemic financial crises, credit interacted with high capital ratio indicator.*

	(1) Full	(2) Full	(3) Post	(4) Post	(5) Post	(6) Post
Δ_5 Loans/GDP	0.86^{***}	0.55^{***}	0.45	0.10	0.56	-0.04
	(0.17)	(0.18)	(0.29)	(0.24)	(0.41)	(0.29)
High capital	0.03^{***}	0.01	-0.01	-0.01		
	(0.01)	(0.01)	(0.01)	(0.01)		
High capital (market-based)					-0.00	-0.01
					(0.02)	(0.02)
Δ_5 Loans/GDP x High capital	0.04	0.38	0.26	0.23	0.48	0.31
	(0.30)	(0.27)	(0.36)	(0.24)	(0.59)	(0.44)
Macro controls	No	Yes	No	Yes	No	Yes
Asset risks	No	Yes	No	Yes	No	Yes
AUC	0.75	0.80	0.76	0.84	0.67	0.79
	(0.03)	(0.03)	(0.05)	(0.04)	(0.06)	(0.05)
Observations	1735	1277	1004	887	410	410

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy. All models include country fixed effects. Coefficients are marginal effects. Interactions are between lagged 5-year average annual changes in loans-to-GDP and dummies indicating whether the lagged capital ratio is above (high) or below (low) the respective sample median. Macrocontrols includes volatilities of real GDP per capita, inflation and short-term interest rates as well as averaged real GDP per capita growth, inflation, and short term interest rates over the previous five years. Asset risks include average changes of real house prices and the volatility of house price growth over the previous five years and three lags of log excess returns on the bank index if available, on the general index otherwise. See text. Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Rapid balance sheet expansions—that is, credit booms—lie at the heart of financial crisis dynamics. If more skin in the game induces prudent behavior by banks, we would expect to find in the data that credit booms occurring at high levels of bank equity are considerably less likely to end in a crisis than credit booms financed with less equity. Hence we define an indicator variable for high levels of capital, specifically when the lagged capital ratio of the banking sector is above the median in the respective sample.

We then test the proposition using interaction terms in our original model. Table A.11 provides no support for the view that higher capital has disciplining effects. The interaction coefficients for 5-year average annual credit expansion and the indicator for a high capital ratio are typically positive, for the full sample and the post-WW2 period. This holds both for book values of capital (columns 1 to 4) and market values of capital (columns 5 and 6). The inclusion of controls for asset risk and macroeconomic risk predictors lowers the coefficients, but does not change the overall picture. Credit booms financed with more capital are as dangerous as credit booms financed with more debt.

N. Baseline probit model results without changes in credit/GDP

Table A.12: *probit models for systemic financial crises, full sample.*

	(1)	(2)	(3)	(4)	(5)	(6)
Capital ratio	0.16^{***}					
	(0.03)					
Δ_5 Capital ratio		-0.02				
		(0.96)				
LtD ratio			0.06^{***}			
			(0.01)			
Δ_5 LtD				0.40^{***}		
				(0.08)		
Non-core ratio					0.01	
					(0.03)	
Δ_5 Non-core ratio						0.54^{**}
						(0.24)
AUC	0.67	0.62	0.68	0.67	0.62	0.63
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Observations	2018	1773	1978	1743	1923	1698

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year average annual changes (Δ_5) or in one-period lagged levels. Coefficients are shown as marginal effects. All models include country fixed effects. The null fixed-effects only model has AUC = 0.60 (0.03). Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.13: *Probit models for systemic financial crises, post-WW2 sample.*

	(1)	(2)	(3)	(4)	(5)	(6)
Capital ratio	-0.12					
	(0.31)					
Δ_5 Capital ratio		-0.09				
		(2.20)				
LtD ratio			0.06***			
			(0.00)			
Δ_5 LtD				0.40***		
				(0.08)		
Non-core ratio					0.09***	
					(0.02)	
Δ_5 Non-core ratio						0.65**
						(0.27)
AUC	0.59	0.60	0.80	0.73	0.83	0.65
	(0.06)	(0.06)	(0.04)	(0.06)	(0.03)	(0.05)
Observations	1081	1001	1084	1004	1081	1001

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year average annual changes (Δ_5) or in one-period lagged levels. Coefficients are shown as marginal effects. All models include country fixed effects. The null fixed-effects only model has AUC = 0.59 (0.06). Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.14: *Probit models for systemic financial crises, pre-1914 sample.*

	(1)	(2)	(3)	(4)	(5)	(6)
Capital ratio	0.02					
	(0.16)					
Δ_5 Capital ratio		0.51				
		(1.39)				
LtD ratio			0.12**			
			(0.05)			
Δ_5 LtD				0.61*		
				(0.32)		
Non-core ratio					0.19	
					(0.12)	
Δ_5 Non-core ratio						1.42**
						(0.68)
AUC	0.64	0.66	0.70	0.70	0.66	0.68
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	532	462	531	461	498	433

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year average annual changes (Δ_5) or in one-period lagged levels. Coefficients are marginal effects. All models include country fixed effects. Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

O. Comparing predictive accuracy across probit models

Table A.15: *AUCs from multivariate probit models for systemic financial crises.*

	(1) Full model	(2) Excl. credit growth	(3) Excl. capital ratio	(4) Excl. non-core ratio
Full sample				
AUC	0.749	0.688	0.707	0.746
$H_0 : AUC = AUC^{Full}$, p-value		0.013	0.015	0.573
N	1671	1671	1671	1671
Pre-WW1 sample				
AUC	0.731	0.679	0.728	0.700
$H_0 : AUC = AUC^{Full}$, p-value		0.038	0.880	0.388
N	405	405	405	405
Post-WW2 sample				
AUC	0.843	0.821	0.840	0.740
$H_0 : AUC = AUC^{Full}$, p-value		0.217	0.644	0.007
N	1004	1004	1004	1004

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

P. Probit models without country fixed effects

Table A.16: *Probit models for systemic financial crises, full sample, no fixed effects.*

	(1)	(2)	(3)	(4)	(5)	(6)
Capital ratio	0.16^{***}					
	(0.04)					
Δ_5 Capital ratio		0.09				
		(1.00)				
LtD ratio			0.04^{***}			
			(0.02)			
Δ_5 LtD				0.42^{***}		
				(0.09)		
Non-core ratio					0.01	
					(0.02)	
Δ_5 Non-core ratio						0.52^{**}
						(0.24)
AUC	0.64	0.53	0.63	0.61	0.52	0.53
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
Observations	2018	1773	1978	1743	1923	1698

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year average annual changes (Δ_5) or in one-period lagged levels. Coefficients are marginal effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.17: *Probit models for systemic financial crises, post-WW2 sample, no fixed effects.*

	(1)	(2)	(3)	(4)	(5)	(6)
Capital ratio	0.11					
	(0.17)					
Δ_5 Capital ratio		-0.34				
		(2.06)				
LtD ratio			0.05***			
			(0.01)			
Δ_5 LtD				0.37***		
				(0.08)		
Non-core ratio					0.07***	
					(0.01)	
Δ_5 Non-core ratio						0.61***
						(0.23)
AUC	0.55	0.51	0.74	0.68	0.74	0.57
	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)
Observations	1149	1064	1152	1067	1149	1064

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year average annual changes (Δ_5) or in one-period lagged levels. Coefficients are marginal effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Q. Probit models excluding the global financial crisis

Table A.18: *Multivariate probit models for systemic financial crises, full sample excluding the global financial crisis.*

	(1)	(2)	(3)	(4)	(5)	(6)
Capital ratio	0.18***					
	(0.03)					
Δ_5 Capital ratio		0.09				
		(0.92)				
LtD ratio			0.06***			
			(0.02)			
Δ_5 LtD				0.38***		
				(0.08)		
Non-core ratio					-0.03	
					(0.04)	
Δ_5 Non-core ratio						0.49**
						(0.25)
AUC	0.70	0.63	0.68	0.67	0.63	0.63
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
Observations	1865	1620	1766	1536	1711	1491

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year average annual changes (Δ_5) or in one-period lagged levels. Coefficients are marginal effects. All specifications include a country fixed effect. Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

R. Probit models excluding the US and the UK

Table A.19: *Multivariate probit models for systemic financial crises, full sample excluding the US and the UK.*

	(1)	(2)	(3)	(4)	(5)	(6)
Capital ratio	0.16^{***}					
	(0.03)					
Δ_5 Capital ratio		0.04				
		(1.00)				
LtD ratio			0.05^{***}			
			(0.02)			
Δ_5 LtD				0.38^{***}		
				(0.08)		
Non-core ratio					-0.00	
					(0.03)	
Δ_5 Non-core ratio						0.52^{*}
						(0.27)
AUC	0.68	0.63	0.67	0.67	0.63	0.64
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Observations	1768	1553	1728	1523	1725	1520

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year annual average changes (Δ_5) or in one-period lagged levels. Coefficients are marginal effects. All models include country fixed effects. Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.20: *Multivariate probit models for systemic financial crises, post-WW2 sample excluding the US and the UK.*

	(1)	(2)	(3)	(4)	(5)	(6)
Capital ratio	-0.09					
	(0.34)					
Δ_5 Capital ratio		1.24				
		(2.01)				
LtD ratio			0.06^{***}			
			(0.00)			
Δ_5 LtD				0.36^{***}		
				(0.07)		
Non-core ratio					0.07^{**}	
					(0.03)	
Δ_5 Non-core ratio						0.73^{**}
						(0.32)
AUC	0.57	0.60	0.80	0.74	0.85	0.66
	(0.07)	(0.07)	(0.05)	(0.07)	(0.04)	(0.06)
Observations	945	875	948	878	945	875

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy and the regressors are in smoothed 5-year annual average changes (Δ_5) or in one-period lagged levels. Coefficients are marginal effects. All models include country fixed effects. Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

S. Country-decade fixed effects

Table A.21: *Multivariate probit models for systemic financial crises, full sample including country-decade fixed effects.*

	(1)	(2)	(3)	(4)	(5)	(6)
Δ_5 Loans/GDP	3.93^{***}	2.50^{**}	3.39^{***}	2.77^{***}	1.39	2.08^{**}
	(0.83)	(0.97)	(0.80)	(0.91)	(0.94)	(0.99)
Capital ratio	-1.23			1.28		
	(1.47)			(1.12)		
LtD ratio		0.45^{**}			0.35^{**}	
		(0.20)			(0.14)	
Non-core ratio			0.90^{***}			0.77^{***}
			(0.27)			(0.26)
Macrocontrols	No	No	No	Yes	Yes	Yes
Asset risk	No	No	No	Yes	Yes	Yes
AUC	0.72	0.74	0.73	0.82	0.83	0.83
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	530	521	511	402	393	393

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy and regressors are lagged by one period. Coefficients are marginal effects. All models include country-decade fixed effects. Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

T. Crisis chronology: robustness

Table A.22: *Multivariate probit models for systemic financial crises, using Baron, Verner, and Xiong (2018) crisis chronology, controlling for asset risk.*

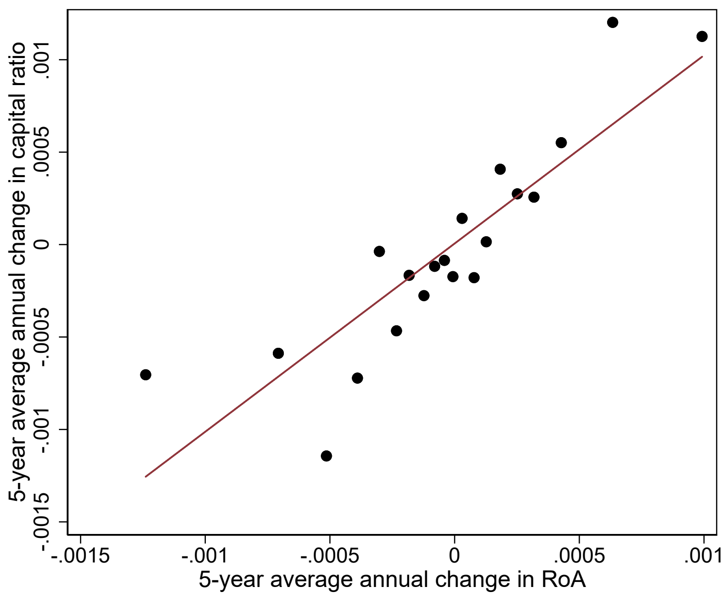
	(1) Full	(2) Full	(3) Post	(4) Post	(5) Full	(6) Full	(7) Post	(8) Post
Δ_5 Loans/GDP	0.93^{***}	0.72^{***}	0.89^{***}	0.42^{*}	0.91^{***}	0.72^{***}	0.91^{***}	0.46^{**}
	(0.16)	(0.19)	(0.14)	(0.21)	(0.15)	(0.19)	(0.13)	(0.23)
Capital ratio	0.13^{***}	0.15	0.30	0.02				
	(0.04)	(0.10)	(0.34)	(0.30)				
Δ_5 Capital ratio					0.05	-0.02	3.71	2.17
					(1.29)	(1.83)	(2.35)	(2.13)
Macrocontrols	No	Yes	No	Yes	No	Yes	No	Yes
Asset risk	No	Yes	No	Yes	No	Yes	No	Yes
AUC	0.72	0.77	0.71	0.83	0.71	0.76	0.72	0.83
	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
Observations	1735	1329	1067	939	1721	1326	1061	936

Notes: The table shows probit classification models where the dependent variable is a financial crisis dummy based on Baron, Verner, and Xiong (2018). All models include country fixed effects. Coefficients are marginal effects. Macrocontrols include volatilities of real GDP per capita, inflation and short-term interest rates as well as averaged real GDP per capita growth, inflation, and short term interest rates over the previous five years. House price changes are changes of real house prices over the previous five years. Excess stock returns are three lags of excess return on the bank index if available, on the general index otherwise. Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

U. Instrumenting changes in capital ratios

The surprising finding that more capital increases the likelihood of a crisis (albeit by a very small amount indistinguishable from zero statistically) runs counter to intuition. Thus, our strategy of controlling for observable factors that simultaneously explain crisis risk and are correlated with capital may have been insufficient. Regulators, market participants, or both could force banks to increase capital buffers when crisis risk is perceived to be high. This type of simultaneity bias could be masking the true relationship. Here, we will use an instrumental variable approach to address potential endogeneity. The instrument relies on variation in the wiggle room that banks have to adjust capital buffers by retaining profits. Cohen and Scatigna (2016) show that retained earnings have been the most important source of bank capital increases in advanced economies after the financial crisis and that banks also retained a significant fraction of earnings in earlier periods.

Figure A.8: *RoA as an instrument for capital ratio changes*



Notes: The figure shows binned scatterplots for 5-year average changes in capital ratios and 5-year average changes in RoA. Observations are collapsed into 20 equal sized bins according to 5-year average annual changes in RoA. Each point represents the group specific means of 5-year average annual changes in capital ratios and 5-year average annual changes in RoA. A fitted regression line is shown in red.

This behavior is also reflected in balance sheet data. As of 2018Q3, undivided profits account for 37.8% of total bank equity capital of commercial and savings banks in the US, which is slightly below the average share for the post-1984 period.[16] The higher profits are relative to total assets, the more banks can increase capital ratios by retaining these profits in the bank. Hence, retained earnings are a natural instrument for variation in capital ratios that can be justifiably be considered independent of perceptions of impending financial fragility.

We will exploit this relationship using data for banking sector profit and loss accounts from Richter and Zimmermann (2018) and instrument changes in capital ratios with changes in return on assets (RoA), the ratio of net income after tax to book assets. We define the 5-year change in this variable as $\Delta_5 RoA_{i,t} = RoA_{i,t} - RoA_{i,t-5}$. Including controls for asset growth and bank risk premia ensures that we capture only variation in capital ratios that is driven by changes in RoA that are unrelated to risk taking, following Meiselman, Purnanandam, and Nagel (2018). For the instrument to be relevant, a positive first-stage association between changes in RoA and changes in the capital

[16] Numbers are based on data from the "FDIC - Quarterly Banking Profile Time Series Spreadsheets".

ratio is required. Figure A.8 presents evidence of such a strong relationship between 5-year average changes in RoA and 5-year average changes in capital ratios.

There is no formal way to evaluate the validity of the instrument with just identification, as it is the case here. However, the economic justification seems clear. In good times, returns on assets increase. Banks will then retain some of the higher profits earned. Controlling for asset growth and bank risk, banks acquire more "skin in the game," which in turn allows us to evaluate whether it reduces future crisis risk. It turns out that even as we are able to obtain a more intuitive link between capital and crisis risk, this link is tenuous economically and statistically, as we will see next.

Table A.23 presents the instrumental variable probit results for the post-WW2 sample and starts from a simple benchmark model including only changes in the loans-to-GDP ratio over the previous five years, as shown in the first column; this model has an AUC of 0.75. In the second column, we now add changes in the capital ratio over the last five years. The change in the capital ratio is insignificant—just as in our previous exercises—and it does not add any predictive accuracy to the benchmark model; the AUC is still 0.75. In column (3), the IV model now instruments changes in the capital ratio with changes in RoA. The first-stage regression (unreported) confirms the relevance of the instrument and has an *F*-statistic of 45.05. The coefficient for changes in capital ratios instrumented with RoA turns negative. But the coefficient of the capital ratio remains insignificant and does not add any predictive accuracy in comparison to previous models. Thus, if our IV strategy purges the estimates of endogeneity, it does not alter our main finding. Columns (4) to (6) follow the same strategy, but also include macrocontrols and asset risks as in our previous exercises. The message of the table is clear: changes in capital ratios are unrelated to financial crisis risks, even when we account for endogeneity. The results are statistically and economically small.

Table A.23: *Instrumental variable regression.*

	(1) No Cap	(2) Cap	(3) IV	(4) No Cap	(5) Cap	(6) IV
Δ_5 Loans/GDP	0.72***	0.72***	0.73**	0.26*	0.27	0.27
	(0.09)	(0.09)	(0.31)	(0.15)	(0.17)	(0.25)
Δ_5 Capital ratio		0.16	-0.23		0.27	-0.10
		(2.02)	(7.83)		(1.50)	(4.35)
Asset risks	No	No	No	Yes	Yes	Yes
Macrocontrols	No	No	No	Yes	Yes	Yes
AUC	0.75	0.75	0.72	0.85	0.85	0.83
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)
Observations	844	844	844	749	749	749

Notes: The table shows probit classification models where the dependent variable is the financial crisis dummy. Column (1) includes 5-year average annual changes in loans-to-GDP. Column (2) additionally includes 5-year average annual changes in capital ratios. In column (3) 5-year average annual changes in capital ratios are instrumented with 5-year average annual changes in RoA. The F-statistic of the first stage regression for the model is 45.05. Columns (4), (5) and (6) additionally include macrocontrols and asset risks. Macrocontrols includes volatilities of real GDP per capita, inflation and short-term interest rates as well as averaged real GDP per capita growth, inflation, and short term interest rates over the previous five years. Asset risks include average changes of real house prices and the volatility of house price growth over the previous five years and three lags of log excess returns on the bank index if available, on the general index otherwise. Coefficients shown are marginal effects. All models include country fixed effects. Clustered (by country) standard errors in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

V. Local projections with standard errors clustered on country and year

Table A.24: *Normal versus financial recessions, real GDP per capita by capital ratio, with controls, full sample, standard errors clustered by country and year.*

Dependent variable: change in 100 × log real GDP per capita relative to Year 0

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	-1.79***	-0.19	2.15***	3.80***	5.27***	9.24***
	(0.13)	(0.30)	(0.34)	(0.45)	(0.41)	(1.39)
Financial recession, high capital ratio	-1.45*	-2.96***	-3.52***	-2.44**	-2.79***	-13.16***
	(0.79)	(0.98)	(0.89)	(1.03)	(0.84)	(3.49)
Financial recession low capital ratio	-1.19*	-4.92***	-7.56***	-9.28***	-9.45***	-32.40***
	(0.64)	(1.08)	(1.44)	(1.42)	(0.68)	(4.68)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.560	0.336	0.336	0.325	0.394	0.328
H_0: financial high = low, p-value	0.77	0.10	0.03	0.00	0.00	0.00
Observations	210	210	210	210	210	210

Notes: Standard errors (clustered by country and year) 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. Corresponds to Table 9 in the main text.

W. Local projections with continuous measure and standard errors clustered on country and year

Table A.25: *Normal versus financial recessions, real GDP per capita with continuous capital ratios, with controls, full sample, standard errors clustered by country and year.*

Dependent variable: change in 100 × log real GDP per capita relative to Year 0

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Normal recession	-1.76***	-0.19	2.07***	3.75***	5.23***	9.10***
	(0.13)	(0.31)	(0.34)	(0.44)	(0.42)	(1.38)
Financial recession	-1.31**	-4.05***	-5.76***	-6.25***	-6.50***	-23.88***
	(0.54)	(0.83)	(0.78)	(1.01)	(0.57)	(3.17)
Normal recession × capital ratio	-0.03	-0.06	0.05	-0.04	-0.06	-0.14
	(0.03)	(0.05)	(0.08)	(0.09)	(0.09)	(0.31)
Financial recession × capital ratio	-0.05	0.11**	0.21**	0.28***	0.31***	0.86**
	(0.04)	(0.05)	(0.10)	(0.10)	(0.08)	(0.33)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.565	0.339	0.327	0.301	0.383	0.313
H_0: normal = financial, p-value	0.47	0.00	0.00	0.00	0.00	0.00
H_0: normal × capital = financial × capital, p-value	0.56	0.00	0.18	0.01	0.00	0.01
Observations	210	210	210	210	210	210

Notes: Standard errors (clustered by country and year) 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. Corresponds to Table 10 in the main text.

X. Local projections using pre-2006 sample

Table A.26: *Normal vs. financial recessions, capital ratio bins above and below historical average, controls included, pre-2006 sample.*

100 × log real GDP per capita

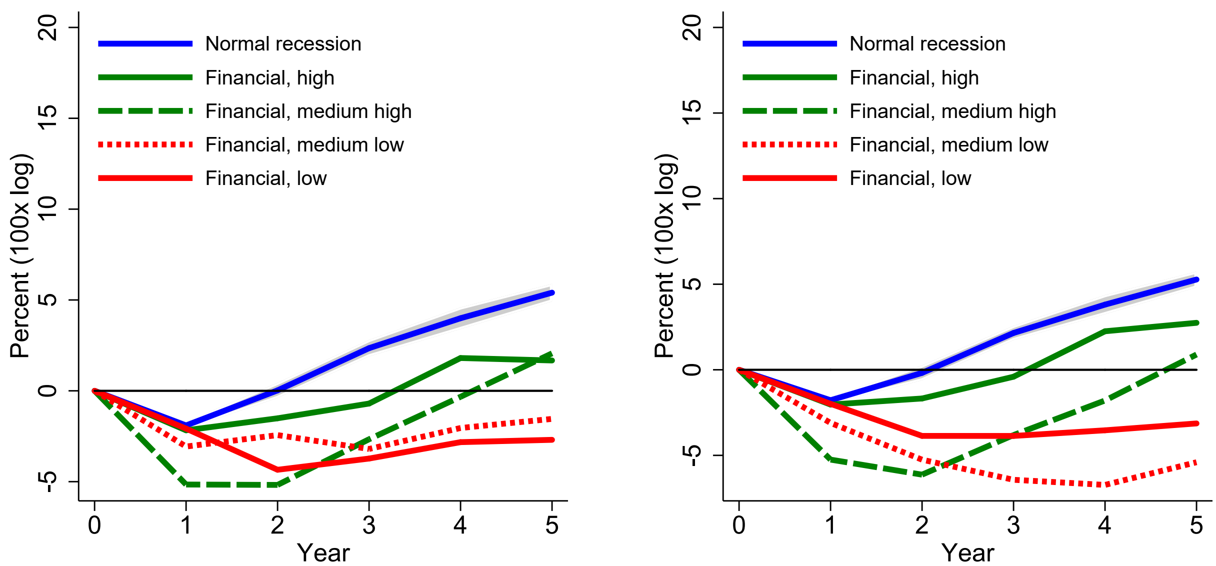
	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	-1.75***	-0.07	2.35***	4.14***	5.65***	10.33***
	(0.14)	(0.28)	(0.29)	(0.41)	(0.34)	(1.28)
Financial recession, high capital ratio	-0.34	-3.15**	-4.12***	-3.43*	-4.19**	-15.22***
	(0.48)	(1.18)	(1.05)	(1.64)	(1.84)	(4.89)
Financial recession, low capital ratio	-2.42***	-4.82***	-7.67***	-8.60***	-7.81***	-31.33***
	(0.82)	(1.18)	(1.86)	(2.05)	(1.73)	(6.78)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.606	0.311	0.353	0.330	0.400	0.337
H_0: financial high = low, p-value	0.01	0.13	0.16	0.05	0.19	0.06
Observations	193	193	193	193	193	193

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 the historical average. See text.

Y. Local projections based on capital ratio quartiles

Figure A.9: *Normal versus financial recessions binned by pre-crisis capital ratio, real GDP per capita by capital ratio*

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



Notes: This figure displays the average path of real GDP per capita after financial recessions depending on the capitalization of the banking sector in the year prior to to the peak. The specification follows Equation 7 and interacts the financial recession dummy with a dummy $q_{j,i,t(p)}$ that is 1 if the lagged banking sector capital ratio at the peak is in the j-th quartile of all financial recessions, and zero else.

$$\Delta_h y_{i,t(p)} = \sum_{i=1}^{I-1} \alpha_{i,h} D_{i,t(p)} + \mu_h + \sum_{j=1}^{4} \gamma_h^j d_{i,t(p)} \times q_{j,i,t(p)} + \epsilon_{i,t(p)}.$$

The grey area is the 90% confidence region for the normal recession path. Full sample results: 1870-2015, excluding world wars and 5-year windows around them.

Z. Return predictability: univariate results

Table A.27: *Balance sheet measures and mean returns on the bank equity index.*

Cumulative returns	(1) 1-year	(2) 2-year	(3) 3-year	(4) 1-year	(5) 2-year	(6) 3-year
Panel A	RHS: Δ_3 Loans/GDP			RHS: Δ_3 Assets/GDP		
See column header	-0.041***	-0.082***	-0.113***	-0.021***	-0.037***	-0.061***
	(0.005)	(0.011)	(0.018)	(0.007)	(0.010)	(0.015)
R^2	0.022	0.045	0.062	0.009	0.014	0.027
Observations	914	883	854	914	883	854
Panel B	RHS: Capital ratio			RHS: Δ_3 Capital ratio		
See column header	-0.061	-0.105	-0.117	-0.017	-0.007	0.040
	(0.049)	(0.094)	(0.131)	(0.017)	(0.030)	(0.041)
R^2	0.004	0.005	0.005	0.001	0.000	0.001
Observations	914	883	854	914	883	854
Panel C	RHS: Δ_3 LtD ratio			RHS: Δ_3 Non-core ratio		
See column header	-0.027***	-0.059***	-0.085***	-0.001	-0.007	-0.035*
	(0.008)	(0.021)	(0.032)	(0.006)	(0.015)	(0.021)
R^2	0.008	0.019	0.027	0.000	0.000	0.005
Observations	901	870	841	886	855	826

Notes: The dependent variable is the log excess return on the bank equity index from Baron and Xiong (2017) cumulated over h years, where h is specified in the column header. RHS variables are standardized at the country level using past data to avoid look-ahead bias. All specifications include country fixed effects. Standard errors in parentheses are computed using the Driscoll-Kraay method accounting for autocorrelation of up to 17 lags. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.