THE MACRO-ECONOMICS OF INEQUALITY GRK 2281

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Date: September 2020

RTG 2281 – Discussion Papers

No. 2020-8

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Funded by Deutsche Forschungsgemeinschaft German Research Foundation

The Profit-Credit Cycle*

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Keywords: Credit cycles, bank profitability, banking crises.

JEL classification codes: E32, E44, G01, G21

*This work is part of a larger project kindly supported by a research grant from the Bundesministerium für Bildung und Forschung (BMBF). Special thanks to participants at the Frontiers in Financial History Workshop 2018 in Rotterdam, the EDP Jamboree 2018 in Florence, the CESifo Workshop on Banking and Institutions 2019 in Munich, and the 19th FDIC-JFSR Fall Banking Research Conference, as well as seminar participants at the Banque de France, Board of Governors of the Federal Reserve, BI Norwegian Business School, Bundesbank, Erasmus School of Economics Rotterdam, ESADE, IESE, Norges Bank, Sveriges Riksbank, Universitat Pompeu Fabra, University of Bonn, University of Luxembourg and University of Mainz. We are grateful to Christian Bayer, Pedro Bordalo, Christian Eufinger, Roger Farmer, Andrej Gill, Florian Hett, Dmitry Kuvshinov, Yueran Ma, Enrico Perotti, José-Luis Peydró, Moritz Schularick, Kasper Roszbach, Daniele Verdini, Gian-Luca Violante for helpful comments and to Matthew Baron for sharing data.

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1. Introduction

The credit cycle takes center stage in the scholarly analysis of the 2007/2008 crisis. The financial turmoil was preceded by a boom in private credit in many countries, just as so many other crises episodes before (Schularick and Taylor, 2012). More generally, the credit cycle also predicts medium-term output growth, but economic forecasters often fail to account for this relationship (Mian et al., 2017). Asset return data suggest they are not alone: capital markets often neglect the treacherous link between credit expansions and downside risk (Baron and Xiong, 2017; Fahlenbrach et al., 2017; Krishnamurthy and Muir, 2017). In response to the output risks associated with credit expansions, policy-makers today monitor credit aggregates closely and apply a widening range of macro-prudential tools, once they detect overheating. While these policies are often effective in dampening credit growth (Akinci and Olmstead-Rumsey, 2018), they are rather a treatment of symptoms than causes. This is no surprise as the understanding of the ultimate sources of credit supply expansions and how they turn into a crisis is still limited (Mian and Sufi, 2018).

In this paper, we revisit the origins and turning points of the credit cycle. It is well documented that firms and managers overpredict future earnings when profits are high and that this has consequences for investment (Gennaioli et al., 2016; Greenwood and Hanson, 2015). We show that there is a similar pattern underlying bank lending. What we observe in the data is in fact a "profit-credit cycle". An increase in bank profitability predicts a credit expansion in the next years, but also elevated crisis risk down the road. Banking panics often occur after profits start declining during such boom episodes. These findings connect well with older ideas of "displacements" in the credit market triggering waves of optimism followed by a "Minsky moment" (Kindleberger, 1978; Minsky, 1977) and mesh nicely with new modeling approaches to the credit cycle based on extrapolative expectations (Bordalo et al., 2018; Greenwood et al., 2019).

To study the profit-credit relationship, we introduce a new dataset on bank profitability in 17 advanced economies over the last 145 years. The data come from banking sector profit and loss accounts and allow us to systematically assess the relationship between bank profits, the credit cycle, and financial instability in modern financial history. One advantage of our accounting data is that profits are, by definition, backward looking and enable us to study the link between realized outcomes and subsequent lending. Credit spreads and stock returns on the other hand, which have been studied in the previous literature (Baron et al., 2020; Baron and Xiong, 2017; Krishnamurthy and Muir, 2017) do not necessarily reflect realized outcomes and incorporate expectations about the future. Furthermore, our accounting data cover a large share of the overall banking system, while equity and bond prices are often only available for a small subset of the banking sector. For a subsample of countries and episodes we were furthermore able to decompose bottom line bank profitability into its sources – revenue, costs and loan losses – and its uses – funds paid out to shareholders and funds retained as equity in the balance sheet. Our new dataset is complemented by the data of the Macrohistory Database (Jordà et al., 2017), which provides us with credit aggregates, a chronology of banking crises and a large number of control variables for our investigation.

We find that bank profitability leads the credit cycle. High bank profits are followed by credit expansions. We measure profitability as return on equity (RoE) or return on assets (RoA) and proxy a sequence of increasing or decreasing profits with the three-year change in this return measure ($\Delta_3 RoE$ and $\Delta_3 RoA$). Our results imply that a one standard deviation higher $\Delta_3 RoE$ predicts a 0.2 standard deviation higher change in credit-to-GDP over the subsequent three years. This is equivalent to an increase of the credit to GDP ratio by 4.9% instead of the sample average of 3.4% over a three year window. This relationship remains robust when we include additional controls, time effects and analyze subsamples. It holds for alternative measures of profitability or credit growth, during and outside of financial crises and on a country-by-country level. We show in the appendix that these results also carry over to the bank level using panel data from Federal Reserve call reports.

Policy-makers may be predominantly concerned about large credit expansions as these are often associated with the left tail of macroeconomic growth outcomes. To study these boom episodes separately, we rely on an indicator variable for the start of a large credit boom, defined by the three-year change in credit-to-GDP being elevated by more than one country-specific standard deviation. In line with our previous results, we find that the start of a credit boom episode can be forecasted with increasing profitability. During the ensuing boom RoE and RoA return to their mean values within a few years. The ratio of total bank profits to GDP remains elevated throughout the boom due to increasing quantities of intermediated funds. This evidence suggests that there would be ample room for the banking sector to increase capital through retained earnings during credit booms to shield the economy from harm during the bust (Jordà et al., 2020).

Which mechanisms can explain the strong association between profits and the credit cycle? We first show that the relationship cannot be explained by credit demand. An outward shift in credit demand should be associated with high interest rate spreads during the credit expansion. We find the opposite: the price of credit – a corporate bond spread – is negatively associated with recent improvements in profitability. Focusing on expansions in credit supply, we distinguish between financial constraints and time-varying beliefs as explanations for the profit-credit cycle. High profits, if not paid out completely to shareholders, increase net worth in the banking sector and thereby relax borrowing constraints (Bernanke and Gertler, 1989; Holmstrom and Tirole, 1997; Kiyotaki and Moore, 1997). In our long-run data, we find evidence consistent with such a net worth channel. Bank capital ratios and retained earnings, as measures of the level and change in bank net worth, predict credit expansions.

However, we provide several findings that cast doubt on whether the "profit-credit cycle" can be explained exclusively by financial constraints. First, the relationship between profits and future lending growth remains stable and significant when we introduce direct controls for net worth. We find the same strong link between profits and credit growth in specifications that include the capital ratio and changes in banking sector capital. Second, when decomposing bank profitability into loan losses, revenues and costs, we find that decreasing loan losses are associated with expanding credit, while lower costs or increasing revenues are not. If the relationship between profitability and credit expansion would simply be due to the effect of profits on net worth, we would expect that the source of profits is largely irrelevant and results for all sources should be similar.

Third, we rely on the idea that dividends paid to shareholders do not relax financial constraints in the banking sector. Decomposing profits into dividends and retained earnings, we find a significant effect of dividend payments on future credit expansion, while controlling for retained earnings. Finally, when we include the current level and recent changes in profitability in one specification, the coefficients for both variables are positive and significant. This suggests that not only additional net worth (measured by RoE levels), but also the change of RoE relative to previous periods matters for credit expansion. These findings are consistent with expectations-based credit cycle models (Bordalo et al., 2018; Greenwood et al., 2019). In these models, positive news – displacements in the language of Minsky (1977) – are extrapolated into the future and thereby trigger a wave of optimism. It is during these episodes that investors willingly supply credit, to be systematically disappointed in the following years.

To study the expectation formation process in further detail, we use data from a survey among bank CFOs in the United States. We find that recent changes in profitability are strongly associated with measures of optimism and expected profits. The link between realized and past profitability is weaker, and as a result, bank CFOs make predictable forecast errors. When current profits are high, bank CFOs are optimistic, but realized future earnings are lower than expected. We then show that survey expectations and optimism are reflected in the aggregate credit cycle. Higher optimism today is associated with higher lending volumes over the next 12 months. This creates a link between forecast errors and lending, implying that extrapolation could be associated with a misallocation of credit.

Motivated by the Minsky (1977)-narrative, we study the link between bank profitability and the incidence of banking crises in the second part of the paper. We find that increases in profitability predict financial instability over the medium term. A one standard deviation higher increase in profitability between years $t-3$ and t is associated with a one percentage point higher crisis likelihood in $t+3$. This corresponds to more than a 25 percent increase relative to a baseline crisis frequency of 3.1%. Looking at the transition from a boom into a crisis, we find that crises are associated with a decline in the growth of profitability shortly before their onset. Unsurprisingly, profitability then drops further in the year of a banking crisis and remains low for several years thereafter.

Using data on crisis characteristics collected by Baron et al. (2020), we then assess whether this pattern is specific to certain types of banking crises in order to gain insights on the underlying mechanisms. We find that the reversal of fundamentals – improving profitability followed by a decline shortly before the crisis – is a peculiarity of banking panics. While panics are predicted by increasing profitability, non-panic banking crises are preceded by declining profitability already three years prior. For a panic to occur, creditors' expectations about bank asset returns must be extremely negative, such that bank capital would not be able to absorb losses and creditors' claims are at stake. Our evidence hence suggests that expectations of creditors turn extremely negative when they are surprised by a sudden reversal in bank fundamentals following a boom. Panics then occur as a sudden end to a boom, while non-panic crises occur after prolonged periods of weak fundamentals.

Taken together, the credit-cycle patterns we document are consistent with the model of Bordalo et al. (2018) where good news create overoptimism, and subsequently incoming disappointing news lead to sharp reversals in expectations and banking panics.[1] The relationship between bank profitability, especially loan losses, and crisis also lines up well with previous studies on the behavior of market-based risk metrics before crises: credit spreads (Krishnamurthy and Muir, 2017) and stock market volatility (Danielsson et al., 2018) have both been found to be low in the prelude to a crisis. In a similar vein, Meiselman et al. (2018) show that elevated bank profits are measuring risk in the cross-section of banks. High *RoE* levels during the boom are linked to a worse performance of banks during the crisis.

[1] Note that changes in expectations are based on fundamentals, consistent with models of fundamentals-based bank runs (Goldstein and Pauzner, 2005; He and Xiong, 2012).

Our paper contributes to three strands of research. One strand discusses patterns of the credit cycle (Aikman et al., 2015; Dell'Ariccia et al., 2016) and identifies markers that help to tell different kinds of credit booms apart (Gorton and Ordonez, 2020; Kirti, 2020; Richter et al., 2020). A rapidly growing literature surveyed in Mian and Sufi (2018) studies the interplay of credit and business cycles with a focus on credit supply based explanations. Our results support the view that credit supply plays an important role in shaping the credit cycle and shows that credit booms start when banking sector profitability has been increasing.

Second, our paper extends the behavioral credit cycle literature. Evidence for overextrapolation of recent shocks or trends is pervasive. Greenwood and Shleifer (2014) show that survey-based investor expectations are extrapolative and hard to reconcile with rational expectations models. Similar results have been obtained analyzing macroeconomic expectations of professional forecasters (Bordalo et al., 2020), households' house price expectations (De Stefani, 2020; Kuchler and Zafar, 2019) and expectations in laboratory experiments (Landier et al., 2018). Recent research relates the extrapolation bias to fluctuations in real investment (Gennaioli et al., 2016) and incorporates extrapolative biases in models of the credit cycle (Bordalo et al., 2018; Greenwood et al., 2019).

It is important to note, that our data on bank profitability allow us to show that such a relationship holds for the bank credit cycle, while most previous studies focused on cyclical developments in the bond market (Greenwood and Hanson, 2013), or linked expansions in bank credit with data on prices and defaults from the bond market (Greenwood et al., 2019; Krishnamurthy and Muir, 2017). Linking bank profitability to bank credit is important, as the underlying theory of extrapolation most likely applies within a specific asset-class. Kuvshinov (2018) shows that measures of asset market sentiment are not necessarily correlated across asset classes, so that extrapolation seems to be domain-specific.

Third, our paper is related to a literature that studies the relationship between net worth and credit intermediation in models with financial frictions (Bernanke and Gertler, 1989; Holmstrom and Tirole, 1997; Kiyotaki and Moore, 1997). A vast literature builds on these early contributions, studying alternative frictions and amplification mechanisms and integrating the mechanisms into richer macroeconomic models (e.g. Brunnermeier and Sannikov, 2014). The profit-credit cycle is consistent with these mechanisms, but our results suggest that this channel alone cannot account for it. In that regard, recent attempts to integrate belief-driven cycles into models that feature amplification through intermediaries seem in the light of our results particularly promising (Bordalo et al., 2019; Kaplan et al., 2020; Krishnamurthy and Li, 2020).

2. A NEW DATASET ON BANK PROFITABILITY

This paper is built around a novel long-run dataset on bank profitability across countries and time. We construct new return on equity and return on asset series for 17 countries from 1870 to today using banking sector income statements. So far, research with long-run historical data on credit cycles and systemic banking crises heavily relied on banking sector balance sheet information (Jordà et al., 2020; Schularick and Taylor, 2012). A second strand of the literature recently started to incorporate market prices for debt and equity into the analysis (Baron et al., 2020; Baron and Xiong, 2017; Krishnamurthy and Muir, 2017). Banking sector income – in particular realized banking sector profitability – has been largely ignored. Adding data from the income statement creates a link between balance sheet data and market prices. The new dataset therefore complements these existing data. Our main profitability series – return on equity (RoE) – is computed by dividing total profits of the banking system by book equity:

$$RoE = \frac{Net\ profits\ after\ Tax}{Book\ Equity} \tag{1}$$

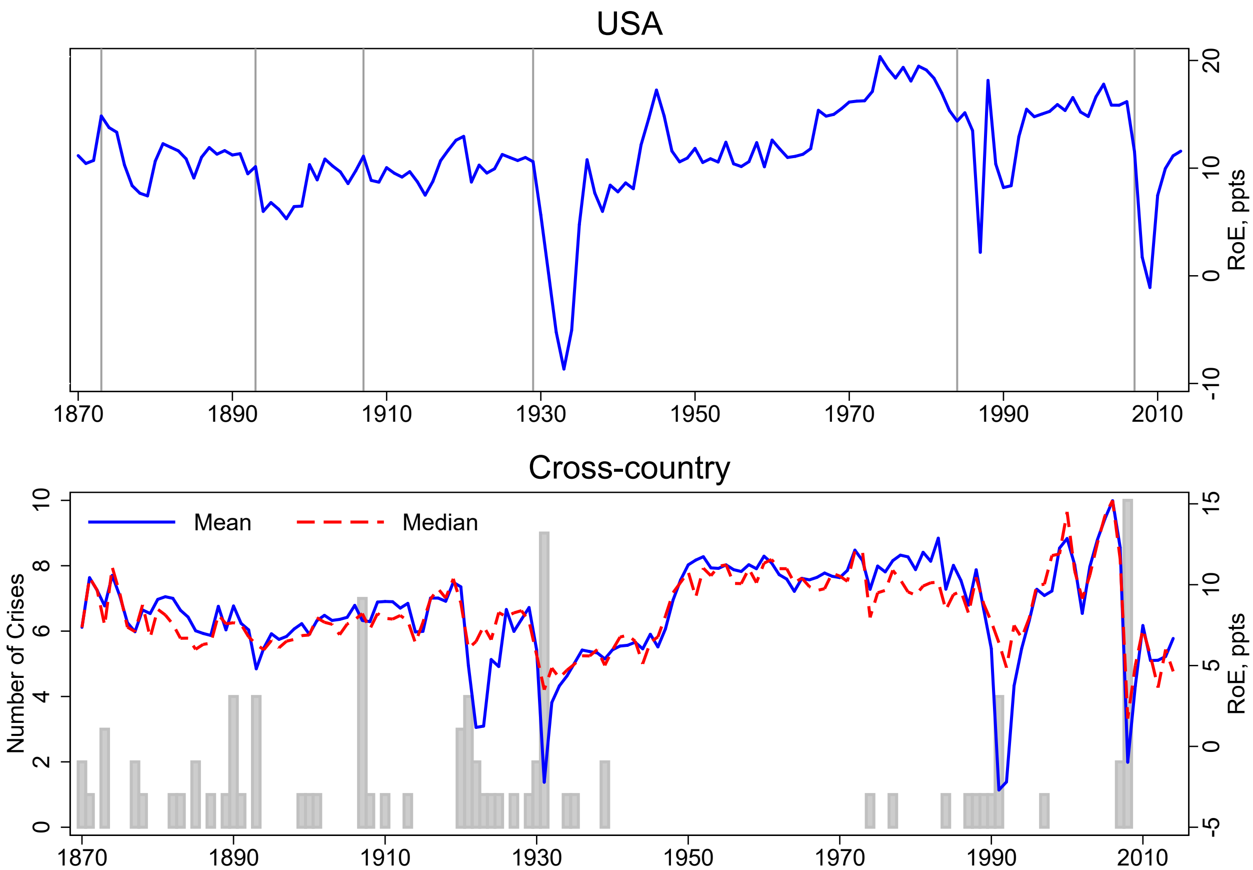
The numerator of the equation measures accounting income of the banking system after the deduction of all relevant expenditures and corporate taxes. The denominator includes paid-in capital, reserves and retained earnings. The equity items also include profits carried forward and the issuance premium gained by selling stocks above their nominal value. Aside from the return on equity series, we also construct a return on asset series by dividing profits by total assets instead of total equity.[2]

The data come from a wide range of sources including publications of the OECD, central banks, banking supervisory institutions, work of banking historians and individual bank reports. The new series includes on average more than 125 years of data for each country in our sample. The paper is complemented by a detailed Internet Appendix describing sources and data construction. Summary statistics of the profitability measures can be found in Table A1.1.[3]

[2] Return on equity and return on assets are connected through the leverage ratio of the underlying financial institutions. Due to sampling and coverage differences, the implicit leverage ratio of the return on equity and return on asset series in some cases differs slightly from the leverage ratio of Jordà et al. (2020).

[3] A large share of the dataset is based on aggregate banking statistics. In some countries, we gathered data of the largest commercial banks to extend the data back into the 19th century. Relying on data of a few banks might generate excess volatility compared to the aggregate banking sector statistics and add bank idiosyncrasies to the final series. However, in most cases the deviations are likely small, as the respective banking systems were dominated by a small number of banks (e.g. Canada) with a large market share. Another issue is related to the use of accounting data. We treat this data at face value. The sophistication of accounting standards and practice however varied significantly historically. As a consequence, the data

Figure 1: *Long-run evolution of RoE in the United States and across sample countries*



Notes: This figure displays the evolution of *RoE* in % between 1870 and today for the USA and for a cross-country mean (median). Vertical bars indicate starting years of systemic financial crises in the USA and the number of countries experiencing the start of a financial crisis respectively (see appendix for dates).

Figure 1 illustrates the data. It shows the *RoE* series for the United States and yearly sample averages. The vertical lines in the upper graph indicate systemic banking crises in the US and grey bars in the cross-country graph indicate the number of countries with systemic banking crises in a given year. We rely on the narrative chronology by Jordà et al. (2017) to identify systemic banking crises events. Several features stand out: Bank profitability, measured by *RoE*, was relatively stable over the last 145 years. *RoE* fluctuated around 8 percent in most countries (see also the summary statistics in Table A1.1). In some countries – such as the United States – there is a gradual upward trend in *RoE* in the second half of the 20th century. Major deviations from the trend follow or coincide with systemic banking crises. These crises often drive bank profitability into negative territory. For

might be distorted by profit smoothing and hidden reserves in bank balance sheets. In our empirical analysis, we will therefore focus especially on changes in profitability and the resulting estimates are most likely downward biased by profit or dividend smoothing.

example, the RoE series for the United States shows three major negative shocks with RoE around or below zero: the Great Depression, the S&L crisis and the Global Financial Crisis. The defining feature of the cross-country averages are the extraordinarily low profits during clustered crisis events. Comparing profitability in crisis and non-crisis episodes reveals that RoE in a crisis-year is around 7% lower than the non-crisis average. However, not all systemic banking crises are characterized by pronounced negative profitability. While some crises nearly wiped out the entire banking sector capital, others are difficult to eyeball in the profitability series (e.g. the crisis of 1907 in the United States).

Our new dataset also allows us to decompose banking sector profits into sources and uses. Drawing from additional banking sector accounting information, we separate RoE by the use of funds into a dividend and a retained earnings component. We gathered data on dividends directly and back out retained earnings as the difference between profits and dividends. Furthermore, we were able to obtain information on the sources of bank profitability. We decompose profits into revenues (net interest plus net fee income), operating costs and loan losses. We then compute 3-year changes in all profitability variables (e.g. RoE) as a proxy for medium-term changes

$$\Delta_3 RoE_{i,t} = RoE_{i,t} - RoE_{i,t-3}. \tag{2}$$

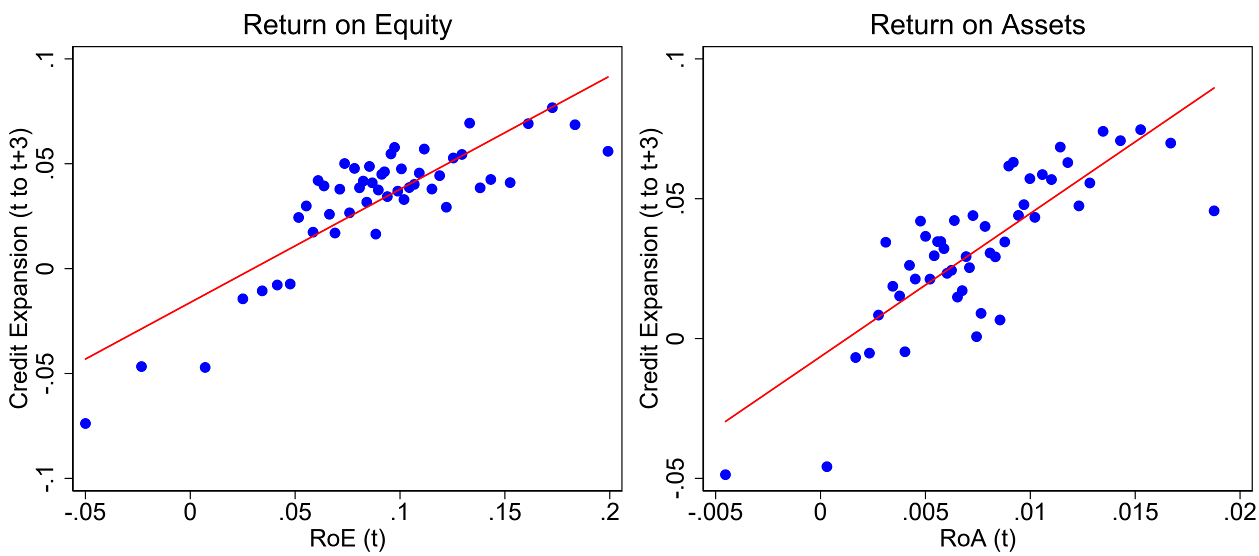
As there are no clear trends in RoE over our sample period, this variable is on average close to zero. The bank profitability data is in some countries dominated by extreme loss events during crises (see Figure B.1). We therefore winsorize all profitability measures at the 2.5% level to ensure that empirical results will not be driven by extreme outliers in profitability. The main results of the paper also hold in the raw data with the same significance level and similar point estimates. Our main dependent variable to analyze the relationship between profitability and credit cycles will be the change in the credit-to-GDP ratio over a three-year interval (similar to Mian et al., 2017):

$$\Delta_3 y_{i,t+3} = (Credit/GDP)_{i,t+3} - (Credit/GDP)_{i,t} \tag{3}$$

Credit here refers to bank credit extended to the domestic private non-financial sector. It includes loans to households as well as loans to non-financial firms. In contrast to profitability measures, there has been an upward trend in the ratio of credit to GDP over the past 150 years and $\Delta_3 y_{i,t}$ is around 3.4% on average.

3. Bank profitability and the credit cycle

Figure 2: *Binned scatterplot for the relationship between profitability and credit-to-GDP changes*



Notes: The figure links bank profitability and subsequent three-year changes in credit to GDP. Observations are collapsed into 50 equal sized bins according to profitability (RoE or RoA). Each point represents the group specific means of profitability and credit expansion after controlling for country fixed effects and a time trend. Fitted regression lines illustrate the correlation between bank profitability and subsequent credit expansion.

What is the relationship between bank profitability and credit growth? This section establishes that increasing bank profitability is a significant and robust predictor of subsequent credit expansions.

Figure 2 graphically illustrates the relationship between current RoE or RoA and credit expansion over the following years. In both panels, the data are collapsed into 50 equal-sized bins according to profitability measure and the graph displays the mean profitability for observations in each of these bins. In addition, on the y-axis, the mean of three-year credit-to-GDP changes for each of the 50 groups is presented. The graph shows the relationship of residuals after controlling for country fixed effects and including a time trend to account for the long-term decline in RoA. Both panels display a strong positive correlation between profitability and credit expansion.

We will now assess the relationship between profits and credit more formally. Since there is a strong time trend in RoA, we will focus on the two previously defined measures of medium-term variation in profitability, $\Delta_3 RoE$ and $\Delta_3 RoA$. We assess their relationship with the credit cycle using three year changes in the credit-to-GDP ratio as the dependent variable. Similar to the approach in Mian et al. (2017) we estimate variants of equation

$$\Delta_3 y_{i,t+3} = \alpha_i + \beta^{\Delta RoE} \Delta_3 RoE_{i,t} + \sum_{\tau=0}^{2} \gamma_\tau \Delta y_{i,t-\tau} + \eta X_{i,t} + \theta Z_{i,t} + u_{i,t+3}, \tag{4}$$

where we include changes in profitability, $\Delta_3 RoE_{i,t}$ and $\Delta_3 RoA_{i,t}$ as well as a distributed lag of the dependent variable ($\sum_{\tau=0}^{2} \Delta y_{i,t-\tau}$). $X_{i,t}$ is a vector of macrocontrols including the three most recent values of real GDP growth, short-term interest rates, long-term interest rates, inflation, the current account-to-GDP ratio as well as log real GDP per capita to account for the state of development in our long run sample. As a second set of controls ($Z_{i,t}$), and as a first step towards disentangling possible channels, we add two proxies that account for financial constraints in the banking sector: the capital ratio of the banking sector as a measure of leverage constraints and three-year changes in bank capital relative to GDP as a measure of net worth in the banking sector (Adrian et al., 2019). We exclude data from the two world wars to avoid measuring the effects of wartime government intervention in the banking sector.

Table 1 column (1) shows that an increase in profitability over the past three years ($\Delta_3 RoE_{i,t}$) predicts significantly higher credit expansion over the following three years ($\Delta_3 y_{i,t+3}$). A similar result emerges when we include changes in RoA, $\Delta_3 RoA_{i,t}$, in column (4). Banks extend more credit when measures of realized profitability start looking better over time. Adding macroeconomic controls in (2) and (5) reduces the coefficients slightly, but the results remain highly significant. Consistent with a role of intermediary leverage, we find that a high capital ratio is associated with increases in the credit-to-GDP ratio over the following years – relaxed funding constraints are associated with increased lending. Increases in the ratio of capital to GDP as a measure of aggregate net worth do not predict credit expansion. Importantly, including both measure of financial constraints does not affect the results for the profitability measures.

How sizable is the effect of profits on lending? Increasing $\Delta_3 RoE_{i,t}$ ($\Delta_3 RoA_{i,t}$) by one standard deviation is associated with a 1.53% (1.48%) higher increase in credit-to-GDP over a three-year window. The mean of three-year changes in credit-to-GDP in our non-war estimation sample is 3.4%. Our estimates hence imply that this rate of change increases by almost 50 percent when realized profitability growth is elevated by one standard deviation. Our long run evidence shows that booms in profitability are an important vector to understand credit expansions.

Table 1: *Multivariate models for changes in credit-to-GDP, baseline specification*

	Dependent variable: $\Delta_3 y_{i,t+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t}$	0.42***	0.34***	0.33***			
	(0.06)	(0.04)	(0.04)			
$\Delta_3 RoA_{i,t}$				4.68***	3.88***	3.89***
				(0.85)	(0.69)	(0.69)
$Capital\ Ratio_{i,t}$			0.23***			0.23***
			(0.07)			(0.07)
$\Delta_3(Capital/GDP)_{i,t}$			-0.06			-0.17
			(0.24)			(0.23)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
R^2	0.12	0.19	0.20	0.11	0.19	0.20
Observations	1636	1492	1491	1642	1498	1491

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $\Delta_3 RoE_{i,t}$ and $\Delta_3 RoA_{i,t}$. All specifications control for three lags of credit-to-GDP changes. Columns (2), (3), (5) and (6) add a vector of macroeconomic control variables described in the text. Columns (3) and (6) additionally control for financial constraint proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

3.1. Robustness

In the following subsections, we show that this relationship is a robust feature of the data, the relationship is mainly driven by loan losses, and that profitability also helps to predict large credit booms. We first discuss the robustness of the relationship between bank profitability and credit expansion identified before.

Subsamples: In Table 2 we look at subsamples of the data. All specifications include the full set of control variables. In a first step we restrict the sample to the post Bretton-Woods era to understand whether the strong relationship can also be observed in the current international monetary framework. We find that the results are robust to restricting the analysis to this time period. The same is true in a subsample of pre-2000 data, which we analyse to ensure that the relationship was not only a feature of the credit cycle that found a sudden end in the 2007/2008 crisis. In column (3), we use non-overlapping windows of observations in the dependent variable to deal with autocorrelation introduced through overlapping data and results remain highly significant. In column (4), we address possible cross-country correlation of variables and include year-fixed effects. The year fixed effects

Table 2: *Multivariate models for changes in credit-to-GDP, subsamples and time effects*

	Dependent variable: $\Delta_3 y_{i,t+3}$				
	(1) Post-1973	(2) Pre-2000	(3) No overlap	(4) Year effects	(5) Crisis
$\Delta_3 RoE_{i,t}$	0.25***	0.27***	0.29***	0.20***	0.21***
	(0.05)	(0.07)	(0.05)	(0.04)	(0.03)
$Crisis_{[t-2,t]}$					-0.04**
					(0.02)
$Crisis_{[t-2,t]} \times \Delta_3 RoE_{i,t}$					0.27
					(0.20)
Country fixed effects	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓
Year effects				✓	
R^2	0.35	0.17	0.18	0.36	0.23
Observations	640	1304	496	1491	1483

	Dependent variable: $\Delta_3 y_{i,t+3}$				
	(1) Post-1973	(2) Pre-2000	(3) No overlap	(4) Year effects	(5) Crisis
$\Delta_3 RoA_{i,t}$	4.15***	3.06***	3.55***	2.61***	2.42***
	(0.93)	(0.95)	(0.59)	(0.70)	(0.52)
$Crisis_{[t-2,t]}$					-0.04**
					(0.02)
$Crisis_{[t-2,t]} \times \Delta_3 RoA_{i,t}$					1.68
					(2.38)
Country fixed effects	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓
Year effects				✓	
R^2	0.35	0.17	0.18	0.36	0.22
Observations	640	1304	496	1491	1491

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $\Delta_3 RoE_{i,t}$ $and \Delta_3 RoA_{i,t}$. All specifications control for three lags of credit-to-GDP changes and a vector of financial constraint proxies and macroeconomic control variables (see text in section 3). Column (1) uses only post-1973 data. Column (2) uses only pre-2000 data. Column (3) restricts the data to non-overlapping observations only. Column (4) includes year-fixed effects. Column (5) includes a banking crisis dummy and its interaction with profitability measures. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

increase the R^2 to more than 0.3 in both cases, indicating that there is a high degree of cross-country correlation in credit expansion, as identified in other studies (Jordà et al., 2019; Rey, 2016). The coefficients on profitability measures remain however highly significant.

Finally, we include in (5) a dummy for a banking crises occurring in the last three years (i.e. between $t-2$ and t) and its interaction with profitability measures. This exercise is addressing two concerns. First, the relationship could be entirely driven by low credit growth following high losses in a banking crisis. As the first coefficient in column (5) shows, this is not the case. Profitability changes remain a robust predictor of credit expansion even when we account for crisis events. The second row shows that credit expansion is significantly dampened following crisis episodes. The second issue we seek to address is whether the relationship between profitability and credit expansion is stronger during a crisis episode. If the relationship was primarily driven by financial constraints in the banking sector, we would expect that the effect is stronger in crisis periods when these constraints are more likely to be binding. In both specifications, the interaction is positive, but insignificant. Another way to address this question is to focus on the relationship in a crisis only. In Table A2.1 we include only the three years after the start of systemic banking crises into the regression sample. We find coefficients similar to our baseline estimates: large losses during crisis episodes translate into significantly lower credit expansion, but they do so in the same way as profits do in non-crisis episodes.

Alternative credit measures: The appendix presents further robustness tests with respect to variable definitions. In a first step, we vary the dependent variable. So far, $\Delta y_{i,t+3}$ referred to the three-year change in the credit-to-GDP ratio. In Table A2.2 we replace credit-to-GDP with logged real private credit per capita to rule out the possibility that the effect is driven by the denominator. The results are in line with our previous findings. In Table A2.3 we move away from credit variables and look at the bank-assets-to-GDP ratio. The findings are similar to those for credit variables. In Table A2.4 we ask whether the relationship is similar for non-credit assets. Here, we find weaker results, so the mechanism seems to be more relevant for credit expansion than for other bank assets.

Alternative profit measures: Furthermore, the appendix also shows results for different definitions of the explanatory variables. In Table A2.5 we vary the denominator and normalize net income by GDP and CPI. In Table A2.6 we include levels in profitability measures instead of changes. In all these specifications, profitability robustly predicts credit expansion.

Timing: We explore the dynamic relationship between profits and credit growth by shifting the dependent variable over time in appendix section A5. The response of the credit-to-GDP ratio to variation in profitability measures is strongest over the subsequent three years – our baseline evidence – and slowly dissipates at longer horizons. We also find that profit changes and credit growth are contemporaneously negatively correlated. This evidence indicates that high bank profitability and the credit cycle are unlikely to be linked through correctly anticipated improvements of economic fundamentals. The expansion is associated with decreasing rather than improving bank profitability, in line with the observed decline in output (Mian et al., 2017).

Country level evidence: In Figure A2.1 we plot the coefficients at the country level. We run a time series regression of $\Delta_3 y_{i,t+3}$ on profitability measures for all our sample countries one by one. The graphs show that the coefficients are all positive and significant in a majority of countries, so that the strong association between profitability and credit expansion seems to be a common feature across our sample countries.

Bank level evidence: The channels that link profits and subsequent credit growth should also be operative at the bank level. Indeed, the literature already provides evidence that higher bank capital is associated with more lending (Jiménez et al., 2017) and that loan officers extrapolate from their recent experiences (Carvalho et al., 2020). In appendix section A6 we study whether the relationships we are describing here also hold in US bank level panel data. This allows us to control for financial constraints at the bank level which could matter if aggregate leverage ratios are hiding changes in the distribution of leverage ratios. The data also allows to rule out that aggregate credit demand is driving results by including time fixed effects. We find that the relationship between profits and credit expansion remains highly significant.

3.2. Decomposing profitability

So far, our analysis was based on bottom-line measures of profitability, RoE and RoA, which are both based on net income of the banking sector. We now re-estimate the profit-credit relationship for three major constituents of bank profits: revenue, operating costs and loan losses. This decomposition will help us to gain further insights into the mechanisms underlying the profit-credit cycle.

We define six new variables, expressing each of the separate profit components relative to equity and assets to maintain comparability to the baseline estimates. We then run regressions of the following form

$$\Delta_3 y_{i,t+3} = \alpha_i + \beta \Delta_3 (Revenue/Equity)_{i,t} + \eta X_{i,t} + u_{i,t+3}\,, \qquad (5)$$

Table 3: *Multivariate models for changes in credit-to-GDP, profit components*

	Dependent variable: $\Delta_3 y_{i,t+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	$\frac{Revenue}{Equity}$	$\frac{Costs}{Equity}$	$\frac{LoanLosses}{Equity}$	$\frac{Revenue}{Assets}$	$\frac{Costs}{Assets}$	$\frac{LoanLoss}{Assets}$
$\Delta_3 Change_{i,t}$	-0.01	-0.10	-0.27***	0.40	-1.14	-2.52***
	(0.05)	(0.09)	(0.06)	(0.65)	(2.57)	(0.53)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓
R^2	0.22	0.22	0.24	0.22	0.22	0.24
Observations	855	855	855	855	855	855

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on levels and three-year changes in banking sector revenue (net interest + net fee income), costs (administrative expenses) and loan losses. All specifications control for three lags of credit-to-GDP changes and a vector of balance sheet constraint and macroeconomic control variables (see text in section 3). All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

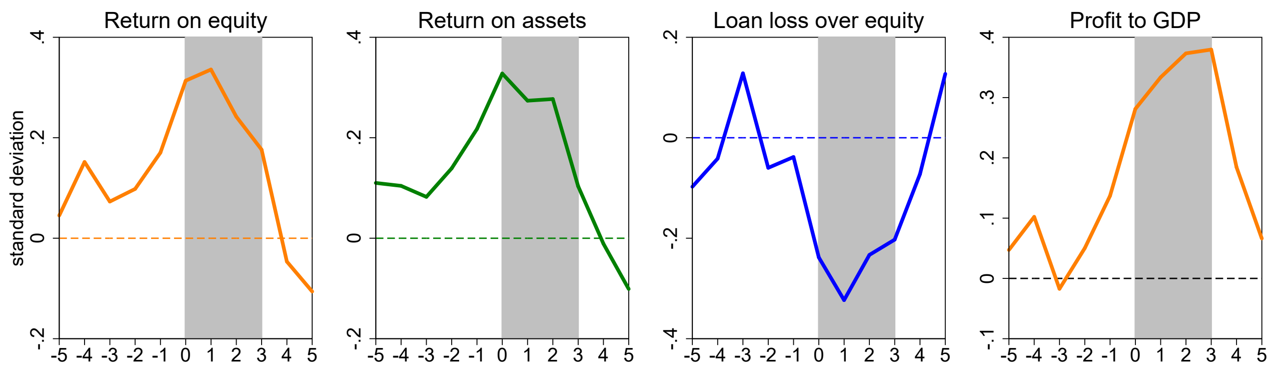
where we replace $\Delta_3(Revenue/Equity)_{i,t}$ with costs and loan losses and vary the denominator between *Equity* and *Assets* across specifications. The results are shown in Table 3. The results for loan losses are highly significant. A decrease in loan losses is associated with subsequent credit expansion. Revenues and cost variables only display a weak relationship with subsequent credit expansion. Table A6.6 presents corresponding evidence at the bank level for our sample of US banks. Again, loan losses are highly significant.[4]

We will look at the channels that link profits and credit expansion in more detail below, but this finding is already at odds with models exclusively based on financial constraints. Financial constraints most likely do not depend on the sources of income. Hence, we should observe similar coefficients for all three profitability components. However, we find that there is something particular about loan losses and the source of income contains information over and above the raw change in leverage or net worth. While not necessarily unique to these theories, the pattern is consistent with models that feature updating of beliefs based on recent credit market outcomes. In Bordalo et al. (2018) agents' expectations overweight states of the world that have become more likely in the light of new data. Applied to our setting, news about low or decreasing loan losses could lead agents to assign an inflated probability to future states of the world with low defaults. These low expected losses enter the lending decisions of banks and thereby create an incentive to expand lending in line with the empirical results presented above.

4 In the bank level data, changes in non-interest expenses turn out to be a significant predictor of credit growth as well.

3.3. Credit Booms

Figure 3: *Event study of profitability around credit boom dates, standardized*



Notes: These figures display the evolution of profit variables around credit booms. All variables are detrended and standardized with mean zero and standard deviation one by country. Observations are classified as boom years when $\Delta_3 Loans/GDP_{i,t}$ exceeds one standard deviation. 0 refers to a year in which a credit boom starts. The grey area marks the three-year window used to define the credit boom. Solid lines display means of variables around the start of a boom. See text.

The previous subsections have shown that there is a tight link between bank profitability and subsequent credit growth. While this relationship is interesting per se, policymakers naturally care more about large credit booms which are often followed by costly crises (Schularick and Taylor, 2012). How then is profitability related to these large credit booms?

The notion of a large credit boom implies a strong deviation from normal circumstances. To be consistent with the other exercises, we will identify large credit booms from the three-year change in the ratio of credit to GDP. As normal circumstances may differ across countries, we first standardize the three-year change in the ratio of credit to GDP at the country level. We then define year t as the start of a credit boom if the change of the credit to GDP ratio between year t and year $t+3$ exceeds one standard deviation.[5] With this definition, the probability to experience the start of a credit boom is 4.9% per year (95 booms), which is roughly similar to the frequency of banking crises. When we look at the starting years of the booms, we see that many well-known historical boom episodes are reflected by this definition. For example, we detect the start of a credit boom in 10 of our sample countries between 2000 and 2005.

In Figure 3 we show the evolution of profitability variables around these credit boom episodes. The graphs are centered around the start of a credit boom as defined above. Starting with the evolution of RoE, we see that unusually large three-year increases in

5 If there are subsequent observations fulfilling this condition, we group all these observations into one credit boom episode and define the first year of this boom episode as the starting year.

credit-to-GDP are preceded by an increase in RoE. RoE is close to the sample average 5 years prior to the start of the boom and increases on average by a third of a country-specific standard deviation until the credit boom starts in $t = 0$. RoE peaks at the start of the credit boom and starts falling as the boom continues.[6] 4 years into the boom, RoE is back at the sample mean. The patterns are almost the same when we look at RoA or when we constrain the sample to post 1945 credit booms in Figure A2.2. In the third panel, we see that loan losses are a major driver of these developments. Loan losses are decreasing before the credit boom starts. Once the credit boom is underway, loan losses start increasing again and they are back to the sample mean 5 years after the credit boom started. The fourth panel shows the evolution of bank profits relative to GDP around credit boom dates. The pattern here differs slightly from the previous graphs. While profitability ratios, profits per unit of equity or assets, are reversing quickly during the boom, profits relative to GDP remain elevated for some more years. Increasing quantities of intermediated funds balance decreasing profits per unit during the boom.

Given the strong association between credit expansion and crisis likelihood, and taking into account the beneficial effects of bank capital during a crisis (Jordà et al., 2020), it may be optimal if banks increase capital buffers during credit expansions. Our results suggest that there exists additional wiggle room for banks to increase capital buffers during booms, strengthening the case for recent regulatory efforts to implement countercyclical capital requirements and to limit dividend payouts.[7]

Turning to a formal econometric model to study the link between profitability and large credit booms, we estimate probit regressions with the indicator variable $B_{i,t}$ for the start of a boom as the dependent variable. We assume, as is standard in the literature, that the probability of a boom start conditional on observables $X_{i,t}$ can be represented in terms of the normal cumulative distribution function,

$$Pr[B_{i,t} = 1 | \alpha_i, X_{i,t}] = \Phi(\alpha_i + \beta X_{i,t}). \tag{6}$$

Here α_i is a country fixed effect and $X_{i,t}$ includes three-year changes in profitability and a vector of macroeconomic control variables. The results are shown in Table 4. The odd-numbered columns show estimates with profit changes and country fixed effects only

6 Based on our definition the boom lasts at least for three years, these three years are marked in grey in the graph. Note that many of the booms we detect last actually longer and credit is elevated for a few more years.

7 Figure A2.3 shows that capital ratios remain constant or increase slightly during the boom. For a subsample of booms our data allows us to distinguish between profits that are paid out and profits that are retained as equity. Figure A2.3 shows a significant share of profits is paid out to shareholders at later stages of the boom.

Table 4: *Multivariate probit models for boom prediction*

	$\Delta_3 RoE_{i,t}$		$\Delta_3 RoA_{i,t}$		$\Delta_3 LoE_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
See column header	0.22**	0.24***	3.64***	3.02***	-0.35***	-0.33***
	(0.11)	(0.09)	(0.80)	(1.07)	(0.06)	(0.08)
Country fixed effects	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
AUC	0.65	0.75	0.66	0.75	0.66	0.75
Observations	1658	1491	1669	1491	944	889

Notes: The table shows probit classification models where the dependent variable is a an indicator that is one at the start of a credit boom and zero else. Coefficients are marginal effects. Controls includes the three most recent values of short and long term interest rates, GDP growth, inflation and the current account as well as three-year changes in credit-to-GDP between $t-3$ and t. Country clustered standard errors in parentheses. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

while the even-numbered columns also include the full set of control variables. Three-year changes in RoE, RoA and LoE (loan losses relative to equity) are significantly related to the start of a large credit expansion. A one standard deviation higher $\Delta_3 RoA$ is associated with an increase of one percentage point in the probability of experiencing the start of a credit boom. Given the average boom frequency of 4.9%, this is a quite sizable effect.

4. Channels

This section studies the mechanism that links bank profitability and credit growth in further detail. First, we present evidence in favor of the hypothesis that bank profitability is associated with expansions in credit supply. We then distinguish between different credit supply channels and find that the relationship cannot be fully explained by financial constraints of intermediaries and is instead consistent with mechanisms featuring time-varying beliefs and extrapolation.

4.1. Credit demand and supply

Credit expansions follow improvements in bank profitability. This relationship could be due to an increase in the supply of credit or due to higher demand for credit. In our data, a simple test can help to distinguish between demand and supply-based explanations. More specifically, the two yield conflicting predictions regarding the price of credit during a credit expansion. The price of credit should be high if credit expansions after high bank profitability are due to an outward shift in credit demand. On the other hand, the price of credit should be low if high profitability is associated with increased supply of credit by the banking sector. We use data on bond spreads from Kuvshinov (2018) as a measure of the price of credit to test these competing hypotheses.[8] We analyse the relationship between spreads and three-year changes in profitability:

$$Bond\ spread_{i,t+1} = \alpha_i + \beta\Delta_3 RoE_{i,t} + \gamma X_{i,t} + u_{i,t}. \tag{7}$$

The results are presented in column (1) of Table 5. The price of credit in the next period is negatively associated with recent changes in profitability. In combination with our baseline result, namely an expansion of credit following improvements in bank profitability, this suggests that credit supply explanations better capture the dynamics than demand side explanations. This result is robust to adding financial constraint proxies and macroeconomic controls as can be seen in columns (2) and (3).The price of credit is low when banking sector profitability increases. This finding corroborates earlier work on supply driven credit cycles (Krishnamurthy and Muir, 2017; Mian et al., 2017) adding an explanation for expansions in credit supply.

Table 5: *Multivariate models for credit spreads*

	Dependent variable: $Bond\ Spread_{i,t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t}$	-1.04***	-1.07**	-0.84**			
	(0.35)	(0.48)	(0.43)			
$\Delta_3 RoA_{i,t}$				-20.93***	-19.92***	-20.23***
				(6.75)	(5.68)	(5.15)
Country fixed effects	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Financial constraints			✓			✓
R^2	0.00	0.09	0.11	0.01	0.09	0.11
Observations	1279	1279	1279	1279	1279	1279

Notes: This table reports regressions of credit spreads in $t+1$ on three-year changes in RoE. Column (2) adds the vector of macroeconomic control variables, column (3) additionally includes financial constraint proxies (see text in section 3). All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

[8] Hence, like usually done in this literature, we implicitly assume that lending standards in bond and bank credit markets are correlated. The advantage of bond spreads compared to data on lending rates is that they are forward-looking and immediately reflect lending conditions for new credit and greater data availability.

4.2. Disentangling supply based explanations

In a next step, we want to distinguish between two possible credit supply explanations of the profit-credit cycle. Here, we collect two additional pieces of evidence which suggest that financial constraints alone cannot explain the profit-credit relationship. First, we decompose return on equity into retained earnings over equity ($REToE$) and dividends over equity (DoE) for a subset of countries and years. The underlying idea of this exercise is simple. Dividends paid out to shareholders are not available in the banking sector to relax financial constraints. We can hence use DoE as a measure of profitability that is unrelated to changes in net worth. Applying this logic, the results in columns (1) and (2) of Table 6 confirm that the link between profits and credit expansion goes beyond a pure financial constraints channel. Column (1) shows that the growth in DoE over the previous three years is a predictor of credit expansion over the next three years. Retained earnings are robustly linked to subsequent credit expansion in column (2), but their addition does not affect the relationship between dividends and subsequent credit expansion.[9]

As a second piece of evidence, we include the 3-year change in profitability together with the level of additional net worth gained over the three-year window in one specification. We compute this measure as the sum of profits over the three year window, scaled by pre-existing capital or assets. Controlling for the cumulative profits over the three-year window, $\Delta_3 RoE$ is a proxy for the path the banking sector took to arrive at a certain level of profitability. When agents update expectations overweighing recent information, this path will affect expectations. Under diagnostic expectations for example, for the same level of three-year accumulated profits, agents may be more optimistic when profits over this period have been increasing as opposed to recent decreases. Columns (3) and (4) show that three-year changes in profitability predict a credit expansion over the next years, even when controlling for the level of additional net worth gained over this period. We repeated these two exercises using bank level data from the United States. The results in Table A6.7 confirm the aggregate findings presented here.

4.3. Survey expectations and credit expansions

The long run data shows that profitability in the banking sector predicts credit expansion. As we have argued before, this relationship is consistent with models of credit cycles that feature extrapolative expectations. A quickly growing literature is using survey responses

[9] Since retained earnings directly measure changes in net worth, we do not include indirect controls of financial constraints here.

Table 6: *Multivariate models for changes in credit-to-GDP*

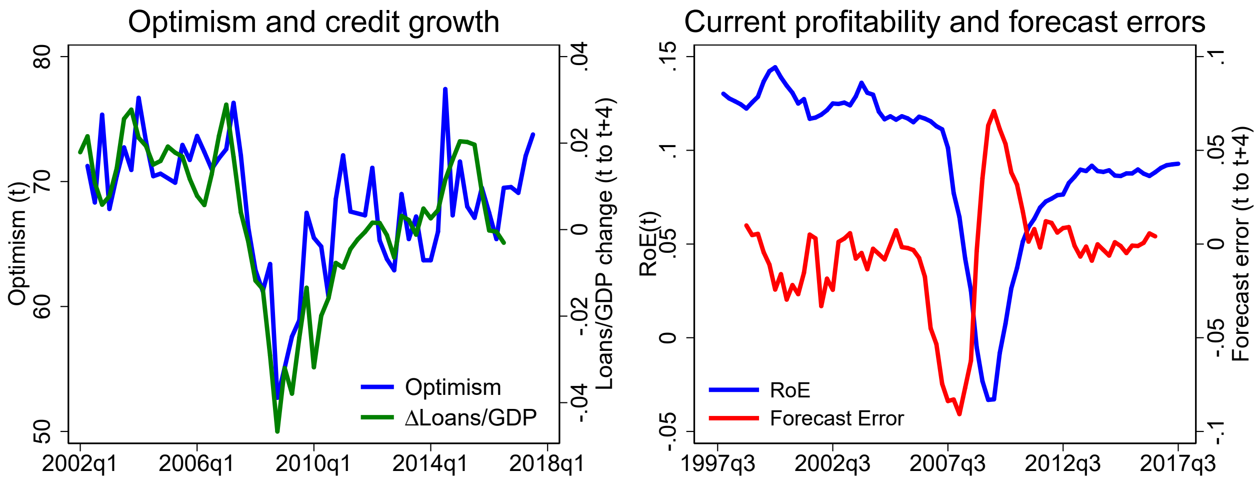
	Dependent variable: $\Delta_3 y_{i,t+3}$			
	Uses of profits		Profit path	
			RoE	RoA
	(1)	(2)	(3)	(4)
$\Delta_3 Dividends\ over\ Equity_{i,t}$	0.85***	0.78***		
	(0.24)	(0.25)		
$\Delta_3 Retained\ earnings\ over\ Equity_{i,t}$		0.22***		
		(0.07)		
$3-year\ Accumulated\ Profits_{i,t}$			0.10***	1.02***
			(0.03)	(0.27)
$\Delta_3 Change_{i,t}$			0.28***	3.37***
			(0.04)	(0.66)
R^2	0.186	0.200	0.224	0.221
Country fixed effects	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓
Control variables	✓	✓	✓	✓
Observations	949	949	1485	1486

Notes: This table reports regressions of credit-to-GDP changes for t to $t+3$. Columns (1) and (2) focus on the uses of profits by decomposing $\Delta_3 RoE_{i,t}$ into changes in dividends over equity ($\Delta_3 DoE_{i,t}$) and retained earnings over equity ($\Delta_3 RETоE_{i,t}$). Columns (3) and (4) study the profit path and include both, the level of accumulated profits ($RoE_{i,t}$) and the change ($\Delta_3 RoE_{i,t}$) in the same regression. All specifications control for the three most recent values of credit-to-GDP changes and macroeconomic control variables (see text in section 3). All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

to understand how economic agents are actually forming their expectations (e.g. Bordalo et al., 2020). Survey-based information about bankers' expectations is however scarce, especially in a long run cross-country setting. We therefore complement our approach with an analysis of recent survey data from the United States. Based on responses of bank CFOs (from the Duke CFO Global Business Outlook, 2018), we ask whether optimism and expectations about future profitability are related to recent changes in profitability and to subsequent changes in bank credit.

The Duke CFO Global Business Outlook (2018) asks respondents to rate their optimism about the financial prospects of their own company on a scale from 0-100, with 0 being the least optimistic and 100 being the most optimistic. CFOs are further asked about their expectations of changes in earnings over the next twelve months. For both questions, we have quarterly data on the mean response of CFOs from the banking and finance industry (starting in 2002 and 1998 respectively). We combine these measures with quarterly accounting information on realized profitability and credit growth for the US banking

Figure 4: *CFO expectations and the profit-credit cycle*



Notes: The left panel presents the evolution of bank CFO optimism and subsequent 4-quarter changes in the ratio of net loans and leases to GDP (between t and $t+4$) in the United States. The right-hand panel displays the evolution of bank RoE_t and time t return on equity forecast errors ($RoE_{t+4} - E_t[RoE_{t+4}]$) of bank CFOs in the United States between 1997 and 2017. See text.

sector.[10] The baseline relationships between profitability measures and subsequent credit growth in this sample mirror the correlations in the long-run cross-country data (see Figure A4.1 in the appendix). When we look at the consistency of the two survey measures, we find that reported CFO optimism and earnings growth expectations are indeed highly correlated (see Figure A4.2).

To study the links between profitability, optimism and credit growth, the left panel of Figure 4 shows that optimism at time t and changes in the credit-to-GDP ratio between t and $t+4$ (i.e. over one year) track each other closely. The banking sector extends more credit over the following year, when CFO optimism is elevated today. Optimism is an appealing measure for credit market sentiment, but it is important to note that optimism could be justified by subsequent developments in profitability. We therefore rely on additional survey responses about expected changes in earnings in the next 12 months to compare realized and expected profitability. We first calculate the time t expectation of RoE_{t+4} multiplying actual earnings over the past twelve months at time t with expected earnings changes over the next twelve months scaled with time t equity capital.

$$E_t[RoE_{t+4}] = \frac{ExpectedChange_{t\rightarrow t+4} \times \sum_{i=0}^{3} NetOperatingIncome_{t-i}}{EquityCapital_t} \tag{8}$$

[10] Quarterly balance sheet and income information are based on FDIC statistics. We use aggregated data from quarterly banking profile spreadsheets, in particular "Assets and Liabilities of FDIC-Insured Commercial Banks and Savings Institutions" and "Quarterly Income and Expense of FDIC-Insured Commercial Banks and Savings Institutions". The data can be accessed here https://www.fdic.gov/bank/analytical/qbp/.

Table 7: *Relationship between profitability, expectations about future profitability and credit supply conditions*

	$\Delta Optimism$	ΔRoE_{t+4}	$\Delta E_t(RoE_{t+4})$	$\Delta Error$	$\Delta\% Tightening$
	(1)	(2)	(3)	(4)	(5)
ΔRoE_t	1.70***	0.06	0.73***	-0.66***	-7.14***
	(0.52)	(0.14)	(0.19)	(0.23)	(0.99)
R^2	0.08	0.00	0.17	0.10	0.18
Observations	57	78	73	69	82

Notes: This table reports estimates for univariate regressions of expectation measures on the change in RoE. In column (1), the dependent variable is the quarterly change in optimism from the bank CFO survey, in column (2) the quarterly change in realized earnings between t and t+4 normalized with equity capital at time t, in column (3) the quarterly change in expected earnings between t and t+4 normalized with equity capital at time t, in column (4) the quarterly change in the difference between realized and expected earnings between t and t+4, and in column (5) the change in the net percentage of domestic banks tightening standards for C&I loans to large and middle-market firms. Newey-West standard errors in parentheses are computed using the automatic bandwidth selection procedure in Newey and West (1994). *, **, ***: Significant at 10%, 5% and 1% levels respectively.

We compare $E_t[RoE_{t+4}]$ to realized RoE_{t+4} computed as realized earnings over the following twelve months also scaled with time t equity capital. We refer to the difference between the two as the time t forecast error ($Error_t = RoE_{t+4} - E_t[RoE_{t+4}]$). The time series for this variable is visualized in the right-hand panel of Figure 4 together with realized profitability over the past twelve months. The negative relationship between the two measures suggests that CFOs are too optimistic (expected profitability is higher than realized profitability) when current RoE is high and vice versa.

Table 7 presents empirical tests of these relationships. In column (1), we find a positive and significant relationship between changes in optimism and changes in RoE. An increase in profitability is associated with a more optimistic outlook of the average CFO on the future financial prospects of the bank. Column (2) shows that this optimism is not justified in the data. There is in fact no association between changes in RoE today and the change over the next year. At the same time, in line with the optimism measure, expectations of profitability over the following year are elevated if RoE increases (column (3)). As a result, expectations are systematically biased. The difference between realized and expected earnings, the forecast error, is negatively related with changes in RoE. Put differently, an increase in RoE is associated with an increase in expected profitability relative to realized profitability over the following year. In column (5), we study the implications for credit supply conditions. The dependent variable here is the change in the net percentage of banks tightening standards for loans to large and middle-market firms from the Federal Reserve's senior loan officer opinion survey. The negative coefficient implies that a significant fraction of banks loosens credit standards when RoE increases. Appendix Table A4.1 and Table A4.2

Table 8: *Multivariate models for changes in credit-to-GDP, profitability and expectations*

	Dependent variable: 4-quarter change in credit/GDP				
	(1) *Optimism*	(2) RoE_t	(3) $E_t(RoE_{t+4})$	(4) *Error*	(5) *%Tightening*
RHS variable (see column header)	0.13***	0.48***	0.36***	-0.19***	-0.02**
	(0.04)	(0.02)	(0.03)	(0.03)	(0.01)
R^2	0.79	0.88	0.85	0.71	0.66
Controls	✓	✓	✓	✓	✓
Observations	56	75	71	71	75

Notes: The dependent variable is the change in the ratio of net loans and leases to GDP between t and t+4. In column (1) this change is regressed on optimism from the bank CFO survey, in column (2) on realized earnings between t-4 and t normalized with equity capital at time t, in column (3) on expected earnings between t and t+4 normalized with equity capital at time t, in column (4) on the difference between realized and expected earnings between time t and t+4 normalized with equity capital at time t, in column (5) on the net percentage of domestic banks tightening standards for C&I loans to large and middle-market firms. Newey-West standard errors in parentheses are computed using the automatic bandwidth selection procedure in Newey and West (1994). *, **, ***: Significant at 10%, 5% and 1% levels respectively.

show very similar results for RoA as an alternative profitability measure and consistent but weaker results when excluding the years 2007-2009.[11]

In a second step, we link these variables to the credit cycle. Gennaioli et al. (2016) shows that firm investment is explained by earnings expectations of CFOs. We now ask whether this pattern also holds for banks, interpreting credit growth as banks' investments. In the quarterly US data, we measure credit growth as the change in the ratio of net loans and leases to GDP between t and $t+4$. Column (1) in Table 8 confirms that 4-quarter changes in credit are predicted by optimism, where lagged credit growth, a crisis and a recession dummy, as well as GDP growth, interest rates and bank capital ratios are included as control variables. In column (2) we include realized profitability over the past year. Columns (3) and (4) analyze the relationship between profit forecasts and credit growth. The profit forecast itself (column 3) is positively related to subsequent credit growth. When expected profits are high, credit grows rapidly. The forecast error is negatively related to credit growth: credit growth is low when bank CFOs are excessively pessimistic and it is high when they are excessively optimistic. Finally, column (5) illuminates one possible channel and shows that a tightening (loosening) in the standards at which banks supply credit is associated with lower (higher) credit growth over the following year.

[11] It is clear from the graph that most of the variation is during and shortly after the 2007/2008 financial crisis. Figure 4 shows that the crisis was a surprise to bank CFOs. The positive forecast error after the crisis also suggests that bank CFOs were excessively pessimistic (compared to realized profits one year later) when profits were lowest during the crisis.

Overall, the findings are consistent with the idea that bankers' expectations rely excessively on recent performance. Furthermore, survey-based measures of expectations are linked to credit growth, and expectational errors are reflected in the growth rate of credit.

4.4. Discussion of results

We find that bank profits predict credit growth in general, and that increases in profitability forecast large credit booms. The results in this section suggest that these credit expansions are driven by credit supply rather than demand. Disentangling different supply-based explanations, the results are consistent with the predictions of recent behavioral credit cycle models that incorporate time-varying beliefs due to overweighting of recent experience. The analysis of recent survey data on bank CFO expectations supports this interpretation.

The relationship between recent fundamentals, in particular loan losses, and subsequent credit expansion corroborates earlier work by Greenwood and Hanson (2013) who find that bond issuance increases after periods of low defaults in a US time series. They note that one possible explanation for this result are extrapolative expectations. Our new long run data on bank profitability and the decomposition into sources and uses of funds allows us to carefully separate time-varying expectations from financial constraints, and we arrive at a similar conclusion. Furthermore, the long run bank profitability data also allows us to jointly study the bank credit cycle and recent bank performance, instead of linking bond market developments and bank credit (Kirti, 2020).

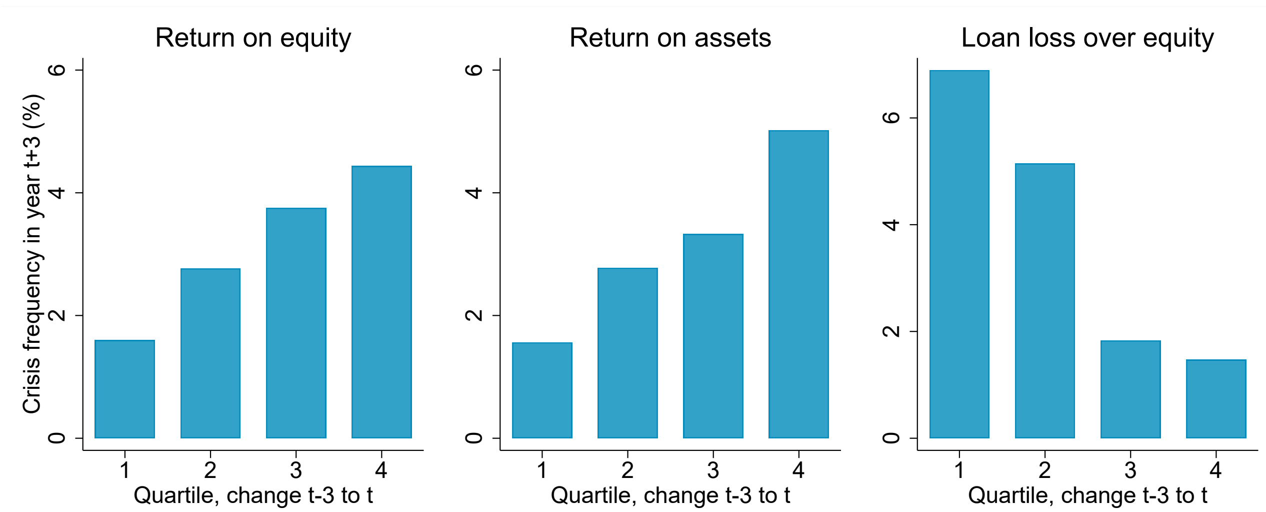
Similar to our results, Baron et al. (2020) document a positive relationship between shareholder returns and subsequent credit expansion. However, the accounting data have two important advantages relative to market based data. Shareholder returns largely reflect expectations about future profitability or time-varying discount rates and not current fundamentals (Cochrane, 2017; Shiller, 1981). Hence, a relationship between shareholder returns and subsequent outcomes could simply mean that shareholders correctly anticipate future developments: low returns would then forecast low future GDP growth, which may be associated with little profitable lending opportunities for banks. The accounting data on past profitability allows us to circumvent this problem. Furthermore, as noted by Meiselman et al. (2018), due to the concavity of bank asset returns equity prices are most likely informative during a crash, but not very informative during good times. This is reflected in the differences between Baron et al. (2020) and our results. While they find stock returns to be particularly informative about future credit growth during stock market crashes, we find that also large credit booms can be forecasted with increases in profitability.

5. Profits and Crisis

Minsky (1977) and recent formalizations thereof such as Bordalo et al. (2018) and Greenwood et al. (2019) suggest that increases in profitability should be associated with optimism and credit expansion first, and with predictable crises a few years later when optimism wanes. We have seen that credit booms can be forecasted with profitability measures. We now show that banking crises a few years ahead can also be predicted with increases in bank profitability. Furthermore, we will show that bank profitability allows us to characterize the transition from credit boom to crisis and to distinguish between panic and non-panic crises.

5.1. Predicting Crises

Figure 5: *Crisis probability in t+3 by change in profitability*



Notes: This figure shows the relationship between changes in RoE (RoA and LoE) between $t-3$ and t and financial crisis frequencies for the year $t+3$. Observations are sorted into four equal-sized bins according to the increase in RoE (RoA) between $t-3$ and t. Vertical bars indicate the frequency of financial crises in year $t+3$ for each of the bins.

Is there a systematic relationship between increases in profitability and banking crisis risks? As a simple way to study this relationship, we sort observations into four equal-sized bins based on the change in profitability (RoE and RoA) between $t-3$ and t. Figure 5 shows the frequency of the start of banking crises in year $t+3$ (as a measure of medium term crisis risk) for each bin. We rely on the narrative chronology by Jordà et al. (2017) to identify crises events. The yearly banking crisis start frequency in our sample is 3.1%. Focusing on RoE in the left panel, we see that banking crisis frequencies in $t+3$ are below 2% in the bin with the lowest changes in RoE over a three year window. This is in stark contrast to

Table 9: *Crisis frequency in t+3 by credit growth level and profit change quartile*

	$\Delta_3 RoE_{i,t}$ quartile				$\Delta_3 RoA_{i,t}$ quartile				
Credit growth	1	2	3	4	1	2	3	4	Mean
Low	0.00	1.24	1.90	2.58	1.26	1.27	1.89	2.63	1.91
Medium	1.88	2.47	4.29	2.52	0.61	3.14	4.29	2.48	2.80
High	2.45	3.77	6.21	8.23	1.84	4.40	4.35	9.55	4.67
Mean	1.46	2.49	4.15	4.45	1.24	2.94	3.52	4.89	3.13

observations in the highest quartile of increases in RoE where the crisis frequency in $t+3$ exceeds 4%. A similar pattern is observable looking at crisis frequencies when binning observations based on $\Delta_3 RoA$. Here, the frequency of a banking crisis in the year $t+3$ rises up to about 5% if the three-year change in RoA is in the top quartile. Finally, the right panel looks at changes in loan losses and the frequency of future financial crises is highest when loan losses declined the most, as shown by the crisis frequency of more than 6% in the lowest quartile of loan loss changes. Figure A3.1 and Figure A3.2 show that similar patterns can be observed when restricting the sample to post 1945 data or when using a chronology of banking panics from Baron et al. (2020).

In a second step, we ask whether different crisis frequencies in quartiles of $\Delta_3 RoE$ and $\Delta_3 RoA$ are due to the relationships between profits and credit only, or whether profits contain additional information. In Table 9, we look again at the frequency of crises for the different quartiles of profitability increases. The mean values reported in the bottom row of the table correspond closely (with small sample differences) to the probabilities displayed in Figure 5. Here, we additionally divide each quartile in the profitability distribution ($\Delta_3 RoE$ and $\Delta_3 RoA$) into three bins based on changes in the ratio of credit-to-GDP. In the right column, we report the crisis frequency for low, medium and high credit growth observations. As expected, the frequency of crises in $t+3$ is increasing in credit growth. Focusing on the results in Table 9, we see that crises frequencies are generally increasing from left to right, and from the top to the bottom. Both dimensions, profitability increases and credit expansion are associated with crisis incidence. No crisis occurred in the last 150 years when $\Delta_3 RoE_{i,t}$ was in the lowest quartile (column 1) of observations and credit growth was also low. When credit growth was higher (third row), the frequency of crises increased (2.45%), but was still well below the sample average (3.13%). Focusing on high credit growth (third row), the table shows that crisis incidence three years ahead increases to more than 8 percent, when we move to the highest quartile of profitability increases. These patterns are also reflected in the right panel that uses $\Delta_3 RoA$ to bin the data.

We will now explore these relationships econometrically using prediction models that relate changes in bank profitability to the likelihood of experiencing a financial crisis. Specifically, we estimate a probit model for a financial crisis starting in country i in year $t+3$, denoted by the indicator variable $C_{i,t+3}$,

$$Pr[C_{i,t+3} = 1|\alpha_i, X_{i,t}] = \Phi(\alpha_i + \boldsymbol{\beta} X_{i,t}). \tag{9}$$

$X_{i,t}$ includes three-year changes in profitability as well as a vector of control variables. The control vector contains 3-year changes in credit to GDP to proxy for the well-known relationship between credit and financial crises (Schularick and Taylor, 2012). $\boldsymbol{\beta}$ denotes the vector of coefficients of interest for the various specifications. We follow the literature and include country fixed effects to account for cross-country heterogeneity in the risk of experiencing a financial crisis.

Table 10 reports marginal effects for the relationship between changes in profitability measures and crisis likelihood in year $t+3$. The odd-numbered columns show results only including the country fixed effects, even-numbered columns also include 3-year changes in credit to GDP. The results confirm the visual impression from the binned scatterplots. Column (1) shows that an increase in RoE over three years by 5 percentage points (about 1 standard deviation) is associated with a 1 percentage point higher crisis probability in year $t+3$. This result is unaffected by the inclusion of credit as a control variable in column (2). The relationship between increases in profitability and crisis risk goes above and beyond the mere effect of profitability on credit expansion and the associated increase in crisis risk. We obtain similar results with $\Delta_3 RoA$ and $\Delta_3 LoE$. Table A3.1 shows that these patterns are robust to using panic banking crisis chronology from Baron et al. (2020).

5.2. Transition into crisis

As Mian and Sufi (2018) argue, we are still missing a good understanding of the transition from credit booms into crises. Credit cycle theories featuring diagnostic expectations (Bordalo et al., 2018) predict a sharp reversal when, after a period of good news, fundamentals turn out to be disappointing, i.e. they decrease or grow at a lower pace. We take this idea to the data and operationalize it using the yearly change δ in our main profitability measures. Since $\Delta_3 RoE$ is already a change (over a three-year horizon), the first difference in this

Table 10: *Multivariate probit models for systemic financial crisis prediction*

	$\Delta_3 RoE_{i,t}$		$\Delta_3 RoA_{i,t}$		$\Delta_3 LoE_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Profitability (see column header)	0.21***	0.23***	2.70***	3.05***	-0.31***	-0.40***
	(0.07)	(0.06)	(0.62)	(0.65)	(0.08)	(0.07)
$\Delta_3 Loans/GDP_{i,t}$		0.18***		0.18***		0.26***
		(0.03)		(0.03)		(0.04)
AUC	0.67	0.72	0.67	0.72	0.67	0.74
Observations	1700	1641	1721	1647	916	914

Notes: The table shows probit classification models where the dependent variable is an indicator that is one if the country experiences the start of a financial crisis in year $t+3$ and zero else. Coefficients are marginal effects. Regressors are described in the column header. All models include country fixed effects. Country clustered standard errors in parentheses. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

variable, $\delta\Delta_3 RoE$ measures whether profits are growing at an increasing or decreasing pace. We then run a sequence of probit regressions of the form

$$Pr[C_{i,t+h} = 1|\alpha_i, X_{i,t}] = \Phi(\alpha_i + \boldsymbol{\beta} X_{i,t}), \tag{10}$$

for $h = 0, 1, ..., 5$. In this procedure, we keep the RHS of the equation fixed and move the prediction horizon for a banking crisis into the future. $X_{i,t}$ now includes $\Delta_3 RoE$ and its change $\delta\Delta_3 RoE$ as well as three-year changes in credit-to-GDP ratios. The results for $h = 3$ in column (3) correspond to the specification in Table 10, only that we additionally include $\delta\Delta_3 RoE$. We first see that the results for $\Delta_3 RoE$ do not depend on the exact timing and $\Delta_3 RoE$ captures crisis risk over the medium term ($t+2$ to $t+4$). On the other hand, the coefficient for $\delta\Delta_3 RoE$ in the second row is negative and significant for short horizons of 1 or 2 years: while three-year increases in profitability are associated with a higher probability of crisis in the medium term, the short-term risk of a crisis increases sharply once the profitability spurt is wearing off. For completeness, column (1) shows the contemporaneous correlation between profitability measures and crisis indicators. Both measures are significantly negative, indicating that crisis are associated with strong decreases in RoE. The second panel shows that these patterns are similar for RoA and Appendix Table A3.2 shows that these results do not depend on the crisis chronology employed.

Table 11: *Multivariate probit models for systemic financial crisis prediction – crisis transition*

	Dependent variable: Crisis at time...					
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+4	(6) t+5
$\Delta_3 RoE_{i,t}$	-0.30***	0.04	0.26**	0.29***	0.19**	0.02
	(0.04)	(0.08)	(0.10)	(0.08)	(0.09)	(0.11)
$\delta\Delta_3 RoE_{i,t}$	-0.11*	-0.18*	-0.16**	-0.09	0.00	0.06
	(0.06)	(0.11)	(0.06)	(0.07)	(0.09)	(0.08)
$\Delta_3 Loans/GDP_{i,t}$	0.10**	0.18***	0.20***	0.16***	0.10***	-0.01
	(0.04)	(0.03)	(0.02)	(0.03)	(0.04)	(0.03)
AUC	0.87	0.73	0.72	0.73	0.69	0.62
Observations	1667	1650	1633	1616	1599	1582
	Dependent variable: Crisis at time...					
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+4	(6) t+5
$\Delta_3 RoA_{i,t}$	-3.34***	0.94	3.60***	3.61***	2.21*	0.96
	(0.44)	(1.04)	(0.74)	(0.74)	(1.17)	(1.49)
$\delta\Delta_3 RoA_{i,t}$	-1.78**	-2.12**	-2.10***	-0.94	-0.09	-0.13
	(0.71)	(0.84)	(0.63)	(0.73)	(1.28)	(1.04)
$\Delta_3 Loans/GDP_{i,t}$	0.10***	0.19***	0.20***	0.17***	0.10***	-0.01
	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.03)
AUC	0.86	0.72	0.72	0.72	0.69	0.62
Observations	1675	1658	1641	1624	1607	1590

Notes: The table shows probit classification models where the dependent variable is an indicator that is one if there is a crisis in $t+h$ years, specified in the column header. Coefficients are marginal effects. All specifications include country-fixed effects. Country clustered standard errors in parentheses. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

5.3. Panic crises vs. non-panic crises

Banking crises are often associated with bank runs and panics. In fact many banking crisis chronologies rely on the very occurrence of panics to define a crisis. In a recent contribution, Baron et al. (2020) distinguish between crises with and without panics and define panic crises as "severe and sudden withdrawals of funding by bank creditors from a significant part of the banking system". Non-panic crises on the other hand are defined as large declines in bank net worth based on bank index returns. As a result their set of panic crises closely overlaps with the definition of a crisis in other chronologies (as the (Jordà et al., 2017) chronology used in the previous subsections), while the non-panic crises are often less well-known crisis events.

We will now exploit the difference between the two types of crises in the chronology of Baron et al. (2020) to better understand the role of profitablity in the credit-crisis nexus. For holders of short-term debt to panic and withdraw their funds, expectations about bank fundamentals have to be sufficiently negative such that they perceive their stakes to be at risk. Panics can therefore be interpreted as a signal for expectations turning extremely negative. On the other hand, a non-panic crisis indicates that net worth in the financial sector is lost, but there is not a strong reversal of expectations. We will now study how these different crisis types are associated with bank profitability.

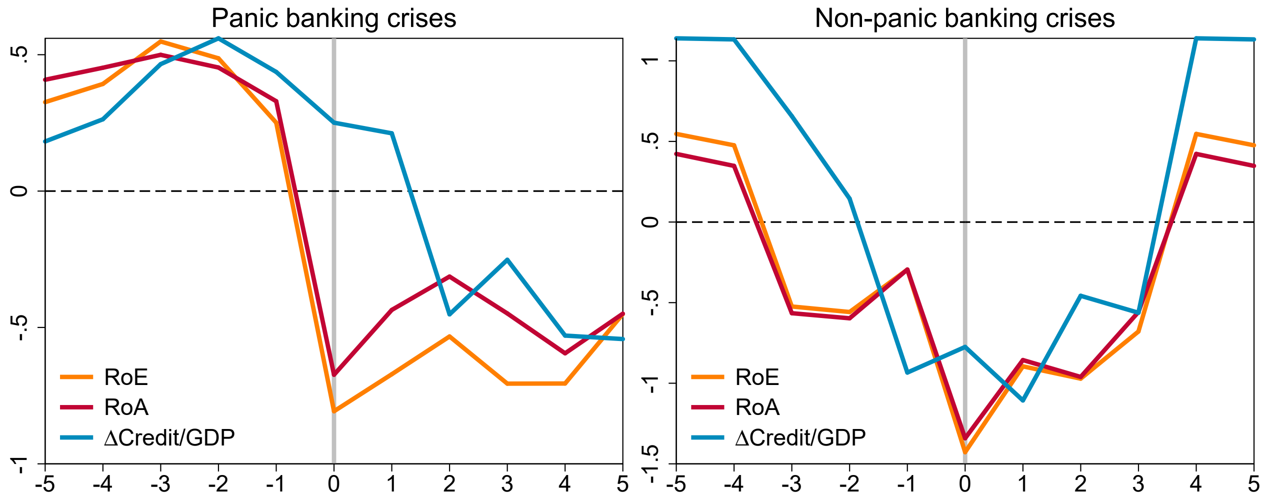
As a first pass of the data, Figure 6 displays the mean evolution of standardized credit and profit variables in the years around crises events with year 0 indicating the start of a banking crisis. Blue lines correspond to the yearly change in the ratio of credit to GDP. The left panel shows that changes in credit-to-GDP are above average in the years prior to panic crisis events and the ratio of credit to GDP starts declining two years after the panic started. The orange and red line display the evolution of standardized RoE and RoA around panic crisis observations. The patterns for both are very similar. Banking sector profitability is high and rising until two years before the crisis. In the two years prior to a crisis, there is a reversal with RoE and RoA being elevated but declining, before they fall below the sample mean once the crisis starts. The right panel in Figure 6 presents the same relationship for non-panic crisis. As in the left panel the crisis year coincides with a profitability trough. But the patterns of the decline are strikingly different. Profitability starts declining several years ahead of a crisis. In the same way, the change in credit to GDP is initially high but starts decreasing in the years prior to the crisis. Appendix Figure A3.3 shows that these patterns also hold for banking crises after 1945.

This finding is reflected in Table 12 where we repeat the specification of Table 10 with panic crisis (in $t + 3$) as the dependent variable in odd-numbered columns and non-panic equity crises (in $t + 3$) in even-numbered columns. While the probability of experiencing a panic in $t + 3$ is increasing in profitability, the probability of experiencing a non-panic crisis is, if anything, decreasing in profitability. The results suggest that panics are more likely when profitability booms created room for optimism and subsequent disappointment, while creditors are less surprised by weak performance when the banking sector performance has been weak for some time.

5.4. Discussion of results

Increases in profitability are associated with subsequent credit expansions. The credit booms that eventually end in banking crises are no exception and are preceded by increases

Figure 6: *Event study of profitability and credit variables around financial crisis dates*



Notes: These figures display the evolution of credit and profit variables around a banking crisis, i.e. 0 refers to a year in which a crisis starts. Crises are panic crises in the left panel and non-panic crises in the right panel. Blue lines display the mean of changes in credit/GDP around crises. The orange (red) line displays RoE (RoA) around crises. All variables have been standardized at the country level.

Table 12: *Multivariate probit models for systemic financial crisis prediction – panic and non-panic crises*

	$\Delta_3 RoE_{i,t}$		$\Delta_3 RoA_{i,t}$		$\Delta_3 LoE_{i,t}$	
	(1) Panic	(2) Non-panic	(3) Panic	(4) Non-panic	(5) Panic	(6) Non-panic
See column header	0.26***	-0.14**	3.07***	-1.50	-0.33***	0.16**
	(0.05)	(0.05)	(0.59)	(1.08)	(0.05)	(0.07)
$\Delta_3 Loans/GDP_{i,t}$	0.18***	0.12***	0.18***	0.13***	0.25***	0.06**
	(0.03)	(0.01)	(0.03)	(0.02)	(0.03)	(0.03)
Country fixed effects	✓	✓	✓	✓	✓	✓
AUC	0.74	0.80	0.73	0.77	0.77	0.93
Observations	1641	668	1647	668	914	354

Notes: The table shows probit classification models. In columns (1), (3) and (5) the dependent variable is an indicator that is one if there is a panic crisis in year $t+3$ and zero else. In columns (2), (4) and (6) the dependent variable is an indicator that is one if there is a non-panic crisis in year $t+3$ and zero else. Coefficients are marginal effects and regressors are described in the column header. All models include country fixed effects. Country clustered standard errors in parentheses. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

in profitability and low loan losses. This finding mirrors previous evidence in the empirical macro-finance literature. Krishnamurthy and Muir (2017) argue that credit spreads are too low prior to financial crises and Danielsson et al. (2018) show that equity volatility is low. Greenwood et al. (2019) argue that credit markets often appear to be "calm before the storm". We find similar evidence in measures of bank profitability.

The evolution of profitability around panic crisis events shares some of the key characteristics of behavioral credit cycle models (Bordalo et al., 2018). Panics, associated with sudden changes in expectations, are preceeded by increases in profitability that create room for optimistic beliefs. The cycle turns when profitability starts declining after a series of good realizations. Non-panic crisis on the other hand only mark the final stage of slow-moving profitability declines. They occur when bank fundamentals in previous years left little room for the buildup of optimism and bank net worth has already been depleted.

6. Conclusion

The Minsky (1977)-cycle starts with a positive displacement. Positive news breed optimism, and lead to a boom in credit markets, but also to elevated crisis risk down the road. In this paper, we set out to study the origins of this boom, to make sense of the bust.

We establish a new robust fact: bank profitability leads the credit cycle. Credit expands following increases in profitability. Decomposing profitability, we find that loan losses play an important role for this relationship between profits and credit aggregates. Our results are consistent with a recent theoretical literature on the role of expectational biases in shaping the credit cycle. When loan losses are low, economic agents seem to extrapolate these conditions into the future, increasing aggregate leverage in the economy. Similarly, when loan losses are high, banks become more pessimistic and the availability of credit is reduced. We show that reported expectations of bank CFOs from survey data are consistent with such a channel. A caveat of the approach taken in this paper is that we cannot causally identify this link. The long-run evidence presented here should therefore be considered in combination with a growing body of micro-level evidence linking individual experiences to expectation formation and credit market conditions (Carvalho et al., 2020; Landier et al., 2018). The empirical relationship between profits and credit expansion is also consistent with a financial constraints channel that links profitability and credit expansion. However, we have presented several findings that are inconsistent with this channel being the main explanation for our finding.

The relationship between profits and credit also helps to understand the transition from boom to bust. Bank profitability increases for a few years and peaks two years prior to a crisis. The following reversal in profits and loan losses marks the turning point of the credit cycle and is often associated with a banking panic. Banking crises without panics on the other hand are characterized by decreasing profitability and low credit growth in preceding years. These results suggest that sudden reversals in expectations may indeed be linked to bad profitability news after a sequence of good news. These findings on the differential paths of credit and profitability around panic and non-panic crises may also help to reconcile seemingly contradictory theories of financial crises: the patterns around panic crises seem consistent with the Minsky-view and recent formalizations thereof. Non-panic crises on the other hand are characterized by persistent bank losses, which may result in excessive risk-taking in the financial sector.

We have taken previous findings on firm investment (Gennaioli et al., 2016; Greenwood and Hanson, 2015) to the study of the credit cycle. Is there anything special about credit as an instrument and banks as intermediaries? Simsek (2013) shows that overoptimism of lenders about downside states matters in particular. A similar reasoning leads us to believe that the biases at the bank level may be more important than at the borrower level. If corporate managers extrapolate and become excessively optimistic, but bankers rationally anticipate the growing risks from corporate optimism, then risk would still be priced. This reasoning is also mirrored in recent theoretical contributions stressing the importance of biased expectations of lenders for credit dynamics (Bordalo et al., 2019; Kaplan et al., 2020).

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Online Appendix

The Profit-Credit Cycle

A. Additional results

A1. Summary statistics

Table A1.1: *Summary statistics*

	Obs.	Mean	S.D.	Min	Max
Return on equity	1816	8.59	7.72	-125.36	40.57
Return on assets	1835	0.77	0.79	-7.71	5.27
Capital ratio	1906	10.14	7.86	0.85	46.86
Credit to GDP	1961	57.37	35.22	0.47	204.52
Δ_3 Credit to GDP	1878	3.42	7.90	-56.09	53.08
Δ_3 Capital to GDP	1836	0.45	1.59	-16.20	10.39
Winsorized income data (2.5% level)					
Return on equity	1816	8.93	5.01	-3.97	20.01
Return on assets	1835	0.78	0.61	-0.26	2.54
Dividends over equity	1164	5.54	2.35	1.32	12.38
Retained earnings over equity	1162	3.01	4.53	-10.24	12.90
Revenue over equity	1151	50.53	28.99	8.73	119.01
Cost over equity	1151	31.99	22.08	2.34	85.63
Loan loss over equity	1032	5.93	6.13	0.24	27.79
Δ_3 Return on equity	1751	-0.23	4.63	-13.83	11.28
Δ_3 Return on assets	1772	-0.03	0.38	-1.21	1.00
Δ_3 Dividends over equity	1096	0.01	1.49	-3.96	3.88
Δ_3 Retained earnings over equity	1092	-0.15	4.68	-13.70	12.09
Δ_3 Revenue over equity	1086	-1.13	9.88	-28.07	21.62
Δ_3 Cost over equity	1086	-0.81	6.75	-20.07	14.81
Δ_3 Loan loss over equity	979	0.10	5.45	-15.80	15.19

Notes: All variables in percentage points. World war periods are excluded.

A2. Robustness: main results

Table A2.1: *Models for changes in credit-to-GDP, subsample of crisis observations*

	Dependent variable: $\Delta_3 y_{i,t+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t}$	0.56***	0.37**	0.34**			
	(0.15)	(0.14)	(0.14)			
$\Delta_3 RoA_{i,t}$				5.69***	4.54***	3.96**
				(1.81)	(1.52)	(1.73)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Financial constraints			✓			✓
R^2	0.20	0.37	0.42	0.17	0.38	0.42
Observations	176	160	160	176	160	160

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $\Delta_3 RoE_{i,t}$ and $\Delta_3 RoA_{i,t}$, where we restrict the sample to up to three observations per financial crisis episode (crisis in $[t-2, t]$). Columns (2), (3), (5) and (6) add a vector of macroeconomic control variables (see text in section 3). Columns (3) and (6) additionally control for financial constraints proxies. All specifications include country fixed effects. Standard errors in parentheses are clustered at the country level. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A2.2: *Alternative dependent variable – real private credit per capita*

	Dependent variable: $\Delta_3 y_{i,t+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t}$	0.79^{***}	0.66^{***}	0.67^{***}			
	(0.23)	(0.18)	(0.18)			
$\Delta_3 RoA_{i,t}$				7.69^{***}	6.73^{***}	7.47^{***}
				(2.31)	(2.01)	(2.00)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Financial constraints			✓			✓
R^2	0.09	0.18	0.19	0.08	0.18	0.18
Observations	1644	1493	1491	1650	1499	1491

Notes: This table reports regressions of real private credit per capita changes from t to $t+3$ on $\Delta_3 RoE_{i,t}$ and $\Delta_3 RoA_{i,t}$. All specifications control for three lags of real private credit per capita. Columns (2), (3), (5) and (6) add a vector of macroeconomic control variables (see text in section 3). Columns (3) and (6) additionally control for financial constraints proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A2.3: *Alternative dependent variable – bank assets/GDP*

	Dependent variable: $\Delta_3 y_{i,t+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t}$	0.57^{**}	0.62^{***}	0.61^{***}			
	(0.22)	(0.21)	(0.19)			
$\Delta_3 RoA_{i,t}$				6.42^{***}	5.91^{***}	5.74^{***}
				(2.00)	(1.88)	(2.00)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Financial constraints			✓			✓
R^2	0.10	0.15	0.15	0.10	0.14	0.14
Observations	1650	1504	1504	1651	1505	1504

Notes: This table reports regressions of bank assets/GDP changes from t to $t+3$ on $\Delta_3 RoE_{i,t}$ and $\Delta_3 RoA_{i,t}$. All specifications control for three lags of bank assets-to-GDP. Columns (2), (3), (5) and (6) add a vector of macroeconomic control variables (see text in section 3). Columns (3) and (6) additionally control for financial constraints proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A2.4: *Alternative dependent variable – non-loan bank assets/GDP*

	Dependent variable: $\Delta_3 y_{i,t+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t}$	0.18	0.33*	0.33*			
	(0.19)	(0.20)	(0.18)			
$\Delta_3 RoA_{i,t}$				1.96	2.81*	2.77*
				(1.48)	(1.63)	(1.65)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Financial constraints			✓			✓
R^2	0.07	0.12	0.12	0.07	0.12	0.12
Observations	1617	1473	1473	1618	1474	1473

Notes: This table reports regressions of non-loan bank assets/GDP changes from t to $t+3$ on $\Delta_3 RoE_{i,t}$ and $\Delta_3 RoA_{i,t}$. All specifications control for three lags of non-loan bank assets/GDP. Columns (2), (3), (5) and (6) add a vector of macroeconomic control variables (see text in section 3). Columns (3) and (6) additionally control for financial constraints proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A2.5: *Alternative profitability measures – profits/GDP and log real profits per capita*

	Dependent variable: $\Delta_3 y_{i,t+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 Profits\ to\ GDP_{i,t}$	2.08***	1.64***	1.61***			
	(0.71)	(0.58)	(0.57)			
$\Delta_3 Log(profits)_{i,t}$				0.03***	0.03***	0.03***
				(0.00)	(0.00)	(0.00)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Financial constraints			✓			✓
R^2	0.10	0.19	0.19	0.13	0.20	0.21
Observations	1635	1491	1491	1512	1372	1372

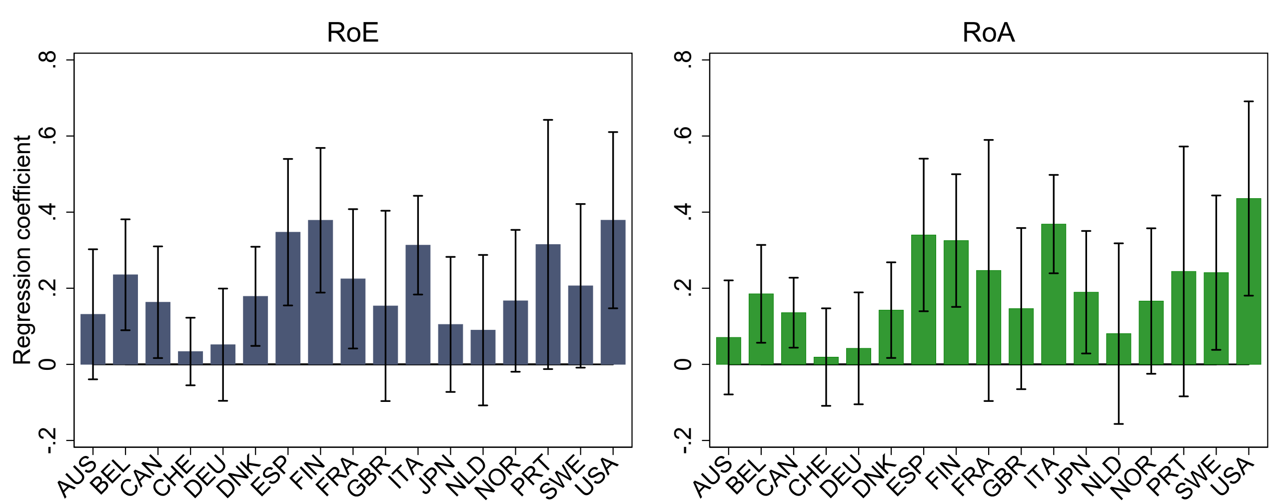
Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $\Delta_3 Profits\ to\ GDP_{i,t}$ and $\Delta_3 log(profits)_{i,t}$. $Log(profits)$ is the logarithm of real profits per capita. All specifications control for three lags of credit-to-GDP changes. Columns (2) and (5) add a vector of macroeconomic control variables (see text in section 3). Columns (3) and (6) additionally control for financial constraints proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A2.6: *Alternative profitability measure – level variables*

	Dependent variable: $\Delta_3 y_{i,t+3}$				
	(1)	(2)	(3)	(4)	(5)
$RoE_{i,t}$	0.50^{***}				
	(0.08)				
$RoA_{i,t}$		5.44^{***}			
		(1.13)			
$Profits\ to\ GDP_{i,t}$			2.51^{***}		
			(0.65)		
$Log(profits)_{i,t}$				0.02^{***}	
				(0.00)	
$LoanLoss/Equity_{i,t}$					-0.52^{***}
					(0.09)
Country fixed effects	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓
Macrocontrols	✓	✓	✓	✓	✓
Financial constraints	✓	✓	✓	✓	✓
R^2	0.24	0.23	0.21	0.21	0.28
Observations	1516	1516	1516	1444	935

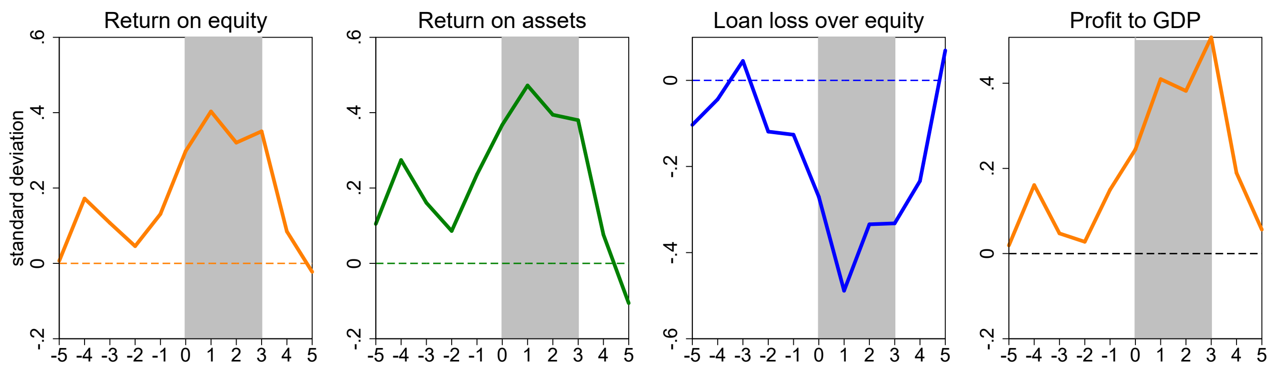
Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on levels of profitability. All specifications control for three lags of credit-to-GDP changes, macroeconomic control variables (see text in section 3) and financial constraints proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Figure A2.1: *Country-level regression coefficients*



Notes: This figure reports regression coefficients and 90% confidence intervals from individual country regressions of credit-to-GDP changes from t to $t+3$ on $\Delta_3 RoE_{i,t}$ and $\Delta_3 RoA_{i,t}$. The specifications $\Delta_3 y_{t+3} = \alpha + \beta\Delta_3 RoE_t + u_{t+3}$ and $\Delta_3 y_{t+3} = \alpha + \beta\Delta_3 RoA_t + u_{t+3}$ are estimated on individual country subsamples. Variables have been standardized by country for comparability of coefficients.

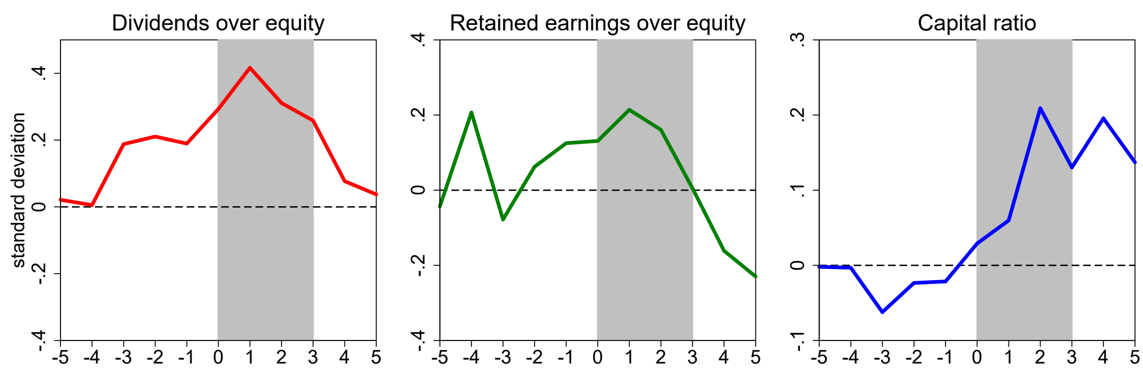
Figure A2.2: *Event study of profitability around credit boom dates after 1945*



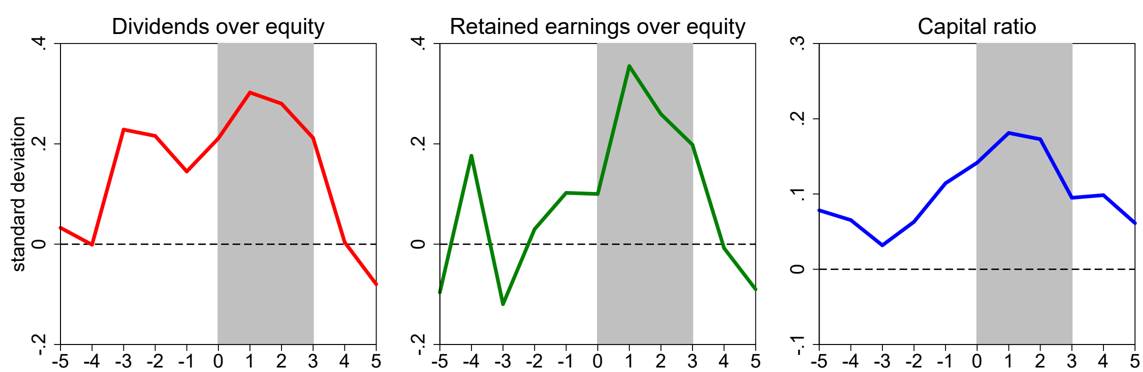
Notes: These figures display the evolution of profit variables around credit booms. All variables are detrended and standardized with mean zero and standard deviation one by country. Observations are classified as boom years when $\Delta_3 Loans/GDP_{i,t}$ exceeds one standard deviation. 0 refers to a year in which a credit boom starts. The grey area marks the three-year window of the credit boom. Solid lines display means of variables in the header around booms.

Figure A2.3: *Event study of profitability around credit boom dates – additional variables*

(a) *Full sample*



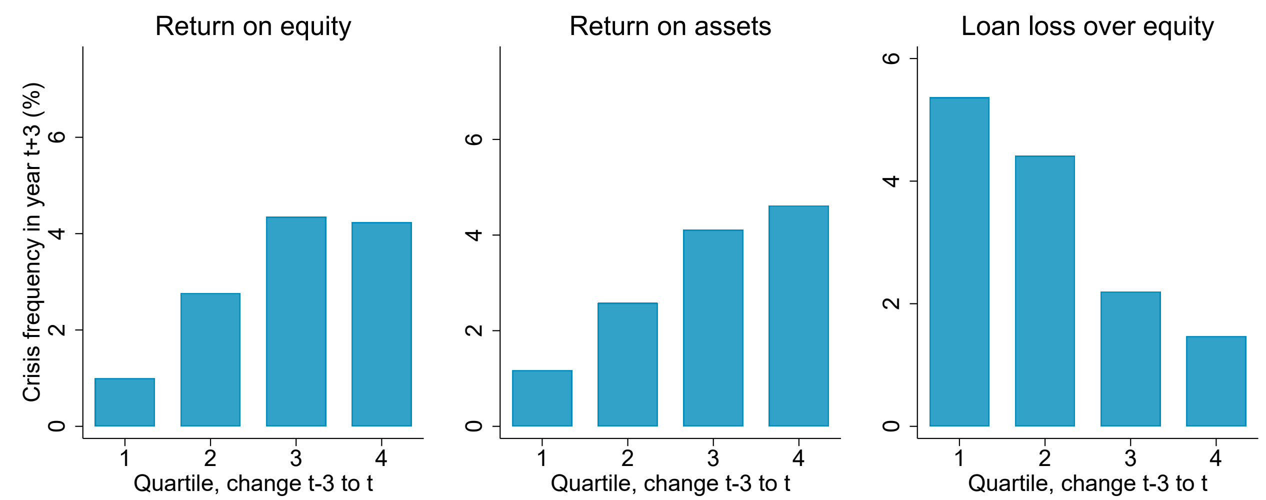
(b) *After 1945*



Notes: These figures display the evolution of profit variables around credit booms. All variables are detrended and standardized with mean zero and standard deviation one by country. Observations are classified as boom years when $\Delta_3 Loans/GDP_{i,t}$ exceeds one standard deviation. 0 refers to a year in which a credit boom starts. The grey area marks the three-year window of the credit boom. Solid lines display means around booms.

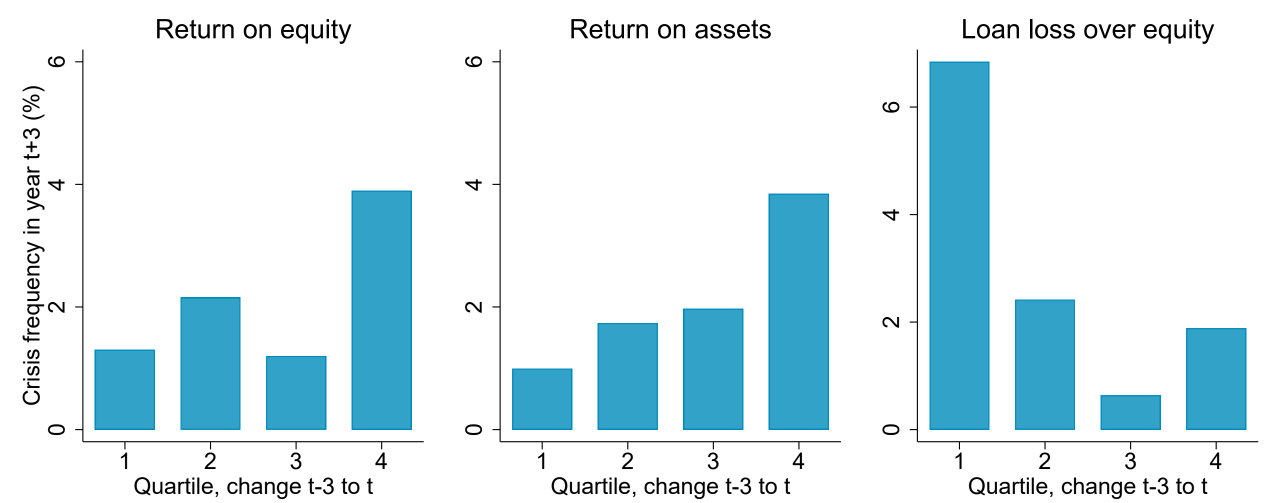
A3. Robustness: profitability around financial crises

Figure A3.1: *Crisis probability in t+3 by change in profitability – BVX panic banking crisis dates*



Notes: This figure shows the relationship between changes in RoE (RoA) between $t-3$ and t and banking panic (Baron et al., 2020) frequencies for the year $t+3$. Observations are sorted into four equal-sized bins according to the increase in RoE (RoA) between $t-3$ and t. Vertical bars indicate the frequency of financial crises in year $t+3$ for each of the bins.

Figure A3.2: *Crisis probability in t+3 by change in profitability – post WW2 sample*



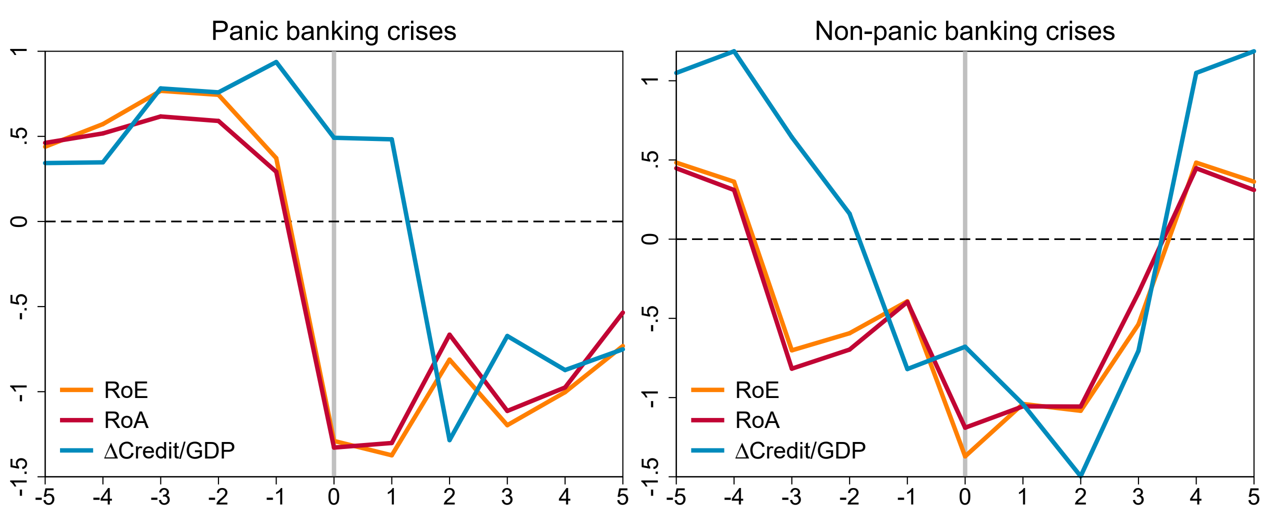
Notes: This figure shows the relationship between changes in RoE (RoA) between $t-3$ and t and financial crisis frequencies (Jordà et al. (2017)-chronology) for the year $t+3$. Observations are sorted into four equal-sized bins according to the increase in RoE (RoA) between $t-3$ and t. Vertical bars indicate the frequency of financial crises in year $t+3$ for each of the bins.

Table A3.1: *Multivariate probit models for systemic financial crisis prediction – BVX panic banking crises*

	$\Delta_3 RoE_{i,t}$		$\Delta_3 RoA_{i,t}$		$\Delta_3 LoE_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Profitability (see column header)	0.25***	0.26***	2.92***	3.07***	-0.25***	-0.33***
	(0.05)	(0.05)	(0.68)	(0.59)	(0.07)	(0.05)
$\Delta_3 Loans/GDP_{i,t}$		0.18***		0.18***		0.25***
		(0.03)		(0.03)		(0.03)
AUC	0.67	0.74	0.67	0.73	0.66	0.77
Observations	1700	1641	1721	1647	916	914

Notes: The table shows probit classification models where the dependent variable is an indicator that is one if the country experiences a banking panic (Baron et al., 2020) in year $t+3$ and zero else. Coefficients are marginal effects. Regressors are described in the column header. All models include country fixed effects. Country clustered standard errors in parentheses. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Figure A3.3: *Event study of profitability and credit variables around financial crisis dates – post 1945*



Notes: These figures display the evolution of credit and profit variables around a banking crisis after 1945, i.e. 0 refers to a year in which a crisis starts. Crises are panic crises in the left panel and non-panic crises in the right panel. Blue lines display the mean of changes in credit/GDP around crises. The orange (red) line displays RoE (RoA) around crises. All variables have been standardized at the country level.

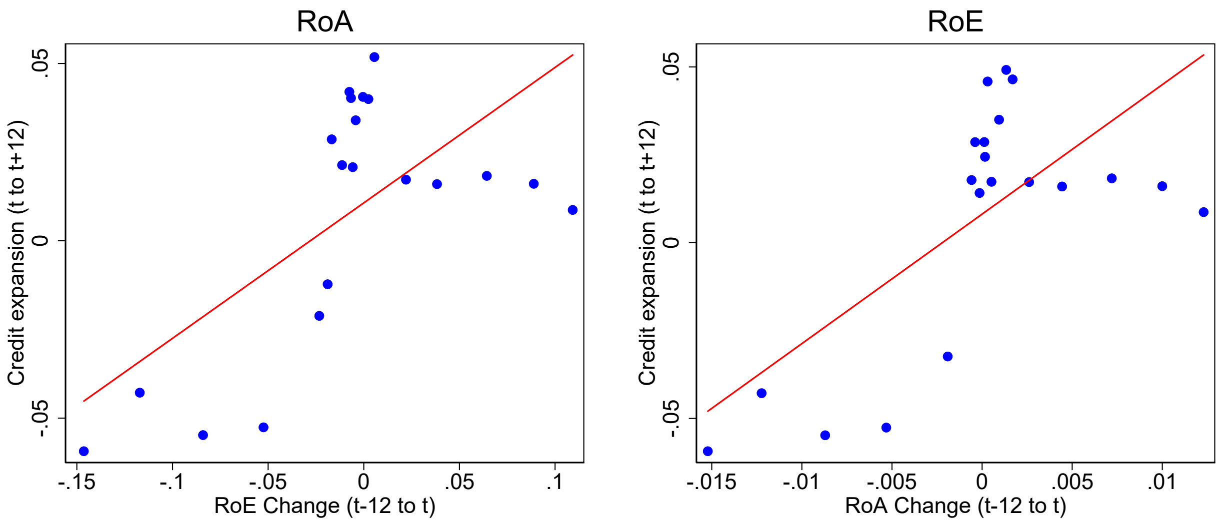
Table A3.2: *Multivariate probit models for systemic financial crisis prediction – BVX panic banking crisis dates*

	Dependent variable: Crisis at time...					
	(1)	(2)	(3)	(4)	(5)	(6)
	t	t+1	t+2	t+3	t+4	t+5
$\Delta_3 RoE_{i,t}$	-0.23***	0.10	0.25***	0.31***	0.20***	-0.00
	(0.05)	(0.08)	(0.08)	(0.06)	(0.07)	(0.09)
$\delta\Delta_3 RoE_{i,t}$	-0.16**	-0.12	-0.20***	-0.07	0.03	0.10
	(0.06)	(0.10)	(0.05)	(0.06)	(0.08)	(0.07)
$\Delta_3 Loans/GDP_{i,t}$	0.11***	0.21***	0.19***	0.17***	0.11***	0.04
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
AUC	0.86	0.75	0.75	0.75	0.68	0.63
Observations	1667	1650	1633	1616	1599	1582
	Dependent variable: Crisis at time...					
	(1)	(2)	(3)	(4)	(5)	(6)
	t	t+1	t+2	t+3	t+4	t+5
$\Delta_3 RoA_{i,t}$	-2.66***	1.24	3.24***	3.65***	2.30**	1.00
	(0.52)	(0.88)	(0.70)	(0.74)	(0.92)	(1.11)
$\delta\Delta_3 RoA_{i,t}$	-2.08***	-1.51	-2.00***	-1.03	0.32	-0.81
	(0.66)	(1.05)	(0.67)	(0.84)	(0.95)	(0.86)
$\Delta_3 Loans/GDP_{i,t}$	0.12***	0.21***	0.19***	0.17***	0.11***	0.04
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
AUC	0.85	0.75	0.75	0.74	0.68	0.63
Observations	1675	1658	1641	1624	1607	1590

Notes: The table shows probit classification models where the dependent variable is an indicator that is one if there is a banking panic in $t+h$ years, specified in the column header. Coefficients are marginal effects. All specifications include country-fixed effects. Country clustered standard errors in parentheses. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

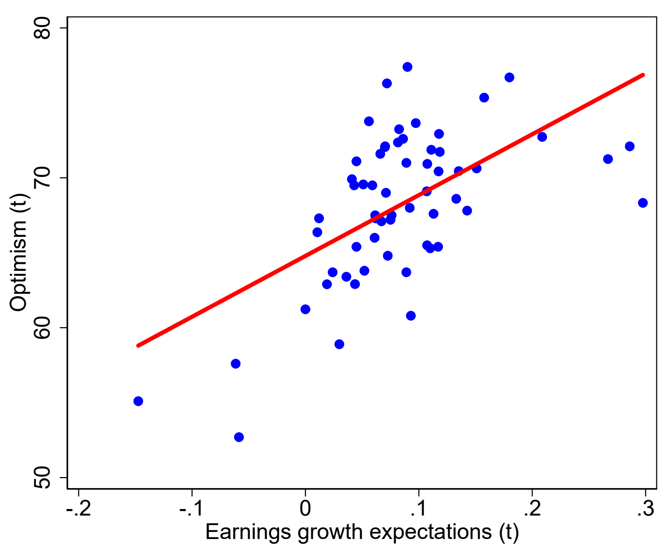
A4. Robustness: survey on earnings expectations

Figure A4.1: *Confirmation of main result: the profit-credit cycle in quarterly US data*



Notes: The figure relates bank profitability and subsequent three-year changes in credit to GDP. Observations are collapsed into 20 equal sized bins according to their profitability (or changes therein). Each point represents the group specific means of profitability and credit expansion. Fitted regression lines illustrate the correlation between bank profitability and subsequent credit growth.

Figure A4.2: *Earnings growth expectations and bank CFO optimism*



Notes: The figure shows the relationship between bank CFO optimism and bank CFO earnings growth expectations. Fitted regression lines illustrate the correlation between the two variables.

Table A4.1: *Relationship between profitability, expectations about future profitability and credit supply conditions*

	$\Delta Optimism$	ΔRoA_{t+4}	$\Delta E_t(RoA_{t+4})$	$\Delta Error$	$\Delta\% Tightening$
	(1)	(2)	(3)	(4)	(5)
ΔRoA_t	16.95***	0.13	0.79***	-0.65***	-72.68***
	(4.15)	(0.14)	(0.19)	(0.22)	(10.34)
R^2	0.08	0.01	0.18	0.10	0.17
Observations	57	78	73	69	82

Notes: This table reports estimates for univariate regressions of expectation measures on the change in RoA. In column (1), the dependent variable is the quarterly change in optimism from the bank CFO survey, in column (2) the quarterly change in realized earnings between t and t+4 normalized with assets at time t, in column (3) the quarterly change in expected earnings between t and t+4 normalized with assets at time t, in column (4) the quarterly change in the difference between realized and expected earnings between t and t+4, and in column (5) the change in the net percentage of domestic banks tightening standards for C&I loans to large and middle-market firms. Newey-West standard errors in parentheses are computed using the automatic bandwidth selection procedure in Newey and West (1994). *, **, ***: Significant at 10%, 5% and 1% levels respectively.

Table A4.2: *Relationship between profitability, expectations about future profitability and credit supply conditions, excluding the years 2007– 2009*

	$\Delta Optimism$	ΔRoE_{t+4}	$\Delta E_t(RoE_{t+4})$	$\Delta Error$	$\Delta\% Tightening$
	(1)	(2)	(3)	(4)	(5)
ΔRoE_t	-0.79	0.02	0.15***	-0.12***	-8.32*
	(1.82)	(0.02)	(0.02)	(0.04)	(4.37)
R^2	0.00	0.02	0.28	0.18	0.08
Observations	45	66	61	57	70

Notes: This table reports estimates for univariate regressions of expectation measures on the change in RoE. In column (1), the dependent variable is the quarterly change in optimism from the bank CFO survey, in column (2) the quarterly change in realized earnings between t and t+4 normalized with assets at time t, in column (3) the quarterly change in expected earnings between t and t+4 normalized with assets at time t, in column (4) the quarterly change in the difference between realized and expected earnings between t and t+4, and in column (5) the change in the net percentage of domestic banks tightening standards for C&I loans to large and middle-market firms. Newey-West standard errors in parentheses are computed using the automatic bandwidth selection procedure in Newey and West (1994). *, **, ***: Significant at 10%, 5% and 1% levels respectively.

A5. Timing

This section extends the baseline setup and describes the dynamic relationship between profitability measures and changes in credit-to-GDP over varying 3-year windows (similar to Mian et al., 2017). In the following equation, the RHS of the equation is held constant, while we shift the dependent variable $\Delta_3 y_{i,t+k}$ in time:

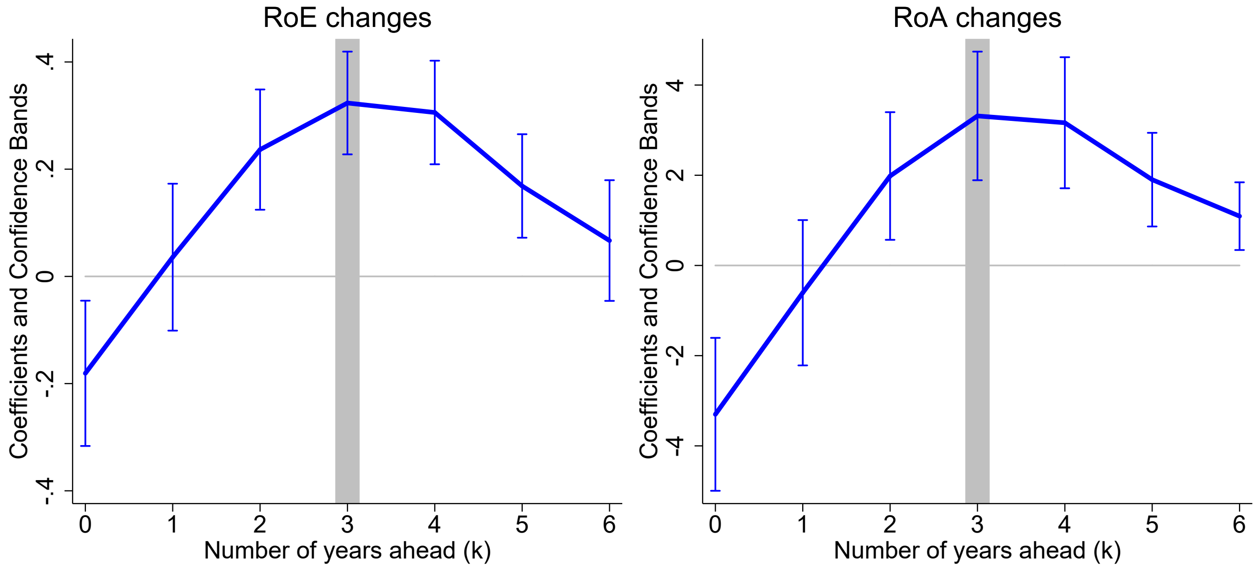
$$\Delta_3 y_{i,t+k} = \alpha_i + \beta \Delta_3 RoE_{i,t} + \eta X_{i,t} + \theta Z_{i,t} + u_{i,t+k} \tag{11}$$

where $k = 0, ..., 6$. The results are shown in Table A5.3. Column (1) ($k = 0$) assesses the contemporaneous relationship between changes in profitability from $t-3$ to t and the change in the credit-to-GDP ratio between $t-3$ and t. In subsequent columns we report the results for a shift of the dependent variable one year further into the future. Column (4) ($k = 3$) is therefore equivalent to our baseline specification. We include the full set of controls except for the three lags of $\Delta y_{i,t}$ (for $k = 0$ the dependent variable is a linear combination of these).

The results in column (1) show that changes in credit-to-GDP and RoE are contemporaneously negatively correlated. Importantly, the relationship is reversed in the medium run: in column (4) ($k = 3$) we see that changes in RoE between $t-3$ and t are positively associated with credit growth between t and $t+3$. The effect is strongest for $k = 3$ and $k = 4$ and the coefficients become smaller for larger k. The lower panel of Table A5.3 shows the equivalent relationship for $\Delta_3 RoA_{i,t}$. The size of the coefficient peaks at $k = 3$ and decays afterwards, much like the $\Delta_3 RoE$ results.

The dynamic relationship between profitability and credit displays a particular pattern: a "profit-credit cycle". This relationship is visualized in Figure A5.3 with changes in return on equity in the left panel and changes in return on assets in the right panel. Both figures show an inverted u-shaped relationship, that is, the response of the credit-to-GDP ratio to variation in profitability measures is strongest over the subsequent three years. This timing is difficult to square with with credit demand explanations. If credit demand was the driver of the relationship, we would have expected to observe increases in credit-to-GDP against good current and future prospects. In that case changes in profitability and credit growth should display a positive contemporaneous correlation or, if households and firms borrow against anticipated good future fundamentals, credit expansion should lead profitability. We find the opposite.

Figure A5.3: *Multivariate models for changes in credit-to-GDP, dynamic relationship*



Notes: This figure displays coefficients from estimating Equation 11 for $k = 0, ..., 6$. See Table A5.3 for more information. Standard errors are dually clustered on country and year. Bars denote 95% confidence intervals around the coefficient estimates.

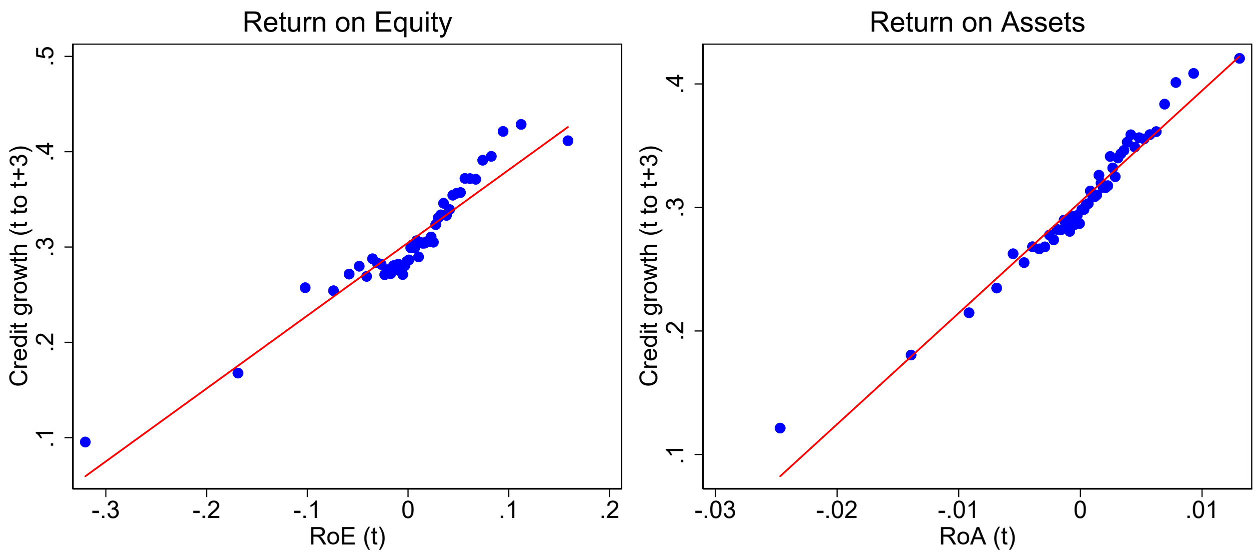
Table A5.3: *Multivariate models for changes in credit-to-GDP, dynamic relationship*

	Dependent variable: $\Delta_3 y_{i,t+k}, k = 0, ..., 5$						
	(1) $\Delta_3 y_{i,t}$	(2) $\Delta_3 y_{i,t+1}$	(3) $\Delta_3 y_{i,t+2}$	(4) $\Delta_3 y_{i,t+3}$	(5) $\Delta_3 y_{i,t+4}$	(6) $\Delta_3 y_{i,t+5}$	(7) $\Delta_3 y_{i,t+6}$
$\Delta_3 RoE_{i,t}$	-0.18***	0.04	0.24***	0.32***	0.31***	0.17***	0.07
	(0.07)	(0.07)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓	✓
R^2	0.24	0.19	0.16	0.13	0.10	0.06	0.05
Observations	1526	1531	1518	1504	1490	1475	1458
	Dependent variable: $\Delta_3 y_{i,t+k}, k = 0, ..., 5$						
	(1) $\Delta_3 y_{i,t}$	(2) $\Delta_3 y_{i,t+1}$	(3) $\Delta_3 y_{i,t+2}$	(4) $\Delta_3 y_{i,t+3}$	(5) $\Delta_3 y_{i,t+4}$	(6) $\Delta_3 y_{i,t+5}$	(7) $\Delta_3 y_{i,t+6}$
$\Delta_3 RoA_{i,t}$	-3.30***	-0.61	1.98***	3.32***	3.16***	1.90***	1.09***
	(0.87)	(0.82)	(0.72)	(0.73)	(0.74)	(0.53)	(0.38)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓	✓
R^2	0.26	0.19	0.15	0.12	0.09	0.06	0.05
Observations	1526	1531	1518	1504	1490	1475	1458

Notes: This table presents results from estimating Equation 11 for $k =, 0, ..., 6$. Each column gradually leads the left-hand-side variable by one year. All specifications control for a vector of net-worth and macroeconomic control variables (see text in section 3). Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively

A6. Bank level dataset

Figure A6.4: *Binned scatterplot for the relationship between profitability and credit growth, bank level data*



Notes: The figure relates bank profitability and subsequent credit growth on a bank level. Bank level observations are collapsed into 50 equal sized bins according to the two profitability measures. Each point represents group specific profitability and credit growth means for our regression sample. Fitted regression lines illustrate the correlation between bank profitability and subsequent credit growth.

To supplement our long run aggregate evidence with bank level results, we employ bank call report data provided by the Federal Reserve. Banks are required to file these reports for regulatory purposes and the data contain detailed quarterly income and balance sheet statements for all US commercial banks. We use data between 1983 and 2012, when all balance sheet and income statement items for our analysis are available in the same format. We first transform quarterly call report data into annual observations, by summing income items over the four quarters of a given year. We then combine yearly income with end-of-year balance sheet values. We exclude bank-year observations with assets or loans being less than one million USD, or with negative equity, and we winsorize all variables at the 2.5% level.

The resulting panel dataset with bank-year observations allows us to run specifications mirroring closely the empirical exercises of aggregate setting. The dependent variable is defined as the change in *net loans and leases* of bank i between year t and year $t+3$. $RoE_{i,t}$ is defined as yearly net income scaled by end-of-year equity. As before, we also compute the three-year change in this variable $\Delta_3 RoE_{i,t} = RoE_{i,t} - RoE_{i,t-3}$.

Figure A6.4 shows scatterplots with the data collapsed into fifty bins, depending on profitability measures. There is a strong positive correlation between the profitability of individual banks ($RoE_{i,t}$ and $RoA_{i,t}$) and their subsequent credit growth. In order to test this relationship more formally, we run the following regression:

$$\Delta_3 y_{i,t+3} = \alpha_i + \alpha_t + \beta \Delta_3 RoE_{i,t} + \gamma X_{i,t} + u_{i,t+3}. \tag{12}$$

Crucially, this regression includes a year fixed effect α_t to absorb aggregate credit demand conditions at time t. α_i is a bank fixed effect that controls for bank specific time-invariant characteristics. β will be the coefficient of interest that refers to the three-year change in profitability ($\Delta_3 RoE_{i,t}$ or $\Delta_3 RoA_{i,t}$). Control variables $X_{i,t}$ are now at the bank level. We include past credit growth, and in addition lagged balance sheet shares of equity, loans, deposits, fed funds (liabilities) and bank size (natural log of assets). Three-year changes in capital proxy for the net worth channel. One advantage in this setup is that we can control for net-worth at the bank level and rule out balance sheet constraints more directly, accounting for the possibility that the distribution of net worth and leverage across banks matters.

The results are shown in Table A6.4. Columns (1) and (4) only include bank and year fixed effects, the subsequent columns add a rich set of bank level controls for bank asset and liability composition and changes in bank net-worth. Across specifications, credit growth over the following 3-year window is signiciantly higher when profitability has been increasing. In line with a net-worth channel, three-year changes in equity capital are associated with elevated subsequent loan growth. Table A6.5 shows that these results are robust when using non-overlapping observations only. Importantly, the bank level results are not affected by the inclusion of time fixed effects. The channel that links profits and subsequent credit growth is not contingent on or subsumed by aggregate credit demand.

Table A6.6 and Table A6.7 replicate two other key results from the aggregate analysis at the bank level. Table A6.6 shows regression evidence for the three major profit components revenue, operating expenses and loan losses mirroring the analysis in Table 3. Again, the profit-credit relationship is largely coming from the loan loss component of banking income. However, bank level operating expenses also show a significant, albeit weaker, association with subsequent credit growth. Table A6.7 replicates Table 6 at the bank level. Column (1) and (2) separate return on equity into a dividend over equity and a retained earnings over equity component and show that both components predict subsequent credit growth at the bank level. Column (3) and (4) include levels and changes of profitability. As argued before, controlling for the level of RoE, three-year changes proxy for the trajectory that led a bank to a certain level of profitability. In line with the expectations channel, changes in RoE are significantly related to subsequent credit growth.

Table A6.4: *Multivariate models for credit growth, bank level data*

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t}$	0.48***	0.32***	0.29***			
	(0.04)	(0.03)	(0.03)			
$\Delta_3 RoA_{i,t}$				5.05***	3.39***	2.86***
				(0.49)	(0.37)	(0.34)
Bank fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓
Control variables		✓	✓		✓	✓
Financial constraints			✓			✓
R^2	0.08	0.20	0.21	0.07	0.20	0.21
Observations	192579	192579	192579	192579	192579	192579

Notes: This table reports regression results from estimating variants of Equation 12 using US Call Report data. The dependent variable $\Delta_3 y_{i,t+3}$ is the three year growth of bank credit (net loans and leases). All variables are winsorized at the 2.5% level. All specifications control for the lagged three-year growth rate of net loans and leases, balance sheet ratios, bank size and financial constraints (see text). All specifications also include bank and year fixed effects. Standard errors in parentheses are dually clustered on bank and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A6.5: *Multivariate models for credit growth, bank level data, non-overlapping observations*

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t}$	0.48***	0.33***	0.30***			
	(0.07)	(0.06)	(0.05)			
$\Delta_3 RoA_{i,t}$				4.96***	3.49***	3.05***
				(0.83)	(0.66)	(0.62)
Bank fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓
Control variables		✓	✓		✓	✓
Financial constraints			✓			✓
R^2	0.08	0.21	0.21	0.08	0.21	0.21
Observations	59043	59043	59043	59043	59043	59043

Notes: This table reports regression results from estimating variants of Equation 12 using US Call Report data. The dependent variable $\Delta_3 y_{i,t+3}$ is the three year growth of bank credit (net loans and leases). All variables are winsorized at the 2.5% level. All specifications control for the lagged three-year growth rate of net loans and leases, balance sheet ratios, bank size and financial constraints (see text). All specifications also include bank and year fixed effects. Standard errors in parentheses are dually clustered on bank and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A6.6: *Multivariate models for credit growth, bank level data*

	(1) $\frac{Revenue}{Equity}$	(2) $\frac{Costs}{Equity}$	(3) $\frac{LoanLosses}{Equity}$	(4) $\frac{Revenue}{Assets}$	(5) $\frac{Costs}{Assets}$	(6) $\frac{LoanLoss}{Assets}$
$\Delta_3 Change_{i,t}$	-0.01	-0.13***	-0.41***	-0.47	-1.69***	-5.40***
	(0.02)	(0.02)	(0.05)	(0.30)	(0.31)	(0.59)
Bank fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓
R^2	0.21	0.21	0.21	0.21	0.21	0.21
Observations	179072	179072	179072	179072	179072	179072

Notes: The dependent variable $\Delta_3 y_{i,t+3}$ is the three year growth of bank credit (net loans and leases). All variables are winsorized at the 2.5% level. All specifications control for the lagged three-year growth rate of net loans and leases, balance sheet ratios, bank size and financial constraints (see text). All specifications also include bank and year fixed effects. Standard errors in parentheses are dually clustered on bank and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A6.7: *Multivariate models for credit growth, bank level data, dividend decomposition and path*

	Uses of profits		Profit path	
			RoE	RoA
	(1)	(2)	(3)	(4)
$\Delta_3 Dividends\ over\ Equity_{i,t}$	0.12***	0.41***		
	(0.03)	(0.05)		
$\Delta_3 Retained\ earnings\ over\ Equity_{i,t}$		0.39***		
		(0.04)		
$3 - year\ Accumulated\ Profits_{i,t}$			0.01	0.28
			(0.01)	(0.18)
$\Delta_3 Change_{i,t}$			0.28***	2.75***
			(0.03)	(0.34)
Bank fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Control variables	✓	✓	✓	✓
R^2	0.24	0.25	0.21	0.21
Observations	75241	75241	192402	192402

Notes: The dependent variable $\Delta_3 y_{i,t+3}$ is the three year growth of bank credit (net loans and leases). All variables are winsorized at the 2.5% level. All specifications control for the lagged three-year growth rate of net loans and leases, balance sheet ratios, bank size and financial constraints (see text). All specifications also include bank and year fixed effects. Standard errors in parentheses are dually clustered on bank and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

A7. Systemic banking crises

Dates of systemic banking crises are based on Jordà et al. (2017).

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

B. Data appendix

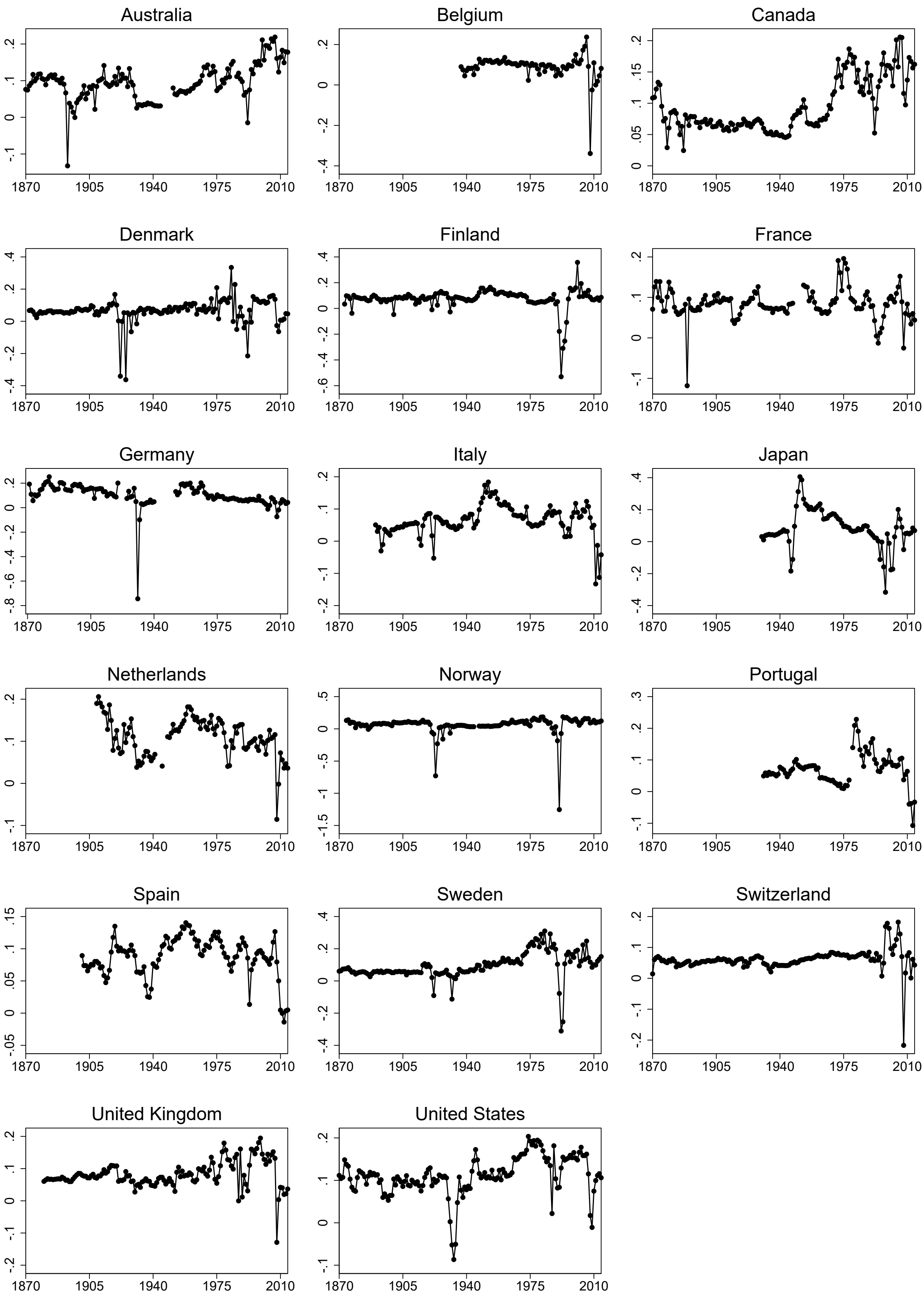
This appendix details the sources of our banking sector profitability estimates for each country. The data contains aggregate profitability series for the banking system and decomposes this profitability into its sources. It includes separate time series for bank return on assets and its main components - revenue (net interest income + net fee income), operating expenses and loan losses. All variables are constructed relative to total assets of the financial system. Items are then rescaled using leverage data from Jordà et al. (2020) (JRST henceforth). We use end of year total capital and total liabilities as denominators in the calculation.

Table B.1: *Variable definitions*

Item	Description
Return on equity	After tax profitability of the banking system relative to end of year equity.
Return on assets	After tax profitability of the banking system relative to end of year assets.
Dividends	Total dividends of the banking system relative to end of year assets.
Costs	Operating expenses of the banking system relative to end of year assets.
Revenues	Total revenue (net interest and fee income) relative to end of year assets.
Loan losses	Loan loss item in the bank income statement relative to end of year assets (charge-offs or provisions for charge-offs).

Our primary goal in constructing the series is consistency across series and within country. We use growth rate splicing if there are significant inconsistencies across sources and coverage, but aim to keep original data levels as much as possible. Maintaining original levels has the advantage that it allows for an bias free construction of ratios and manipulations of the individual series (for example when considering the revenue to cost relationship). We sometimes use profit and loss accounts of individual banks to extend the aggregate series back in time. This data typically relies on the largest banks in a given country. Since we choose the banks based on their historic dominance and not based on their recent success or the survival until today, a potential survivorship bias is unlikely to be large. Finally, the sophistication of accounting standards and practice varied significantly historically. We adjust the data whenever we find the appropriate means to do so. For example, Capie and Billings (2001) provide us with an updated series of banking sector profitability in the United Kingdom that accounts for transactions that involved hidden reserves in the balance sheet. Figure B.1 displays the main profitability series – return on equity – on a country by country basis.

Figure B.1: *Return on equity*



Australia

Table B.2: *Data sources: Australia*

Year	Data source
Bank profitability	
1870–1944	Butlin, Hall and White (1971). Australian banking and monetary statistics, 1817-1945. Reserve Bank of Australia Occasional Paper No. 4A.
1946–1970	White (1973). Australian banking and monetary statistics 1945-1970. Reserve Bank of Australia Occasional Paper No. 4B. Major trading banks.
1971–1980	Statistical Yearbook (various years). Data for joint stock banks.
1981–2001	OECD Banking Statistics. Income statement and balance sheet.
2002–2003	Annual Reports of the four major banks (various years): ANZ, NAB, Commonwealth Bank and Westpac.
2004–2015	Australian Prudential Regulation Authority (2016). Quarterly ADI performance statistics.
Bank P&L components	
1946–1970	White (1973). Australian banking and monetary statistics 1945-1970. Reserve Bank of Australia Occasional Paper No. 4B. Major trading banks.
1963–1974	Statistical Yearbook (various years). Data for joint stock banks.
1981–2001	OECD Banking Statistics. Income statement and balance sheet.
2004–2015	Australian Prudential Regulation Authority (2016). Quarterly ADI performance statistics.
Bank dividends	
1870–1944	Butlin, Hall and White (1971). Australian banking and monetary statistics, 1817-1945. Reserve Bank of Australia Occasional Paper No. 4A.
1946–1974	White (1973). Australian banking and monetary statistics 1945-1970. Reserve Bank of Australia Occasional Paper No. 4B. Major trading banks.
1981–2001	OECD Banking Statistics. Income statement and balance sheet.

Belgium

Table B.3: *Data sources: Belgium*

Year	Data source
Bank profitability	
1937–1980	Rapport Annuel de la Commission Bancaire (various years). All banks for 1944 to 1980 and large banks for 1937 to 1943.
1983–1999	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2000–2017	National Bank of Belgium (various years). Financial Stability Report. All credit institutions.
Bank P&L components	
1981–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2017	National Bank of Belgium (various years). Financial Stability Report. All credit institutions.
Bank dividends	
1981–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.

Canada

Table B.4: *Data sources: Canada*

Year	Data source
Bank profitability	
1870–1967	Annual Reports of major banks (various years): Bank of Montreal, Scotiabank, Canadian Bank of Commerce, Royal Bank of Canada, Bank of Toronto, Dominion Bank, Toronto Dominion Bank (after merger).
1968–1981	Bank of Canada Review (various years). Table A4 of the February or March issue.
1982–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2009–2015	Canadian Bankers Association. Database of Domestic Banks' Financial Results. Fiscal year-end 2006-2015, 8 banks.
Bank P&L components	
1929–1967	Historical Statistics of Canada. Link: https://www150.statcan.gc.ca/n1/pub/11-516-x/3000140-eng.htm. Tables J181-201 and J261-272.
1968–1981	Bank of Canada Review (various years). Table A4 of the February or March issue.
1982–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	Canadian Bankers Association. Database of Domestic Banks' Financial Results. Fiscal year-end 2006-2015, 8 banks.
Bank dividends	
1870–1963	Annual Reports of major banks (various years): Bank of Montreal, Scotiabank, Canadian Bank of Commerce, Royal Bank of Canada, Bank of Toronto, Dominion Bank, Toronto Dominion Bank (after merger).
1964–1967	Historical Statistics of Canada. Link: https://www150.statcan.gc.ca/n1/pub/11-516-x/3000140-eng.htm. Tables J181-201 and J261-272.
1968–1987	Bank of Canada Review (various years). Table A4 of the February or March issue.
1988–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	Canadian Bankers Association. Database of Domestic Banks' Financial Results. Fiscal year-end 2006-2015, 8 banks.

Denmark

Table B.5: *Data sources: Denmark*

Year	Data source
Bank profitability	
1872–1920	Danmarks Statistik (1969). Statistike Underslogelser Nr. 24 Kreditmarkedsstatistik. Link: http://www.dst.dk/Site/Dst/Udgivelser/GetPubFile.aspx?id=19918&sid=kreditm. Table: Bankernes samlede status inden for hovedlandsdele og for hele landet.
1921–1985	Statistical Yearbook (various years).
1986–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	Finansrådet (2015). The sector in figures. Table: Accounting figures.
Bank P&L components	
1875–1920	Abildgren (2017). A chart & data book on the monetary and financial history of Denmark. Working Paper. Sheet S081A
1920–1978	Statistical Yearbook (various years).
1979–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010-2015	Finansrådet (2015). The sector in figures. Table: Accounting figures.
Bank dividends	
1872–1920	Danmarks Statistik (1969). Statistike Underslogelser Nr. 24 Kreditmarkedsstatistik. Link: http://www.dst.dk/Site/Dst/Udgivelser/GetPubFile.aspx?id=19918&sid=kreditm. Table: Bankernes samlede status inden for hovedlandsdele og for hele landet.
1921–1978	Beretning om de danske bankers virksomhed (various years). Official government publication with statistics on all commercial banks.
1979–2004	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.

Finland

Table B.6: *Data sources: Finland*

Year	Data source
Bank profitability	
1870–2010	Herrala (1999). Banking crises vs depositor crises: the era of the finnish markka. Scandinavian Economic History Review. Vol 47, No 2, 5-22. Banking sector balance sheets and income statements in Finland: selected figures. Data continued by the author for the latter years. Data kindly shared by the author.
2011–2016	Statistics Finland Online. Link: http://pxnet2.stat.fi/PXWeb/pxweb/fi/StatFin_Passiivi/StatFin_Passiivi__rah__llai/. Change website to Finnish to access data prior to 2014.
Bank P&L components	
1870–1990	Herrala (1999). Banking crises vs depositor crises: the era of the finnish markka. Scandinavian Economic History Review. Vol 47, No 2, 5-22. Banking sector balance sheets and income statements in Finland: selected figures. Data continued by the author for the latter years. Data kindly shared by the author.
1991–2000	Statistical Yearbook of Finland (various years). Talletuspankit, Dopositionsbanker (deposit taking institutions).
2001–2016	Statistics Finland Online. Link: http://pxnet2.stat.fi/PXWeb/pxweb/fi/StatFin_Passiivi/StatFin_Passiivi__rah__llai/. Change website to Finnish to access data prior to 2014.
Bank dividends	
1870–1955	Aaku (1957). Suomen Liikepankit 1862-1955. Commercial banks.
1979–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.

France

Table B.7: *Data sources: France*

Year	Data source
Bank profitability	
1870–1914	Bouvier, Furet and Gillet (1965). Le mouvement du profit en France au 19e siècle. Paris et La Haye. Data of individual banks is aggregated.
1915–1947	Annual Reports of major banks (various years): Credit Lyonnais and Societe Generale.
1953–1980	Commission de controle de banques (various years). Rapport Annuel.
1980–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.
Bank P&L components	
1980–2006	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2007–2015	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.
Bank dividends	
1870–1913	Bouvier, Furet and Gillet (1965). Le mouvement du profit en France au 19e siècle. Paris et La Haye. Data of individual banks is aggregated.
1988–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.

Germany

Table B.8: *Data sources: Germany*

Year	Data source
Bank profitability	
1871–1882	Annual Reports of major banks (various years): Commerzbank and Deutsche Bank for 1871-1872, Commerzbank, Dresdener Bank and Deutsche Bank for 1873-1882.
1883–1920	Die Deutschen Banken im Jahre (various years). Special publication of 'Der Oekonomist'. Covers largest 50-150 commercial banks.
1925–1944	Annual Reports of major banks (various years): Commerzbank, Dresdener Bank and Deutsche Bank.
1952–1968	Annual Reports of major banks (various years): Commerzbank and Deutsche Bank.
1969–2016	Bundesbank Online. Statistics of banks' profit and loss accounts. Link: https://www.bundesbank.de/Navigation/EN/Statistics/Banks_and_other_financial_institutions/Banks/Statistics_of_the_banks_profit_and_loss_accounts/tables/tabellen.html. Table guv_tab8_en.
Bank P&L components	
1883–1920	Die Deutschen Banken im Jahre (various years). Special publication of 'Der Oekonomist'. Covers largest 50-150 commercial banks.
1969–2016	Bundesbank Online. Statistics of banks' profit and loss accounts. Link: https://www.bundesbank.de/Navigation/EN/Statistics/Banks_and_other_financial_institutions/Banks/Statistics_of_the_banks_profit_and_loss_accounts/tables/tabellen.html. Table guv_tab8_en.
Bank dividends	
1883–1920	Die Deutschen Banken im Jahre (various years). Special publication of 'Der Oekonomist'. Covers largest 50-150 commercial banks.
1979–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.

Italy

Table B.9: *Data sources: Italy*

Year	Data source
Bank profitability	
1890–1973	Natoli, Piselli, Triglia and Vercelli (2016). Historical archive of credit in Italy. Bank of Italy, Economic History Working Papers No. 36.
1974–1992	Annual report of the Bank of Italy (various years).
1993–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	Bank of Italy – Statistical Database. Link: https://www.bancaditalia.it/statistiche/basi-dati/bds/index.html?com.dotmarketing.htmlpage.language=1. All banks.
Bank P&L components	
1974–1992	Annual report of the Bank of Italy (various years).
1993–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	Bank of Italy – Statistical Database. Link: https://www.bancaditalia.it/statistiche/basi-dati/bds/index.html?com.dotmarketing.htmlpage.language=1. All banks.
Bank dividends	
1984–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	Bank of Italy – Statistical Database. Link: https://www.bancaditalia.it/statistiche/basi-dati/bds/index.html?com.dotmarketing.htmlpage.language=1. All banks.

Japan

Table B.10: *Data sources: Japan*

Year	Data source
Bank profitability	
1930–1956	Economic Statistics Annual (1972). Statistics Department, Bank of Japan. Ordinary banks.
1957–1979	Bank of Japan, File CDAB0540. Ordinary Banks.
1980–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2009–2015	IMF Online. Financial Soundness Indicators. Link: data.imf.org/FSI.
Bank P&L components	
1930–1956	Economic Statistics Annual (1972). Statistics Department, Bank of Japan. Income and expenses of ordinary banks.
1956–1979	Bank of Japan, File CDAB0540. Ordinary Banks.
1980–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
Bank dividends	
1980–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.

Netherlands

Table B.11: *Data sources: Netherlands*

Year	Data source
Bank profitability, P&L components and dividends	
1870–1941	Annual Reports of major banks (various years): 1909-1941: Incassobank, Rotterdamsche Bank, Amsterdamsche Bank, Twentsche Bank. 1877-1908: Twentsche Bank, Ontvang- en Betaalkas, Handel en Maatschappij. 1870-1976: Twentsche Bank. Sources: Eisfeld (1916). Das Niederländische Bankwesen. Den Haag. Kiliani (1923). Die Großbanken Entwicklung in Holland und die Mitteleuropäische Wirtschaft. Verlag von Felix Meiner in Leipzig. De Graaf (2012). Voor Handel en Maatschappij – Geschiedenis van de Nederlandsche Handel-Maatschappij, 1824-1964.
1948–1980	Centraal Bureau voor de Statistiek (various years). Maandstatistiek van het financiewezen. Commercial banks.
1981–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2008–2017	De Nederlandsche Bank Online. Link: https://statistiek.dnb.nl/en/downloads/index.aspx#/details/balance-sheet-of-the-dutch-banking-sector-consolidated/dataset/dcb6775e-1afa-4a45-bee0-669be22f8bd5/resource/ebb838b3-fe5f-422d-b6b2-2021ba06b4c98. Balance sheet and income statement of the Dutch banking sector.

Norway

Table B.12: *Data sources: Norway*

Year	Data source
Bank profitability and dividends	
1874–1944	Statistics Norway Online. Various publications. Link: https://www.ssb.no/a/en/histstat/, section 13. Money and credit – Norges private aksjebanker og sparebanker.
1947–1975	Statistical Yearbook of Norway (various years). Forretningsbanker. Driftsregnskap.
1976–1980	Statistical Yearbook of Norway (various years). Offentlige og private banker. Resultatregnskap. Norske forretningsbanker og Norges sparebanker.
1980–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database.
2010–2017	Statistics Norway Online. Link: https://www.ssb.no/en/statbank/table/07880/tableViewLayout1/?rxid=e8526cc9-a688-4b75-857d-2c79e5112586.
Bank P&L components	
1900–1944	Statistics Norway Online. Various publications. Link: https://www.ssb.no/a/en/histstat/, section 13. Money and credit – Norges private aksjebanker og sparebanker.
1976–1980	Statistical Yearbook of Norway (various years). Offentlige og private banker. Resultatregnskap. Norske forretningsbanker og Norges sparebanker.
1980–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database.
2010–2017	Statistics Norway Online. Link: https://www.ssb.no/en/statbank/table/07880/tableViewLayout1/?rxid=e8526cc9-a688-4b75-857d-2c79e5112586.

Portugal

Table B.13: *Data sources: Portugal*

Year	Data source
Bank profitability	
1931–1961	Instituto Nacional de Estatistica, Estatisticas Financeiras (various issues). Bancos, Casas Bancarias e Caixas Economicas.
1962–1978	Instituto Nacional de Estatistica, Estatisticas Monetaria Financeiras (various issues). Group of "Bancos e casas bancario" less "Banco Formento" and "Bank of Portugal".
1980–2007	OECD Banking Statistics. Income statement and balance sheet. Online Database.
2008–2016	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.
Bank P&L components	
1980–2007	OECD Banking Statistics. Income statement and balance sheet. Online Database.
2008–2016	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.

Spain

Table B.14: *Data sources: Spain*

Year	Data source
Bank profitability	
1901–1978	Tafunell (2000). La rentabilidad financiera de la empresa española, 1880-1981: una estimación en perspectiva sectorial. Revista de Historia Industrial 18: 71-112.
1979–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database.
2010–2015	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.
Bank P&L components	
1979–2007	OECD Banking Statistics. Income statement and balance sheet. Online Database.
2008–2015	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.
Bank dividends	
1979–2007	OECD Banking Statistics. Income statement and balance sheet. Online Database.

Sweden

Table B.15: *Data sources: Sweden*

Year	Data source
Bank profitability and dividends	
1870–1997	Swedish Riksbank. Bank Lending and Borrowing 1870-2006. Data source: Hortlund (2005). The long-term relationship between capital and earnings in banking. SSE/EFI Working Paper Series in Economics and Finance No. 611.
1997–2015	Statistics Sweden Online. Link: http://www.statistikdatabasen.scb.se/pxweb/en/ssd/START__FM__FM0402/?rxid=3d618be3-5da4-4cb7-9934-972462441227. Financial Markets – Financial Enterprises. Balance sheets and income statement for all banks.
Bank P&L components	
1870–1997	Swedish Riksbank. Bank Lending and Borrowing 1870-2006. Data source: Hortlund (2005). The long-term relationship between capital and earnings in banking. SSE/EFI Working Paper Series in Economics and Finance No. 611.
1988–1995	Riksbank Yearbook (various years). Banking sector balance sheets and profit and loss account. Available funds and their distribution. All banks.
1997–2015	Statistics Sweden Online. Link: http://www.statistikdatabasen.scb.se/pxweb/en/ssd/START__FM__FM0402/?rxid=3d618be3-5da4-4cb7-9934-972462441227. Financial Markets – Financial Enterprises. Balance sheets and income statement for all banks.

Switzerland

Table B.16: *Data sources: Switzerland*

Year	Data source
Bank profitability and dividends	
1870–1905	Historical Statistics of Switzerland Online. Link: https://www.fsw.uzh.ch/histstat/main.php. Table O.12. Diskontobanken, Kantonalbanken und übrige Emissionsbanken: Passiven, Aktiven und Gewinnrechnung 1826-1910.
1906–2002	Schweizerische Nationalbank. Historische Zeitreihen. Die Banken in der Schweiz. Link: https://www.snb.ch/de/iabout/stat/statrep/statpubdis/id/statpub_histz_arch. Balance sheet data from Table 9. Net profit after taxes from Tables 29.1 and 29.2.
1996–2016	Schweizerische Nationalbank Online. Link: https://data.snb.ch. Annual banking statistics. All banks.
Bank P&L components	
1870–1905	Historical Statistics of Switzerland Online. Link: https://www.fsw.uzh.ch/histstat/main.php. Table O.12. Diskontobanken, Kantonalbanken und übrige Emissionsbanken: Passiven, Aktiven und Gewinnrechnung 1826-1910.
1906–1995	Schweizerische Nationalbank. Historische Zeitreihen. Die Banken in der Schweiz. Link: https://www.snb.ch/de/iabout/stat/statrep/statpubdis/id/statpub_histz_arch. Balance sheet data from Table 9. Income components from Tables 29.1 and 29.2.
1906–1992	Historical Statistics of Switzerland Online. Link: https://www.fsw.uzh.ch/histstat/main.php. Table O.15. Banken (1): Gewinn- und Verlustrechnung 1906-1992.
1993–1995	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues. All banks.
1996–2016	Schweizerische Nationalbank Online. Link: https://data.snb.ch. Annual banking statistics. All banks.

United Kingdom

Table B.17: *Data sources: United Kingdom*

Year	Data source
Bank profitability, P&L components and dividends	
1870–1920	Capie and Webber (1985). Profits and profitability in british banking, 1870-1939. Centre for Banking and International Finance Discussion Paper 18. Series: English and Welsh Joint Stock Banks – Aggregate Profits.
1920–1967	Capie and Billings (2004). Evidence on competition in English commercial banking, 1920—1970. Financial History Review. Volume 11 / Issue 01 / pp 69 - 103.
1968	Ackrill and Hannah (2001). Barclays, The Business of Banking 1690-1996. Cambridge University Press. Tables B1, B2, B4, B6.
1969–1976	CLCB Statistical Unit. London Clearings Banks 1966-1976. Profit and balance sheet statistics. Consolidated accounts.
1977–1979	Ackrill and Hannah (2001). Barclays, The Business of Banking 1690-1996. Cambridge University Press. Tables B1, B2, B4, B6.
1980–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2009–2015	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.

United States

Table B.18: *Data sources: United States*

Year	Data source
Bank profitability	
1870–1918	Historical Statistics of the United States. Link: https://hsus.cambridge.org/HSUSWeb/HSUSEntryServlet. Table: National banks – number, earnings, and expenses: 1869—1998 Cj238-250.
1919–1950	Banking and Monetary Statistics 1914-1941 and 1941-1970. Tables: Member bank earnings, expenses and dividends, 1919-1941. Member bank income, expenses and dividends 1941-70. All FDIC insured commercial banks.
1951–2015	FDIC Online. Historical Statistics on Banking. Link: https://www5.fdic.gov/hsob/HSOBRpt.asp. All FDIC insured commercial banks.
Bank P&L components	
1870–1935	Historical Statistics of the United States. Link: https://hsus.cambridge.org/HSUSWeb/HSUSEntryServlet. Table: National banks – number, earnings, and expenses: 1869—1998 Cj238-250.
1935–1966	FDIC Online. Historical Statistics on Banking. Link: https://www5.fdic.gov/hsob/HSOBRpt.asp. All FDIC insured commercial banks.
1967–2015	FDIC Online. Historical Statistics on Banking. Link: https://www5.fdic.gov/hsob/HSOBRpt.asp. All FDIC insured commercial banks.
Bank dividends	
1870–1918	Historical Statistics of the United States. Link: https://hsus.cambridge.org/HSUSWeb/HSUSEntryServlet. Table: National banks – number, earnings, and expenses: 1869—1998 Cj238-250.
1919–1945	Banking and Monetary Statistics 1914-1941 and 1941-1970. Tables: Member bank earnings, expenses and dividends, 1919-1941. Member bank income, expenses and dividends 1941-70. All FDIC insured commercial banks.
1946–1966	FDIC Online. Historical Statistics on Banking. Link: https://www5.fdic.gov/hsob/HSOBRpt.asp. All FDIC insured commercial banks.
1967–2015	FDIC Online. Historical Statistics on Banking. Link: https://www5.fdic.gov/hsob/HSOBRpt.asp. All FDIC insured commercial banks.