The Profit-Credit Cycle *

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Abstract

Bank profitability leads the credit cycle. An increase in return on equity of the banking sector predicts rising credit-to-GDP ratios in a panel of 17 advanced economies spanning the years 1870 to 2015. The pattern also holds in bank-level data and for the global financial cycle. It is only partially explained by a balance sheet channel where higher retained profits relax net worth constraints. Turning to alternative explanations, we find evidence consistent with behavioral credit cycle models in which agents extrapolate past defaults to expected future credit outcomes. Using recent US data, we show that survey-based profitability expectations and measures of CFO optimism are tightly linked to past profitability, forecast credit growth, and display predictable forecast errors. These patterns are also reflected in the aggregate credit cycle. Increases in profitability not only predict credit expansions, but also elevated crisis risk a few years later.

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1. Introduction

The financial cycle has taken center stage in recent academic and policy debates. The properties of this cycle seem to feature several salient characteristics: financial crises are typically preceded by booms in private credit (Schularick and Taylor, 2012) and credit growth predicts the business cycle over the medium term (Mian et al., 2017a). Furthermore, investors seemingly fail to price these negative effects as large credit expansions predict negative returns to bank equity investors (Baron and Xiong, 2017; Fahlenbrach et al., 2017). While these patterns characterize the often painful aftermath of credit booms, the underlying drivers of rapid expansions in credit markets and the triggers for the subsequent reversal are less well understood.

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 the credit cycle. What we observe in the data is in fact a "profit-credit cycle". An increase in profitability predicts an expansion of credit over the following three years. This finding connects well with older ideas of "displacements" in the credit market triggering waves of optimism (Kindleberger, 1978; Minsky, 1977). It reinforces the importance of funding supply shocks for credit and business cycles (Krishnamurthy and Muir, 2017; Mian et al., 2017b) and meshes nicely with new modelling approaches of the credit cycle using diagnostic or extrapolative expectations (Bordalo et al., 2018; Greenwood et al., 2018). Our results suggest that such biases in expectation formation have important macroeconomic consequences.

To study the profit-credit relationship, we collected a new dataset on bank profitability in 17 advanced economies, starting in 1870. The data allows us to assess the relationship between bank profits, the credit cycle, and financial instability over the past 150 years. The advantage of the data on accounting profitability is that they are, by definition, backward looking. In that sense, profits are distinct from credit spreads and stock prices, which are forward looking, and therefore can only help to assess whether future economic variables were correctly anticipated. Krishnamurthy and Muir (2017) show, for example, that credit spreads, while being too low during the preceding boom, correctly anticipate the severity of a financial recession. Our new dataset is complemented by the data of the Macrohistory Database (Jordà et al., 2017b), which provides us with a large number of control variables for our investigation. For a subsample of countries and episodes we were able to further decompose bank profitability into its sources – revenue, costs and loan losses – and its uses – funds paid out to shareholders and funds retained in the bank.

We find that bank profitability leads the credit cycle. High bank profits are followed by credit expansions. We measure profitability using the level of return on equity (RoE) and proxy a sequence of increasing or decreasing returns with the three-year change of this return ($\Delta_3 RoE$). 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. The relationship remains robust when we include additional controls, time effects and analyze subsamples. The strong relationship is also a prevailing feature in a panel of US banks. Using Federal Reserve call report data, we find that bank level profitability predicts future credit growth even when controlling for unobserved bank heterogeneity, observable time varying bank characteristics, as well as aggregate credit demand using time fixed effects.

Which mechanisms can explain the strong relationship between profitability and subsequent credit growth? High profits, if not paid out completely to shareholders, will 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 a net worth channel, where retained profits increase net worth and lending capacity. Bank capital ratios and changes in aggregate bank capital predict credit expansions. However, the relationship between profits and future lending growth remains significant even in specifications that include the capital ratio and changes in banking sector capital as controls. Decomposing profits into dividends and retained earnings, we find a significant effect of dividend payments on future credit expansion, while controlling for retained earnings. Dividends which are paid out to shareholders should be orthogonal to borrowing constraints. We conclude that a net worth channel alone cannot fully account for the strong relationship between profits and subsequent credit developments.

The timing of the relationship furthermore indicates that it is unlikely that high bank profitability and credit cycles are linked through credit demand due to strong economic fundamentals. Credit demand factors would either create a positive contemporaneous correlation between profits and credit growth, or credit should expand in anticipation of higher future profitability when households and firms borrow against good future fundamentals. However, profits and changes in profitability lead the credit expansion, and our data as well as Baron and Xiong (2017) show that credit expansions are followed by low rather than high subsequent returns.

We then assess if our results are compatible with an expectations-based mechanism. A novel theoretical literature links the credit cycle to behavioral biases in the expectation formation process. In these models agents extrapolate from current default rates when building their expectations about future credit market outcomes (Bordalo et al., 2018; Greenwood et al., 2018). As a result, creditors are too optimistic when default rates are low and too pessimistic when default rates are high. According to these models low loan losses (and thereby high bank profitability) should be associated with optimism and increases in credit supply empirically. When we decompose profitability into loan losses, revenues and costs, we indeed find that decreasing loan losses are associated with expanding credit.

Credit cycle models based on extrapolative expectations furthermore link increases in profitability to excess optimism that is often deflated during a significant reversal. We find that increases in profitability predict financial instability over horizons of more than two years, while the year prior to a banking crisis is often characterized by declining profitability. This result is consistent with models where less favorable news after a series of good news lead to sharp reversals (Bordalo et al., 2018) and also with bank runs that are linked to a perceived weakening of bank fundamentals (Goldstein and Pauzner, 2005). When we focus on the role of loan losses, we find that decreasing loan losses predict financial turmoil a few years ahead. These results mirror the behavior of credit spreads (Krishnamurthy and Muir, 2017) and realized volatility (Danielsson et al., 2018), which have both been found to be particularly low in the prelude to a crisis. Similar to the findings in Baron and Xiong (2017), we further show that bank equity investors are not compensated for these effects and high profitability is associated with low excess returns on the bank equity index over three to six 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 measures of optimism and expected profitability predict subsequent bank lending. Furthermore, profitability expectations are strongly associated with past profitability. The link between realized profitability and past developments is weaker, and as a result bank CFOs make predictable forecast errors. When profits are high, they are too optimistic and when profits are low, they are too pessimistic. These errors are also reflected in lending behaviour. Turning to bank level data, we additionally show that expected future losses, measured as loan loss provisions set aside by banks, increase in past losses. This extrapolation, however, leads to predictable errors. Low provisioning in year t predicts high loan losses in the years $t+2$ to $t+5$ while high provisioning predicts low losses.

Our paper is related to three strands of research. The financial cycle has moved to the center of economic policy making and research after the 2008 financial crisis (see Borio, 2014). One strand discusses potential explanations and policy implications (Aikman et al., 2015; Dell'Ariccia et al., 2016) and identifies markers that help to tell different kinds of booms apart (Gorton and Ordonez, 2016; Richter et al., 2017). A rapidly growing literature studies the relationship between credit and business cycles (Mian et al., 2017a) with a focus on credit supply based explanations. Gilchrist and Zakrajšek (2012) show that credit spreads in bond markets predict economic fundamentals. Krishnamurthy and Muir (2017) argue along similar lines and find that bond credit spreads are low before financial crises. Financial deregulation can be linked to credit supply expansions in the United States in the 1980s (Mian et al., 2017b) and in the run-up to the recent crisis (Di Maggio and Kermani, 2017). Our results can be seen as another piece of evidence for a slowly emerging consensus that puts credit supply-based explanations at the center of the credit cycle.

Second, our paper is related to a literature that studies the relationship between net worth and credit in models with financial frictions (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997). Holmstrom and Tirole (1997) analyze how net worth affects balance sheet debt capacity and lending of banks. All these models generate amplification of initial net worth shocks through the interplay of prices of collateralizable assets or income with borrowing constraints. A vast literature builds on these early contributions, studying alternative frictions, amplification mechanisms and integrating the mechanisms into sophisticated macroeconomic models (e.g. Brunnermeier and Sannikov, 2014). Empirically, Adrian and Shin (2010) show that banks adjust their balance sheets reacting to changes in net worth.

Third, our paper extends the behavioral credit cycle literature. New research relates credit cycles to behavioral biases in agents' expectation formation. Gennaioli et al. (2016) directly connect profitability, expectation formation and investment decisions for US corporates. They show that CFOs extrapolate past performance. The arising expectational errors explain investment decisions on the firm level. A similar pattern drives boom and bust in shipbuilding as demonstrated by Greenwood and Hanson (2015). Bordalo et al. (2018) incorporate biases in expectation formation into a model of the credit cycle. In their model creditors assign higher probabilities to states of the world that have become more likely in light of recent data, leading to excessive credit growth after a number of good realizations and to predictable reversals. In Greenwood et al. (2018) creditors extrapolate default risk. This generates an endogenous feedback mechanism between credit market outcomes and credit market sentiment and a disconnect between the business and the credit cycle. Our results on the relation between loan losses and subsequent credit market outcomes are consistent with the key mechanism in this model.

The structure of the paper is as follows. The next section describes the data. Section 3 documents the profit-credit cycle. Sections 4 and 5 present evidence on the underlying mechanisms linking bank profitability and the credit cycle. Section 6 analyzes banking sector profitability around financial crises. Section 7 concludes.

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 balance sheets and 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., 2017a; Schularick and Taylor, 2012). A second strand of the literature recently started to incorporate market prices for debt and equity into the analysis (Baron and Xiong, 2017; Krishnamurthy and Muir, 2017). Banking sector income – in particular realized banking sector profitability – has been largely ignored. Adding accounting profits creates a natural link between the two strands of literature. The new dataset complements previous data collection efforts which provide us with a large set of macroeconomic and financial variables for our analysis (Baron and Xiong, 2017; Jordà et al., 2017a,b). 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 baseline profitability series, we also construct a return on asset series by dividing profits by total assets. However, due to important structural trends of this series (see Richter and Zimmermann, 2018), we focus in this paper on the return on equity series. Nevertheless, all main results hold when we use RoA in the analysis.[1]

The data comes 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 130 years of data for each country

[1] 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 differs slightly from the leverage ratio of Jordà et al. (2017a).

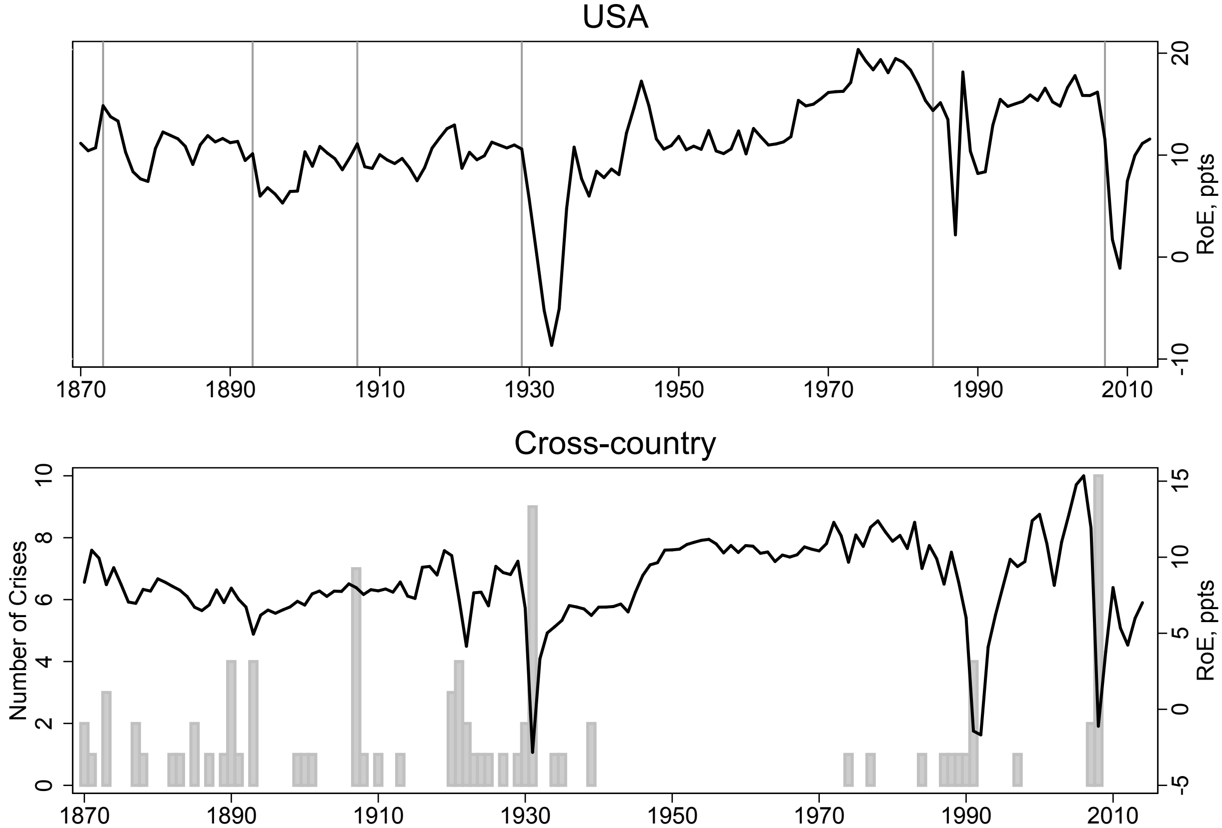
in our sample. A detailed data appendix describing the sources and data construction will be published online.

When constructing the profitability data, we combine micro and macro data. A large share of the dataset is based on aggregate banking statistics. In some countries, we need to rely on data of individual large banks to extend the data back into the 19th century. Relying on data of a few banks might generate excess volatility compared to the 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. Our profit data might also be influenced by survivorship and selection bias. When not capturing the whole sector, our data typically relies on the biggest and most successful 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, the survivorship bias is however unlikely to be large.

Another issue is related to the use of annual report data. We treat this data at face value. The sophistication of accounting standards and practice however varied significantly historically. As a consequence, the data might be distorted by incorrect accounting, in particular profit smoothing and hidden reserves in bank balance sheets. We try to 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. Furthermore, the timing of economic developments and realizations of losses in the annual reports might not coincide. Realized accounting losses often lag the actual shock due to late realization and profit smoothing. Our empirical exercises, especially in the description and analysis of profitability during financial crises, reflect this possibility.

Figure 1 illustrates the data. It shows the RoE series for the United States and averages across the 17 countries in our database. The vertical lines in the US graph indicate banking crisis events in the Macrohistory database and the grey bars in the cross-country graph indicate the number of countries with systemic banking crises in a given year. Several features stand out: Bank profitability, measured by RoE, was relatively stable over the last 145 years. The return on equity 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 return on equity 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 accounting profitability into deep negative territory. For example, the RoE series for the United States shows three major negative shocks with RoE around or

Figure 1: *Profitability in the United States and across the World*



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

below zero: the Great Depression, the S&L crisis and the Great Recession. The defining feature of the aggregate data 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 invisible in the profitability series (e.g. the crisis of 1907 in the United States). These differences are a feature profitability shares with alternative severity measures. Indeed, Figure A1.1 in the appendix shows that profitability and equity returns of commercial banks are highly correlated across systemic crisis episodes.

In addition to the level of the profitability variable, we also compute 3-year changes in RoE as a proxy for medium-term changes in profitability:

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

As there are no clear trends in RoE over our sample period, this variable is on average close to zero. The standard deviation is around 7%, so three-year changes in RoE can be quite sizable.

Our new dataset also allows us to decompose banking sector profitability into its origins and its uses. Drawing from additional banking sector dividend information, we separate $RoE_{i,t}$ into a dividend and a retained earnings component. We define measures of dividends relative to equity DoE and retained earnings as a share of equity $REToE$ directly corresponding to the aggregate RoE series. Since we do not observe retained earnings directly, we proxy for $REToE$ using the residual of 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.

Most non-profit variables are taken from Jordà et al. (2017b). Our main dependent variable is the change in the credit-to-GDP ratio over a three-year interval between time $t-3$ and time t (as in Mian et al., 2017a and Baron and Xiong, 2017):

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

Credit here refers to bank credit extended to domestic private non-financial actors. 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 2.3% on average. Detailled summary statistics can be found in Table A1.1.

3. The relationship between profits and the credit cycle

The relationship between profitability and subsequent credit expansion can be traced back to the ideas of Minsky (1977) and Kindleberger (1978). Minsky (1977) distinguishes five phases of a typical bubble in financial markets: an initial displacement that increases profitability, which is followed first by a financing boom, and afterwards by euphoria. Later in the cycle, some investors start to become cautious about overvaluations, take their profits and walk. Prices decline, more and more investors revise expectations and sell their assets at falling prices until eventually panic breaks out. In this narrative, profitability and credit are intimately linked and it therefore serves as a starting point of our inquiry.

We first document the relationship between bank profitability and credit expansions and show that profitability predicts the credit cycle. This part relies on the two described profit measures, the level of $RoE_{i,t}$ and the change $\Delta_3 RoE_{i,t}$. We assess the medium-term relationship with $\Delta_3 y_{i,t+3}$ as the dependent variable. In our baseline specification, y refers to the ratio of bank credit to GDP and $\Delta_3 y_{i,t+3}$ is defined as the three-year change in this ratio between time t and time $t+3$. Following the approach in Mian et al. (2017a) we estimate variants of equations

$$\Delta_3 y_{i,t+3} = \alpha_i + \beta^{\Delta RoE} \Delta_3 RoE_{i,t-1} + \sum_{\tau=1}^{3} \gamma_\tau \Delta y_{i,t-\tau} + \eta X_{i,t-1} + \theta Z_{i,t-1} + u_{i,t+3}, \tag{4}$$

and

$$\Delta_3 y_{i,t+3} = \alpha_i + \beta^{RoE} RoE_{i,t-1} + \sum_{\tau=1}^{3} \gamma_\tau \Delta y_{i,t-\tau} + \eta X_{i,t-1} + \theta Z_{i,t-1} + u_{i,t+3} \tag{5}$$

where we include changes $\Delta_3 RoE_{i,t-1}$ and levels $RoE_{i,t-1}$ and add three lags of the dependent variable ($\sum_{\tau=1}^{3} \Delta y_{i,t-\tau}$) and a vector of lagged macroeconomic control variables ($X_{i,t-1}$) subsequently. The vector of macrocontrols includes three lags of real GDP growth, the level of real GDP as well as three lags of short term interest rates, long term interest rates, inflation, and the current account-to-GDP ratio. As a second set of controls ($Z_{i,t-1}$) we add two proxies that may account for a net worth channel, the lagged capital ratio of the banking sector and three-year changes in nominal bank capital relative to GDP.

The result in Table 1 column (1) shows that an increase in profitability over the past three years ($\Delta_3 RoE_{i,t-1}$) is followed by significantly higher credit growth ($\Delta_3 y_{i,t+3}$). A similar result emerges when we include the lagged level ($RoE_{i,t-1}$) as in column (4). Banks extend more credit when measures of realized profitability look good. The other columns show that the addition of control variables to the empirical model does not change these results in a major way. Adding macroeconomic controls, in (2) and (5) reduces the coefficients slightly, but the results remain highly significant.

How sizable are the effects? Increasing $RoE_{i,t-1}$ ($\Delta_3 RoE_{i,t-1}$) by one standard deviation is associated with increases in $\Delta_3 y_{i,t+3}$ of about 0.2 (0.17) standard deviations or, as a more tangible benchmark, with a 1.75% (1.5%) increase in credit-to-GDP over a three-year

Table 1: *Predicting changes in credit-to-GDP*

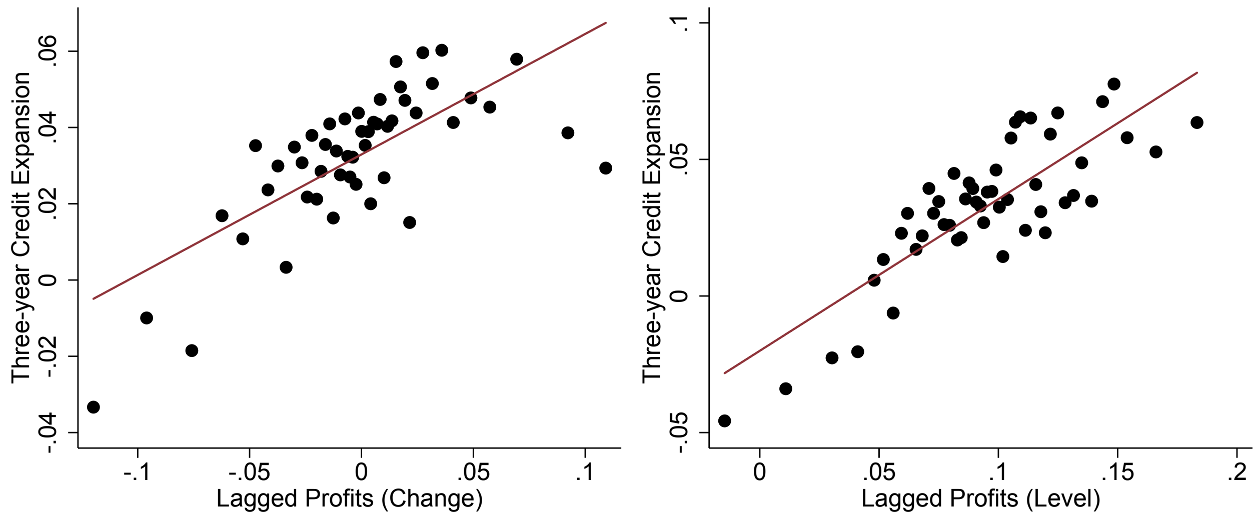
	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t-1}$	0.20***	0.16***	0.15***			
	(0.04)	(0.04)	(0.04)			
$RoE_{i,t-1}$				0.30***	0.26***	0.26***
				(0.05)	(0.05)	(0.06)
$Capital\ Ratio_{i,t-1}$			0.24**			0.25**
			(0.10)			(0.10)
$\Delta_3(Capital/GDP)_{i,t-1}$			0.07			-0.01
			(0.23)			(0.24)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
R^2	0.06	0.11	0.12	0.08	0.13	0.14
Observations	1608	1467	1445	1641	1494	1468

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on RoE_{it-1} and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of credit-to-GDP changes. Columns (2) and (5) add the vector of macroeconomic control variables described in the text. Columns (3) and (6) additionally control for net-worth channel 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.

window. The sample mean of $\Delta_3 y_{i,t+3}$ is 2.2% as the size of the financial sector has been increasing over the past 150 years. Our estimates imply, that these growth rates almost double, when realized profitability is elevated by one standard deviation.

Figure 2 presents scatterplots corresponding to the above specifications using levels and changes in profitability. In both cases, the data are collapsed into 50 bins according to lagged changes or levels of profitability and the graph displays the mean for each of these bins. On the y-axis, the mean of three-year credit growth for each of the 50 groups is presented. The graph shows the relationship of residuals after controlling for variation explained by our covariates. The fitted lines display the strong positive correlation between profit and credit variables, confirming the regression results. The slope in the presented figures is even higher than in the regression because the data has been winsorized for graphical purposes. The location of the highest group of lagged profit changes far below the fitted line is noteworthy. Remember that profits often fall to negative levels during financial crises. This implies that some of the highest positive three-year changes in profitability happen during the recovery of profits to normal levels in the years after such a low. It seems plausible that these post-crisis observations display only average levels of credit expansion

Figure 2: *The Profit-Credit Cycle*



Notes: The figure relates bank profitability and subsequent three-year changes in credit to GDP. Observations are collapsed into 50 equal sized bins according to their profitability. Each point represents the group specific means of profitability and credit expansion after controlling for the full set of covariates from the regressions. Fitted regression lines illustrate the correlation between bank profitability and subsequent credit growth. For graphical purposes the variables have been winsorized at the 2.5 percent level.

despite the strong increases in profitability. We will explore the behavior of profitability around financial crises in more detail below.

In (3) and (6) of Table 1 we add the capital ratio as a control for balance sheet constraints in the banking sector. Adrian and Shin (2010) have argued that book leverage ratios (marked to market) measure net-worth constraints in the banking sector. Consistent with a net worth channel, we find that the inverse of leverage, a high capital ratio, is associated with increases in the credit-to-GDP ratio over the following years – banks use the relaxation of funding constraints in order to increase lending. However, including the capital ratio does not affect the results for the profitability measures. A related possibility is that banks instantaneously lever up against increases in equity and we therefore do not measure these increases via the book capital ratio. In that case we would expect that credit-to-GDP ratio increases depend on changes in the level of aggregate bank capital. We therefore include the three-year changes in the ratio of aggregate bank equity relative to GDP. In the panel regressions reported in Table 1, there is no significant relationship between this variable and future credit expansion.

Subsamples: In Table 2 we show robustness tests of the results with respect to subsamples and excluding windows around financial crises. All specifications include the full set of macro and net-worth control variables from the previous specifications. In a first step we restrict the sample to the post Bretton-Woods era to understand whether the relationship can 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 analyze 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 and find that the results remain highly significant, while the number of observations is reduced to one third. One concern may be that the results are mostly driven by the behavior of profitability and credit around financial crises. To address this issue we exclude in column (4) a 5-year window around financial crises from the sample. We find again that the results are robust and remain highly significant. Finally, in column (5), we address the possible cross-country correlation of variables and include year-fixed effects. Remember that our standard errors are always clustered on the country and on the time dimension. The year fixed effects increase the R^2 to around 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., 2018; Rey, 2016). The coefficients on profitability measures remain however highly significant.

Alternative credit measures: The appendix presents further robustness tests with respect to variable definitions. In a first step, we vary the dependent variable. Here, $\Delta y_{i,t+3}$ referred to the three-year change in the credit-to-GDP ratio. In Table B1.1 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 B1.2 we move away from credit variables and look at the bank-assets-to-GDP ratio. The findings are similar to those for credit variables. This could imply that all asset categories display the same relationship or that credit variables drive the variation in total assets. Hence, in Table B1.3 we ask whether the relationship is similar for the assets in the bank balance sheet that are not credit variables. Here, we find weaker results, so the mechanism seems to be more relevant for credit expansion than for other asset classes.

Alternative profit measures: Furthermore, the appendix also shows results for different definitions of the explanatory variables. In particular, a concern may be that the results are due to bank capital in the denominator of RoE (although this would imply a negative relationship between bank capital and credit expansion, exactly the opposite of the balance-sheet channel). In Table B1.5 and Table B1.7 we vary the denominator and normalize profits by GDP or by total assets and find that results hold. Furthermore, the results are also robust, when we replace RoE with the logarithm of real bank profits in Table B1.6.

Table 2: *Subsamples and time effects*

	Dependent variable: $\Delta_3 y_{it+3}$				
	(1) Post-1973	(2) Pre-2000	(3) Non-overlap	(4) No-crisis	(5) Year effects
$\Delta_3 RoE_{i,t-1}$	0.11^{**}	0.14^{***}	0.22^{***}	0.09^{***}	0.07^{**}
	(0.04)	(0.04)	(0.05)	(0.03)	(0.04)
Country fixed effects	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓
Exclude 5-year window around crises				✓	
Year effects					✓
R^2	0.23	0.12	0.19	0.16	0.30
Observations	631	1258	480	1178	1445

	Dependent variable: $\Delta_3 y_{it+3}$				
	(1) Post-1973	(2) Pre-2000	(3) Non-overlap	(4) No-crisis	(5) Year effects
$RoE_{i,t-1}$	0.27^{***}	0.22^{***}	0.34^{***}	0.22^{***}	0.17^{***}
	(0.08)	(0.05)	(0.04)	(0.06)	(0.05)
Country fixed effects	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓
Exclude 5-year window around crises				✓	
Year effects					✓
R^2	0.25	0.13	0.21	0.17	0.31
Observations	636	1281	488	1197	1468

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $RoE_{i,t-1}$ and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of credit-to-GDP changes and the vector of macroeconomic control variables described in the text. Column (1) uses only post-1973 data. Column (2) uses only pre-2000 data. Column (3) uses non-overlapping windows of three-year credit expansion. Column (4) excludes centered 5-year windows around financial crises. Column (5) includes year-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."

Country level evidence: Finally, in Figure B1.2 we plot the coefficients from country level regressions, where we run a regression of $\Delta_3 y_{i,t+3}$ on lagged profitability measures for all our sample countries one by one. The graphs show that the coefficients are significantly positive in a majority of countries, so that we conclude that the strong association between profitability and credit expansion also holds at the country-level.

Profitability surprises: For changes in profitability to affect expectations, these changes must have been unanticipated. Since we have no direct measure of unexpected profitability changes, we use a regression approach and clean the profitability series from changes that could be expected due to mean reversion in profitability and based on shareholder expectations expressed through returns on the bank equity index. Shareholder return data is from (Baron and Xiong, 2017). The results from this regression are shown in Table B1.9. We then use lagged residuals from this regression as a measure of profit surprises and re-estimate our baseline regressions. The results are presented in Table B1.10 and qualitatively very similar to our previous results. The coefficients cannot be directly compared as we use three-year changes in RoE in the baseline and the approach here provides us with residual changes over a one year horizon. Since the shareholder return data is only available for a subsample of observations and the results are in line with our baseline estimates, we will continue to use the three-year change in RoE in the remainder of the analysis.

3.1. Timing

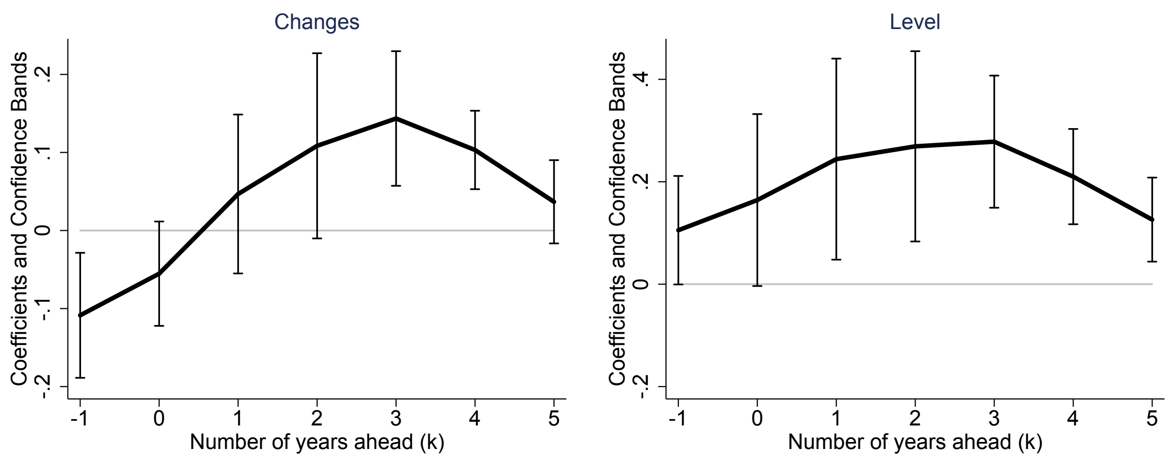
So far, we asked whether variation in credit growth can be explained by past profitability as some accounts of the credit cycle, such as Minsky (1977) suggest. Using a three-year window also allowed us to connect to the findings by Mian et al. (2017a) and Baron and Xiong (2017) who show that three-year changes in credit expansion predict the business cycle and bank equity prices. We now extend this setup and describe the relationship between profitability measures and the change of the credit-to-GDP ratio over varying 3-year windows (similar to Mian et al., 2017a). This will allow us to distinguish between credit supply and demand mechanisms.

Remember, $\Delta_3 y_{i,t}$ refers to the change in the credit-to-GDP ratio between $t-3$ and t. 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:

$$\Delta_3 y_{i,t+k} = \alpha_i + \beta Profitability_{i,t-1} + \eta X_{i,t-1} + \theta Z_{i,t-1} + u_{i,t+k} \tag{6}$$

where $k = -1, 0, ..., 5$ and profitability refers to either $\Delta_3 RoE_{i,t-1}$ or $RoE_{i,t-1}$. The results are shown in Table 3. In the tables, going from left to right, we vary k from -1 to 5. This means that the right hand side of Equation 6 remains fixed and in subsequent columns we report the results for a shift of the dependent variable one year further into the future. In the changes specification Equation 6, this means that column (1) of Table 3 ($k = -1$) assesses the relationship between changes in profitability from $t-4$ to $t-1$ and the change in the credit-to-GDP ratio between $t-4$ and $t-1$. For $k = 3$, this is equivalent to our previous specification, the coefficient $\beta^{\Delta RoE}$ measures the relationship between changes in profitability from $t-4$ to $t-1$ and the change in the credit-to-GDP ratio between t and $t+3$. In all these specifications, we include the full set of controls except the three lags of $\Delta y_{i,t}$ (for $k = 1$ the dependent variable is a linear combination of these). In the level specifications, column (1) displays the relationship between profits in $t-1$ and the change in the credit-to-GDP ratio $\Delta_3 y_{i,t}$ between $t-4$ and $t-1$ ($k=-1$). Column (5) for $k=3$ corresponds again to the baseline specification, the relationship between profits in $t-1$ and the change in credit-to-GDP $\Delta_3 y_{it}$ between t and $t+3$.

Figure 3: *Coefficients at varying horizons*



Notes: This figure displays coefficients from estimating Equation 6 for $k=-1,0,...,5$. Standard errors in parentheses are dually clustered on country and year. Bars denote 95% confidence intervals around the coefficient estimates.

The upper panel presents estimates for Equation 6. Column (1) shows that the change in the RoE between $t-4$ and $t-1$ and the change in credit to GDP between $t-4$ and $t-1$ are negatively correlated, that is decreasing profits are contemporaneously associated with credit expansions. A reason could be that banks lend to less profitable borrowers when they expand lending rapidly. Importantly, the relationship is again reversed in the medium run: In column (5) we see that changes in RoE between $t-4$ and $t-1$ are positively associated with credit growth between t and $t+3$. The effect is strongest for $k=2$ and $k=3$ and the coefficients become smaller for larger k. The lower panel of Table 3 shows that profit levels in $t-1$ and 3-year changes in the credit-to-GDP ratio from $t-4$ to $t-1$ are only weakly correlated. Coefficients and significance change once we shift the dependent variable in time. In columns (2) to (7) a positive and significant relationship is visible, and especially in the medium term ($k=1$ to $k=4$) higher levels of current profitability predict positive changes in the credit-to-GDP ratio. For example, column (5) for $k=3$ shows that high levels of profit in $t-1$ predict credit expansions between period t and $t+3$, this relationship being highly significant. The size of the coefficient peaks for $k=2$ and $k=3$ and decays afterwards, much like the changes results.

Table 3: *The dynamic relationship between profit levels and credit growth*

	Dependent variable: $\Delta_3 y_{it+k}, k = -1, 0, ..., 5$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta_3 y_{i,t-1}$	$\Delta_3 y_{i,t}$	$\Delta_3 y_{it+1}$	$\Delta_3 y_{it+2}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+4}$	$\Delta_3 y_{it+5}$
$\Delta_3 RoE_{i,t-1}$	-0.11***	-0.06	0.05	0.11*	0.14***	0.10***	0.04
	(0.04)	(0.03)	(0.05)	(0.06)	(0.04)	(0.03)	(0.03)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓	✓
R^2	0.25	0.19	0.13	0.11	0.11	0.08	0.07
Observations	1376	1364	1351	1337	1324	1310	1294

	Dependent variable: $\Delta_3 y_{it+k}, k = -1, 0, ..., 5$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta_3 y_{i,t-1}$	$\Delta_3 y_{i,t}$	$\Delta_3 y_{it+1}$	$\Delta_3 y_{it+2}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+4}$	$\Delta_3 y_{it+5}$
$RoE_{i,t-1}$	0.11*	0.16*	0.24**	0.27***	0.28***	0.21***	0.13***
	(0.05)	(0.09)	(0.10)	(0.09)	(0.07)	(0.05)	(0.04)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓	✓
R^2	0.25	0.21	0.17	0.15	0.14	0.10	0.07
Observations	1390	1378	1365	1351	1338	1324	1308

Notes: This table presents results from estimating the specifications in Equation 6 for $k = -1, 0, ..., 5$. Each column gradually leads the left-hand-side variable by one year. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

The dynamic relationship between profitability displays a distinguished pattern: a "profit-credit cycle". Bank profitability and the credit cycle seem inherently linked. High bank profitability today is followed by increases in the credit-to-GDP ratio, while low profitability is followed by years of depressed credit growth. These relationships are visualized in Figure 3. The right panel displays coefficients for the level of profitability and the left panel for changes in profitability. Both graphs display an inverted u-shaped relationship, that is the response of the credit-to-GDP ratio to variation in profitability measures is strongest over the three following years. This timing is inconsistent with credit demand explanations. If credit demand was the driver of this relationship, we would have expected to observe increases in credit-to-GDP against good current and future prospects. In that case profitability and credit expansion should display a positive contemporaneous correlation. If households and firms borrow against good future fundamentals and therefore low defaults, credit expansion should lead profitability. We find exactly the opposite.

3.2. The global credit cycle

Recent studies show that a global financial cycle has emerged in the second half of the 20th century (Bruno and Shin, 2015; Jordà et al., 2018; Rey, 2016). Banks seem to increasingly transmit their funding and domestic conditions across borders. This means that profitability enhancing conditions might be globally correlated. We therefore ask whether a measure of average bank profitability in our sample of advanced economies is associated with global credit credit growth. To answer this question, we compute for each year the average value of the respective variable in our 17 country sample. We then assess whether the average of profitability or profitability changes predicts average growth in credit-to-GDP ratios over the following three years running the following time series specifications

$$\overline{\Delta_3 y_{t+3}} = \alpha + \beta \overline{Profitability_{t-1}} + \eta \overline{X}_{t-1} + \theta \overline{Z}_{t-1} + u_{t+3}. \tag{7}$$

Bank profits predict the credit cycle also at the global dimension. The results in Table 4 are in line with our previous findings, even when including lagged control variables $\overline{X}_{t-1}$ and $\overline{Z}_{t-1}$ in (3) and (4). The coefficients are larger than in the country level analysis and they are highly significant for levels and changes, both with and without control variables. In the appendix, Figure B1.1 visualizes this relationship again using binned scatterplots. The message is clear: once measures of global average profitability are high, a global credit boom follows.

Table 4: *The global profit-credit cycle*

	Dependent variable: $\Delta_3 Global\ Credit_{it+3}$			
	(1)	(2)	(3)	(4)
$\Delta_3 RoE_{it-1}$	0.61***		0.64***	
	(0.10)		(0.08)	
RoE_{it-1}		0.71***		0.80***
		(0.16)		(0.13)
$Capital\ Ratio_{it-1}$			0.01	0.11**
			(0.05)	(0.05)
$\Delta_3 Capital/GDP_{it-1}$			0.18	0.02
			(0.56)	(0.51)
Control variables			✓	✓
R^2	0.29	0.32	0.38	0.39
Observations	117	120	117	117

Notes: This table reports time series regressions of the yearly sample average credit-to-GDP change from t to $t+3$ on the yearly sample averages of RoE_{it-1} and $\Delta_3 RoE_{i,t-1}$. Newey-West standard errors in parentheses are computed with the automatic lag selection procedure in Newey and West (1994). *,**,*** indicate significance at the 0.1, 0.05, 0.01 level, respectively.

4. Net worth channel and behavioral credit cycles

This section studies the role of different mechanisms that may link bank profitability and credit growth. As discussed before, the timing of the profit-credit relationship makes credit demand an unlikely explanation for the relationship (see subsection 3.1). Nevertheless, we will present additional evidence in favor of the hypothesis that bank profitability triggers expansions in credit supply. We will then distinguish between different channels of credit supply expansions. In a first step, we will present a formal framework to distinguish between net worth constraints and expectations. In a next step, we decompose profitability into revenue, costs and loan losses to compare the behavioral credit cycle explanation to other narratives.

4.1. Credit demand and supply

We have established that credit expansions follow high or increasing bank profitability. This relationship could be due to an increase in the supply of credit or due to higher demand for credit. A simple test can help to distinguish between these two explanations. More specifically, supply and demand based explanations yield conflicting predictions regarding the price of credit during a credit expansion. If higher bank profits (i.e. lower loan losses)

Table 5: *Credit spreads*

	Dependent variable: $BondSpread_{it}$	
	(1)	(2)
$\Delta RoE_{i,t-1}$	-0.45** (0.22)	-0.38* (0.21)
Country fixed effects	✓	✓
3 lags of y	✓	✓
Macrocontrols		✓
R^2	0.48	0.47
Observations	1148	987

Notes: This table reports regressions of credit spreads in t on changes in profit variables. All specifications control for three lags of bond spreads. Column (2) adds the vector of macroeconomic control variables described in the text. 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.

are associated with increases in credit demand and credit supply remains fixed, the price of credit should increase following increases in profitability. If the effect of bank profits on lending is due to increased credit supply and demand is constant, the price of credit should go down after an increase in profitability. We will use data on bond spreads (from Kuvshinov (2018)) as a measure of the price of credit to test these hypotheses. Credit spreads are a forward looking variable and profitability news should be incorporated immediately in the price. We will therefore analyse the relationship between spreads and lagged one-year changes in profitability instead of using the three-year change. In our baseline specification, we control for three lags of credit spreads and additionally include country fixed effects

$$y_{i,t} = \alpha_i + \beta^{\Delta RoE} \Delta RoE_{i,t-1} + \sum_{\tau=1}^{3} \gamma_\tau y_{i,t-\tau} + u_{i,t}. \tag{8}$$

The results are presented in column (1) of Table 5. The price of credit is negatively associated with changes in profitability. In combination with our baseline result, namely an expansion of credit, this suggests that credit supply is expanding. This result is robust to adding the vector of macrocontrols as can be seen in column (2).

4.2. Credit supply: a formal framework

To clarify possible channels at play, we provide a simple framework of banks' borrowing constraints in the tradition of Holmstrom and Tirole (1997). The framework allows us to distinguish between a net worth and an expectation based mechanism. Consider a representative bank endowed with equity e_t entering period t. At the beginning of each period t the bank extends loans which return a payoff R_t at the end of the period.[2] Let R_t^E denote the expectation about R_t at the beginning of period t. k_t denotes the total loan scale of the bank. The amount $d_t = k_t - e_t$ must be raised from financiers, whom we call depositors here. These depositors are deep-pocketed and alternatively store the funds, hence their outside option can be normalized to a return of 1. As in Holmstrom and Tirole (1997) bankers are able to pledge only parts of their end-of-period returns to creditors. Here, we assume that the amount ρk_t cannot be pledged.[3]

We furthermore assume that R is uniformally distributed over $(1, 1+\rho)$ with mean $\tilde{R}$, which ensures that projects have a positive NPV, while it is not possible to finance projects with debt only. Furthermore, for ease of exposition, assume that there is no persistence in R. Similar to Greenwood et al. (2018) we assume that expectations R_t^E are a mixture of (i) a rational forward looking component and (ii) a backward looking extrapolative component. In our model, since there is no persistence, the rational component will be equal to the sample mean $\tilde{R}$. We assume that the backward looking extrapolative component is simply given as the last period's return. Expectations can then be written as $R_{t+1}^E = \lambda\tilde{R} + (1-\lambda)R_t$, where $\lambda \in [0,1]$ is a fixed coefficient. $\lambda = 1$ corresponds to the rational expectation and $\lambda = 0$ to the fully extrapolative expectation, where this period's return is the expectation of next periods return.

The following incentive constraint will ensure that bankers do not divert the funds

$$k_t R_t^E - (k_t - e_t) \geq \rho k_t. \tag{9}$$

Specifically, the return from the projects, after repaying depositors, must exceed the return from diverting the funds. We solve this equation for k_t:

$$k_t \leq \frac{e_t}{1 - R_t^E + \rho} \tag{10}$$

[2] We model the return on assets here, as this variable is available for the full dataset we will use. One could also model this using instead of a return on a loan the default rates on loans in order to be closer to the model in Greenwood et al. (2018).

[3] This limited pledgeability of returns can be due to asset diversion, moral hazard, inalienability of human capital and/or limits to arbitrage, see Gersbach and Rochet (2017) for possible microfoundations.

When bank equity is scarce, profit maximization implies that this constraint holds with equality, as profits are increasing in k_t. Equation then (10) shows that credit volume extended by the bank increases in equity capital (net worth) and in expected return of the bank's projects. The profit of the bank is given by:

$$\Pi_t = k_t R_t - (k_t - e_t) - e_t \tag{11}$$

Let r denote the share of profits retained in the bank (fixed coefficient $\in [0,1]$). Then the law of motion that governs changes in bank capital is given by:

$$e_{t+1} = e_t + r\Pi_t \tag{12}$$

The growth of credit between t and $t+1$ is then given by:

$$\frac{k_{t+1}}{k_t} = \underbrace{\frac{1-(\lambda\tilde{R}+(1-\lambda)R_{t-1})+\rho}{1-(\lambda\tilde{R}+(1-\lambda)R_t)+\rho}}_{\text{Change in expectations}} \left(1 + \underbrace{\frac{\frac{r}{e_t}(R_t-1)}{1-(\lambda\tilde{R}+(1-\lambda)R_{t-1})+\rho}}_{\text{Additional net worth}}\right) \tag{13}$$

Proposition 1. Equation 13 yields the following predictions about the relationship between profitability measures (RoE_t) and credit expansion (k_{t+1}/k_t):

(a) Net worth channel (operates with $r > 0$): holding expectations constant, credit expansion k_{t+1}/k_t is proportionally to RoE_t if $r > 0$.

(b) Expectations channel (operates with $\lambda < 1$): controlling for retained earnings over equity, credit growth (i.e. $k_{t+1}/k_t > 1$) increases if $R_t > \tilde{R}$. With $r = 0$, credit expansion is given by $k_{t+1}/k_t = L_t$.

Our simple framework illustrates that the overall effect of high profitability on future credit growth can be disentangled into two separate channels. The first channel runs through additional net worth created by high profitability. Credit increases in accumulated net worth. When r is a constant, credit k_{t+1}/k_t increases proportionally in past profit (RoE_t).

But, there is also a second mechanism at work whenever $\lambda < 1$. When the latest realization of returns was above expectations (here the mean), a change in expectations will imply that credit expands. Controlling for accumulated net worth, credit expands between t and $t+1$, when $R_t > \tilde{R}$. This is because a high R_t increases the expectation of R^E_{t+1} and thereby also the pledgeable return. Earnings based borrowing constraints that are entirely based on current earnings as discussed in Lian and Ma (2018) would correspond to $\lambda = 0$ in this framework. On the other hand, if expectations are unaffected by recent realizations, i.e. $\lambda = 1$, this channel will not operate, as R^E_t will be equal to R^E_{t+1}. We will empirically test whether profitability affects credit above and beyond the net worth channel, which would be consistent with this mechanism.

Note that both channels can work in opposite directions. Specifically, RoE_t can be positive and hence retained earnings are larger than zero as long as $r > 0$. At the same time, the change in expectations multiplier could be below one if $R_t < R^E_t$, as expectations about future profitability are revised downwards due to a low realization. This implies for example, that positive but lower than expected RoE realizations can be sufficient to trigger a credit contraction, without any loss of net worth. While our framework here is very stylized, a similar conclusion is reached in richer models featuring for example diagnostic expectations (Bordalo et al., 2017).

Clearly, the channels are not mutually exclusive. As Equation 13 shows, it can easily be the case that changes in expectations are amplified through the balance sheets of borrowing constrained intermediaries. In our empirical analysis in the next section, we will distinguish between the channels laid out here using data on dividends and retained earnings.

4.3. Retained earnings and dividends

This section sets out to map the overall effect to the channels presented in the theoretical framework. Referring to Equation 13 we want to disentangle the effect into a net worth and an expectations change component. The empirical counterpart to net worth accumulated over the last period are retained earnings over equity ($REToE$). Changes in expectations about the return on bank assets are not directly observed, but we observe unlevered asset returns, which are given by RoA. Hence, in our first specification we use three year changes in this variable ($\Delta_3 RoA$) in order to proxy for the realization of asset returns relative to expectations. We run specifications of the following form

$$\Delta_3 y_{i,t+3} = \alpha_i + \beta \Delta_3 RoA_{i,t-1} + \eta X_{i,t-1} + u_{i,t+k}\,, \tag{14}$$

where the vector of macrocontrols $X_{i,t-1}$ includes all control variables we used in the previous exercises. In column (1) of Table 6, we predict three-year changes in credit-to-GDP with past changes in RoA. The coefficient is positive and significant. Increases in return on assets may however be correlated with retained earnings. Hence, in column (2) the set of control variables, and $RIToE$ and $\Delta_3 RIToE$ are included in the analysis. The coefficient for $\Delta_3 RoA_{it-1}$ remains highly significant. Even when controlling for changes in net worth, we find a link between profitability and future credit expansion, which is in line with the expectations channel laid out above. Furthermore, consistent with the existence of a net worth channel, the coefficient for retained earnings is positive and significant.

In columns (3) to (6) we explore a different approach. Dividends paid out to shareholders are also a measure of profitability, i.e. RoE and DoE are positively correlated, but by definition dividends are orthogonal to the net worth channel. After payout, these funds are not available in the bank as net worth to relax borrowing constraints. In fact, we find empirically that dividends contain almost no information on retained earnings. We can hence use DoE as a measure of profitability that is unrelated to bank equity and therefore unrelated to the net worth channel. Applying this insight, the results in columns (3) to (6) confirm that the link between profits and credit expansion goes beyond the net worth channel. Columns (3) and (4) show that the growth in DoE over the previous three years is a predictor of credit expansion over the next three years. Similarly, the lagged level of DoE helps to forecast three-year credit expansion. All these results are highly significant. The results presented in this section are in line with the basic takeaway from our theoretical framework: there are two channels that link past profits to credit growth. When we standardize the two variables (DoE and $RIToE$), the results suggest that both coefficients are similar in magnitude.

4.4. The role of past loan losses

In this section, we 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 insight into the mechanisms underlying the profit-credit cycle. As explained above, we were able to locate data that allows us to decompose bank profitability into these categories only for a subset of our sample. Hence, the data coverage roughly halves relative to the baseline results. When we analyze the relationship between decomposed profitability and credit expansion, we would expect to observe a positive sign for revenues and a negative sign for costs as well as loan losses. We define three new variables, expressing each of the separate profit components relative to equity to maintain comparability to the

Table 6: *Channels*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoA_{it-1}$	2.62^{***}	3.70^{***}				
	(0.53)	(1.05)				
$\Delta_3 DoE_{it-1}$			0.51^{***}	0.41^{**}		
			(0.18)	(0.17)		
DoE_{it-1}					0.92^{***}	0.83^{***}
					(0.26)	(0.26)
$REToE_{it-1}$		0.23^{**}	0.24^{**}	0.22^{**}	0.24^{**}	0.20^{*}
		(0.09)	(0.10)	(0.10)	(0.12)	(0.11)
$\Delta_3 RETоE_{it-1}$		-0.15^{***}	0.04	0.01	0.03	0.02
		(0.05)	(0.02)	(0.04)	(0.04)	(0.04)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Control variables		✓		✓		✓
R^2	0.05	0.18	0.08	0.18	0.12	0.21
Observations	1654	756	972	756	972	756

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $\Delta_3 RoA_{i,t-1}$, $\Delta_3 DoE_{i,t-1}$ and DoE_{it-1}. Columns (2) to (6) control for $REToE_{it-1}$ and $\Delta_3 RETоE_{i,t-1}$. All specifications control for three lags of credit-to-GDP changes. Columns (2), (4) and (6) add the vector of macroeconomic and net-worth control variables described earlier in the text. 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.

baseline estimates. We then run specifications like

$$\Delta_3 y_{i,t+3} = \alpha_i + \beta \Delta_3 (Revenue/Equity)_{i,t-1} + \eta X_{i,t-1} + u_{i,t+k}\,, \tag{15}$$

where we replace $\Delta_3(Revenue/Equity)_{i,t-1}$ with costs and loan losses and include country fixed effects, lags of the credit growth variable and the full set of controls. The signs of all coefficients are as expected. Revenues are positively related to credit expansion and costs as well as loan losses negatively. However, revenues and costs are insignificant, while the results for loan losses are highly significant. The results show that the relationship between profits and future credit is predominately due to loan losses. A decrease in loan losses, or a low level of loan losses, are associated with subsequent credit expansion. This relationship is a robust feature in the data, even when omitting data windows around financial crises or when looking at individual subsamples of the dataset.

The evidence for a close link between loan losses and credit growth is consistent with the main theoretical mechanisms in behavioral models of the credit cycle. In Bordalo et al.

Table 7: *Decomposition of profit*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3(Revenue/Equity)_{i,t-1}$	0.02 (0.04)					
$(Revenue/Equity)_{i,t-1}$		0.02 (0.04)				
$\Delta_3(Cost/Equity)_{i,t-1}$			-0.08 (0.05)			
$(Cost/Equity)_{i,t-1}$				-0.03 (0.03)		
$\Delta_3(LoanLoss/Equity)_{i,t-1}$					-0.11*** (0.04)	
$(LoanLoss/Equity)_{i,t-1}$						-0.17*** (0.06)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols	✓	✓	✓	✓	✓	✓
R^2	0.15	0.15	0.15	0.15	0.16	0.17
Observations	713	713	713	713	713	713

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on RoE_{it-1} and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of credit-to-GDP changes. Columns (2) and (5) add the vector of macroeconomic control variables described in the text. Columns (3) and (6) additionally control for net-worth channel 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.

(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 decreasing loan losses lead to an inflated probability of states with low defaults. These low expected losses then enter the lending decisions of banks and create an incentive to extend lending. Greenwood et al. (2018) go one step further and introduce a two-way feedback mechanism. In their model creditworthiness of borrowers is partly determined by extrapolating past defaults. Hence, after a recent history of low loan losses, banks lend to firms and households at attractive terms. These cheap refinancing conditions for borrowers also reduce actual defaults. As a result, there is a disconnect between the credit cycle and the business cycle in the model of Greenwood et al. (2018). In the next section we turn to recent US data to analyze the role of expectations in more detail.

5. The expectations channel

This section studies the expectation formation of banks. We will proceed in two steps. First, we use actual optimism and expectations, as reported by bank CFOs, to link past profitability, earnings expectations and future credit growth. These measures are unavailable in a long run setting and we will therefore focus on data from the United States. Second, we study the expectations channel at the bank level and focus on variables that are not available in our aggregate data. In particular, we analyze the relationship between loan loss provisions and actual loan losses. Loan loss provisions can be viewed a proxy for a bank's expectations about loan losses due to defaulting borrowers.

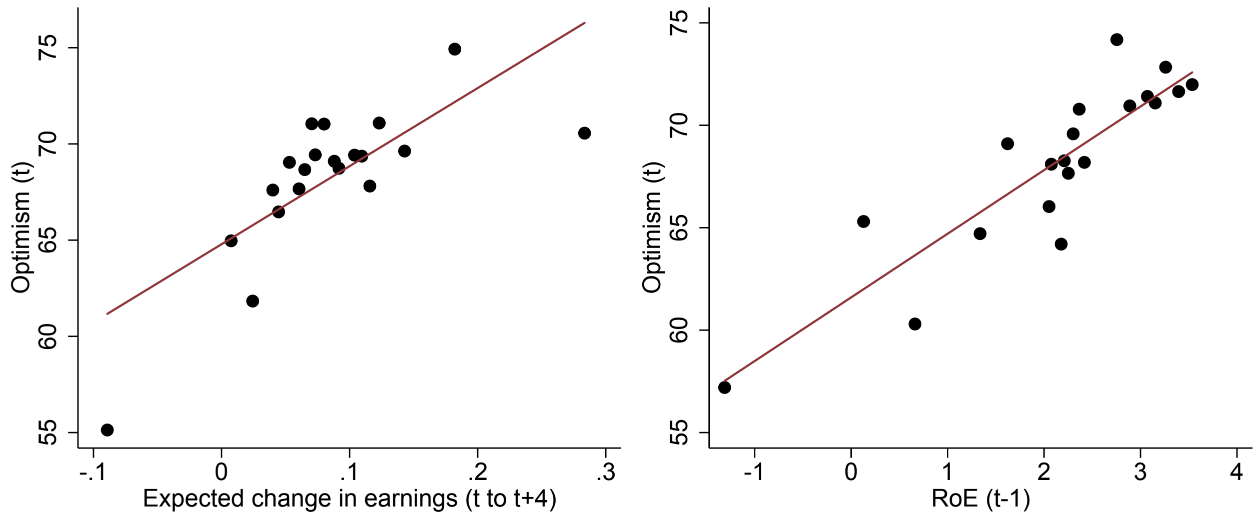
5.1. Survey expectations and credit expansions

In this section, based on aggregated data on survey responses of bank CFOs (from the Duke CFO Global Business Outlook, 2018), we ask whether CFO optimism and expectations about future profitability are related to past profitability, and how future credit growth is related to these measures. We will first analyse whether optimism depends on realized profitability and whether optimism predicts credit growth. We then follow Bordalo et al. (2018) and test whether forecast errors of bank profitability can be predicted from past profitability data, which should not be the case under rational expectations.

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 earnings expectations for the next twelve months. For both questions, we have data on the mean response of CFOs from the banking and finance industry for each quarter. We combine measures of optimism and expectations about 12-months earnings growth in the banking sector, from the quarterly CFO survey, with accounting information on realized profitability of the aggregate banking sector. Balance sheet and income information are based on FDIC statistics.[4] After merging the data, we have a time series of quarterly accounting data and quarterly information on optimism and earnings expectations for the aggregate banking sector in the US. The baseline relationship between profitability measures and subsequent credit growth mirrors the correlation in the long-run macro data (see Figure B3.3 in the appendix).

[4] 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/.

Figure 4: *Optimism, earnings expectations and past profitability*



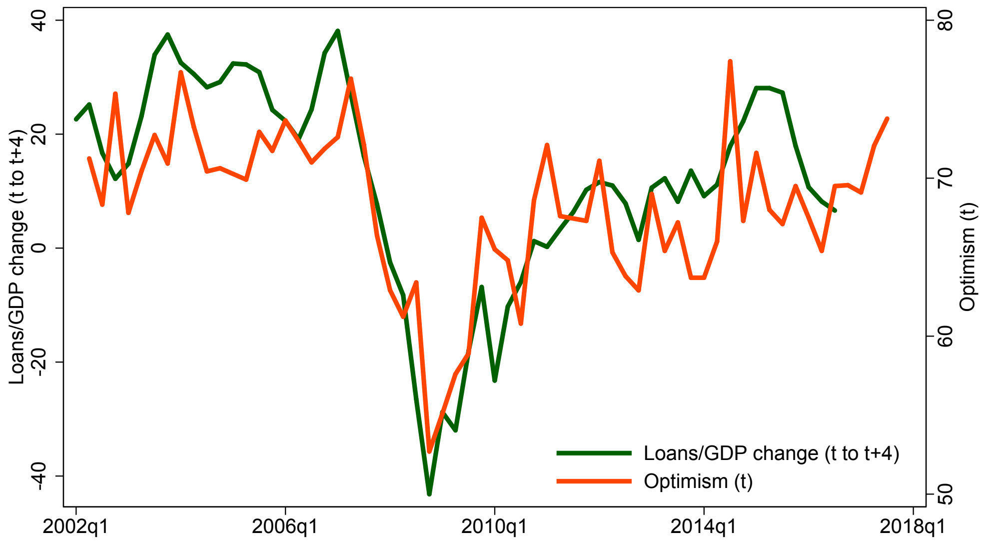
Notes: The left panel presents a binned scatterplot for expected change in earnings over the next twelve months and optimism. The right panel presents a binned scatterplot for the relationship between past profitability RoE_{t-1} and $Optimism_t$. See text for details.

We first check how measures of optimism and earnings expectations are related to each other. In the left panel of Figure 4 we show that the two measures are highly correlated as we would have expected. Optimism at time t comes with higher expectations of earnings in the next four quarters. The right panel of Figure 4 shows a scatterplot for the relationship between our measure of optimism and lagged RoE, where RoE is defined as *Net Operating Income/Total Equity Capital* from the FDIC statistics. Clearly, lagged RoE is positively associated with optimism. Past performance affects sentiment and expectations.

The second question is whether measures of optimism or expectations are associated with credit growth. Figure 5 shows that optimism at time t and changes in the credit/GDP ratio between t and $t+4$ track each other closely. The banking sector extends more credit over the next four quarters, when CFO optimism is elevated today.

In line with behavioral credit cycle models, past profitability affects optimism and optimism is closely associated with credit expansions. But how accurate are expectations; put differently, is optimism justified? To answer this question, we rely on realized and expected measures of profitability. We first calculate the time t expectation of RoE_{t+4} as time t actual earnings from the past 12 months growing with the rate of expected earnings changes (from the CFO survey) and scale expected earnings with time t equity capital. This RoE forecast can be compared to realized RoE_{t+4}, which is computed as realized earnings over the following 12 month, also scaled with time t equity capital. We refer to the difference between the two, actual RoE at time $t+4$ and the time t forecast for $t+4$, as the

Figure 5: *CFO Optimism and credit expansion*



Notes: The figure displays the evolution of the CFO optimism measure and four quarter Loans/GDP changes. See text.

time t forecast error ($RoE_{t+4} - E_t[RoE_{t+4}]$). The time series for this variable is visualized in Figure 6 where we plot the evolution of time t RoE levels and forecast errors made at time t about profitability at $t+4$. Visual inspection suggests that these two variables are negatively related. A negative forecast error means that the realization was worse than expected, hence CFOs were too optimistic. It is no surprise that the forecast error is negative in the run-up and early phase of the financial crisis as realized earnings are low relative to expected earnings. This pattern, however, could also be entirely explained with a bad shock that moves realized returns relative to flat expectations. Hence, the positive forecast error in the aftermath of the financial crisis is more interesting. Observing the bad realization of profitability during the first quarters of the financial crisis, expectations seem to become excessively pessimistic and realized RoE is much higher than expected by bank CFOs. The two series also exhibit a negative correlation before and after the financial crisis.

In Table 8, we conduct an empirical test of these relationships. We run predictive time series regressions of the following form

$$RoE_{t+4} = \alpha + \beta RoE_t + \gamma X_t + \epsilon_{t+4}. \tag{16}$$

In a first step we use current RoE levels to predict the realized one-year ahead RoE, i.e. RoE_{t+4}. We then replace realized returns with expectations of returns $E_t(RoE_{t+4})$ and with forecast errors. Table 8 shows the results for these tests of predictability: Column (1) shows

Figure 6: *Current profitability and forecast errors*

Notes: The figure displays the evolution of bank RoE_t and time t forecast errors ($RoE_{t+4} - E_t[RoE_{t+4}]$) of bank CFOs in the United States between 1997 and 2017. Both variables are measured in percentage points. The variables are described in detail in the footnotes of Table 8.

that RoE at time $t+4$ is predicted by RoE at time t - profitability is persistent. In column (3) we regress the time t expectation of RoE_{t+4} on RoE_t. The coefficient shows that expectations are excessively persistent, the coefficient for the forecast in (3) is larger than the coefficient for realized returns in (1). This difference shows up in (5) where we test whether forecast errors are predictable from past data and regress the forecast error on past returns. The coefficient is negative and significant. This indicates that expectations are systematically biased: expected earnings are too high when current profits are high and too low when current profits are low. Columns (2), (4) and (6) show that these results also hold, when GDP growth and dummies for recessions and financial crises are included in the analysis. As a further robustness check, Table B3.13 in the appendix shows that the relationship also holds when we exclude the years 2007 and 2008 from the analysis.

In a second step we ask whether CFO expectations are related to subsequent credit growth. We measure credit growth as the change in the ratio of net loans and leases to GDP between t and $t+1$. Column 1 in Table 9 shows that changes in credit are predicted by realized RoE_t, where lagged credit growth, a crisis and a recession dummy as well as GDP growth are included as control variables. In (2) we split RoE into two components, Dividends/Equity$_t$ and Retained Earnings/Equity$_t$. Both variables turn out to be highly significant. As before, we interpret this finding as showing that there is a balance sheet channel of RoE_t but an additional role for profitability, going beyond this channel. Columns (3) and (4) analyze the

Table 8: *Profitability and CFO expectations*

	RoE_{t+4}		$E_t(RoE_{t+4})$		$RoE_{t+4} - E_t(RoE_{t+4})$	
	(1)	(2)	(3)	(4)	(5)	(6)
RoE_t	0.85***	0.67***	1.15***	1.18***	-0.30***	-0.50***
	(0.13)	(0.08)	(0.03)	(0.02)	(0.10)	(0.08)
R^2	0.61	0.96	0.98	0.99	0.18	0.85
Controls		✓		✓		✓
Observations	71	71	71	71	71	71

Notes: RoE: Sum of net operating income $t-3$ to t divided by bank capital in t . Expected RoE is computed by combining earnings growth expectations from the survey with actual bank earnings and dividing it by capital in t . Actual RoE is defined as next years earnings divided by capital in t . Error = Actual RoE - Expected RoE. CFO Survey question: Relative to the previous 12 months, what will be your company's percentage earnings change during the next 12 months? Newey-West standard errors in parentheses are computed with the automatic lag selection procedure in Newey and West (1994). *, **, ***: Significant at 10%, 5% and 1% levels respectively.

relaionship between profit forecasts and credit growth. The profit forecast itself (column 3) is positively related to subsequent credit growth. 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. Obviously, in this regression we already use future data and it is with hindsight that we can say that ex-post too optimistic expectations were associated with high credit growth. Table B3.14 shows that these results are robust when we exclude the years 2007 to 2008. The appendix shows some additional specifications that show the robustness of these results to different variable definitions.

We conclude from these findings that bankers expectations may excessively rely on recent data. Furthermore, expectations affect credit growth, presumably through credit supply conditions, and hence expectational errors may be a driver of credit misallocation.

5.2. Bank level analysis

So far, we have documented a new pattern at the aggregate and at the global level: Bank profitability leads the credit cycle. Our results suggest an expectations channel for this relationship. We will now turn to bank level data, where we can use an accounting based measure of expectations. We will first show that profitability is also a leading indicator of credit growth at the bank level – even when controlling for aggregate demand and bank net worth. In a second step, we study banks' provisioning for expected loan losses in more detail.

Table 9: *CFO expectations and credit growth*

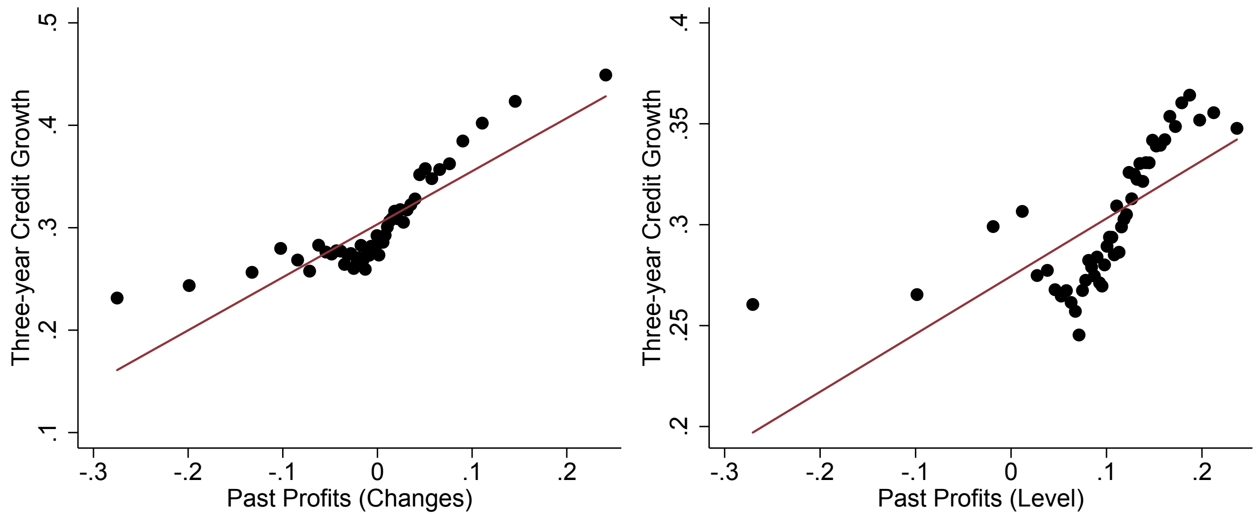
	Credit (Net loans and leases/GDP$_{t+4}$-Net loans and leases/GDP$_t$)			
	(1)	(2)	(3)	(4)
RoE$_t$	364.98***			
	(32.48)			
DoE$_t$		395.61***		
		(62.52)		
REToE$_t$		298.63***		
		(62.58)		
E$_t$ (RoE$_{t+4}$)			284.43***	
			(25.25)	
RoE$_{t+4}$ - E$_t$ (RoE$_{t+4}$)				-234.50***
				(52.25)
R^2	0.88	0.89	0.86	0.75
Controls	✓	✓	✓	✓
Observations	71	71	71	71

Notes: Predictive regressions for changes in credit/GDP between t and t+4. For a definition of the displayed variables see notes in the above panel. Specifications include the lagged dependent variable, the capital ratio and changes therein, a dummy for NBER recessions and a 2007/2008 financial crisis dummy as well as quarterly GDP growth, the fed funds rate and the 5-year treasury constant maturity rate. Newey-West standard errors in parentheses are computed with the automatic lag selection procedure in Newey and West (1994). *, **, ***: Significant at 10%, 5% and 1% levels respectively.

We employ call report data provided by the Federal Reserve. Banks are required to file these call reports for regulatory purposes and the data contains detailed quarterly income statements and balance sheets 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 want to mirror our macro-approach and therefore construct all measures at the bank level in a corresponding way. To transform the quarterly call report data into annual observations, we sum income data over the four quarters of a given year. We then combine the yearly income data with end-of-year balance sheet values.

Profit and credit: The resulting panel dataset with bank-year observations allows us to run specifications corresponding to the equations in the aggregate setting. In the previous section we analyzed the drivers of three-year changes in credit-to-GDP. Here, we use growth rates as a dependent variable and $\Delta_3 y_{i,t+3}$ is defined as the change in volumes of credit extended by bank i between year t and year $t+3$. Credit here specifically refers to the variable *net loans and leases*. $RoE_{i,t}$ is defined as yearly net income scaled by end-of-year equity. As before, we also compute the three-year change in this variable $\Delta_3 RoE_{i,t}$. We exclude bank-year observations with assets and loans being less than one million USD. We

Figure 7: *Bank level evidence*



Notes: The figure relates bank profitability and subsequent credit growth on a bank level. Bank level observations are collapsed into 20 equal sized bins according to their profitability. 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.

also exclude observations with negative equity and winsorize all variables at the 2.5% level. The resulting bank-level regression can now be written as

$$\Delta_3 y_{it+3} = \alpha_i + \alpha_t + \beta^{RoE} Profitability_{i,t-1} + \gamma X_{i,t-1} + u_{it}. \tag{17}$$

Crucially, in this regression α_t is a year fixed effect, controlling for aggregate credit demand conditions in the US at time t. α_i is a bank fixed effect that controls for bank specific time-invariant characteristics. $Profitability_{i,t-1}$ refers to either the lagged level of RoE or to the lagged three-year change in profitability. Control variables $X_{i,t-1}$ are now at the bank level. Here we include past credit growth at the bank level, 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 the nominal values of equity proxy again for the net worth channel. The advantage in this setup is that we can control for net-worth at the bank level and therefore rule out balance sheet constraints more directly.

The results are shown in Table 10. In column (1) we see that 3-year ahead credit growth is higher when profitability has been increasing. The coefficient is positive and highly significant. In line with a net-worth channel, three-year changes in equity capital are associated with stronger loan growth over the following periods ($\Delta_3 Capital_{it-1}$). In column (2) we replace three-year changes of profitability with levels and obtain similar results. In (3) and (4) we repeat the procedure for non-overlapping windows of observations. As we

Table 10: *Bank level evidence*

	Dependent variable: $\Delta_3 y_{it+3}$			
	(1) Full	(2) Full	(3) No-overlap	(4) No-overlap
$\Delta_3 ROE_{it-1}$	0.12^{***}		0.17^{***}	
	(0.02)		(0.05)	
ROE_{it-1}		0.12^{***}		0.20^{**}
		(0.04)		(0.08)
$Capital\ Ratio_{it-1}$	-0.34^{**}	-0.36^{**}	-0.28	-0.30
	(0.15)	(0.15)	(0.19)	(0.21)
$\Delta_3 Capital_{it-1}$	0.04^{***}	0.04^{***}	0.04^{***}	0.04^{**}
	(0.01)	(0.01)	(0.02)	(0.02)
Bank fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Control variables	✓	✓	✓	✓
R^2	0.20	0.20	0.21	0.21
Observations	178605	178605	56122	56122

Notes: This table reports regression results from estimating variants of Equation 17 using US Call Report data. The dependent variable $\Delta_3 y_{it+3}$ is the three year change of bank credit (net loans and leases) on the individual institution level. Credit growth and bank profitability are both winsorized at the 5% level. Columns (1) and (2) report results for all quarters. Column (3) and (4) restrict the data to non-overlapping observations only. Reported controls are on a bank level. All specifications also include bank and year 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.

look at three year changes in credit, this reduces the number of observations to a third. The results do not change much in this non-overlapping sample, compared to the full sample results in (1) and (2).

The results are consistent with the aggregate evidence presented previously. Both, lagged profitability and 3-year changes therein are positively related to subsequent 3-year credit growth. The results are not affected by the inclusion of time fixed effects. Thus, the channel that links profits and subsequent credit growth is not contingent on or subsumed by the state of the aggregate economy. We interpret these results as further suggestive evidence for a supply-side channel, as credit growth does depend on past profitability at the bank level. However, we cannot rule out that banks and firms are exposed to the same regional shocks driving current bank profitability and future credit demand, although the timing of the relationship makes it unlikely.

Figure 7 shows scatterplots with the data collapsed into fifty bins depending on the profitability. There is a strong positive correlation between lagged changes in profitability ($\Delta_3 RoE_{i,t}$) and subsequent credit growth in the right panel and lagged levels of profits

Table 11: *Losses and future reserves*

	Reserves for loan losses				
	(1) 1-year ahead	(2) 2-year ahead	(3) 3-year ahead	(4) 4-year ahead	(5) 5-year ahead
Losses/Loans	0.25***	0.24***	0.20***	0.16***	0.12***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bank fixed effects	✓	✓	✓	✓	✓
R^2	0.09	0.08	0.06	0.03	0.02
Observations	292448	292448	292448	292448	292448

($RoE_{i,t-1}$) and subsequent three-year credit growth in the left panel. However, we also find some evidence for a nonlinearity in this relationship. We observe that the relationship between profitability and credit growth is different at low levels (right panel) of profitability. This pattern is consistent with increased risk-taking at very low levels of profitability, i.e. when franchise values are presumably low.

Losses and reserves: The recent bank level data from the US entail another advantage. Here, in addition to realized loan losses (net charge-offs), we observe allowances / reserves for loan losses in the balance sheet of banks. This variable can be seen as a proxy for expectations about future loan losses. We then relate these reserves to both past and future loan losses. In particular, we use as a measure of realized loan losses from the income statement *net charge-offs on loans* and divide this item by *total loans and leases* in the balance sheet. We also divide the balance sheet item *allowance for loan and lease losses* by *total loans and leases*. These two variables allow us to analyze the relationship between loan losses and the future development of reserves for loan losses in the balance sheet. In particular, we study the following relationship

$$(Allowance/Loans)_{i,t+k} = \alpha_i + \beta(Loan\ Losses/Loans)_{i,t} + \epsilon_{i,t+k}\,, \tag{18}$$

for $k = 1, ..., 5$. The results are presented in Table 11 and show that loan losses predict the provisioning behavior of banks over the next five years. Banks reserve more for future loan losses when loan losses in the recent past were high. The natural follow-up question is, whether this provisioning behavior predicts future losses. We test whether the current amount of loss reserves in the balance sheet as a measure of expected future loan losses does indeed forecast future loan losses, using the following specification

$$(Loan\ Losses/Loans)_{i,t+k} = \alpha_i + \beta(Allowance/Loans)_{i,t} + \epsilon_{i,t+k}\,, \tag{19}$$

Table 12: *Loss reserves and future losses*

	Chargeoffs				
	(1) 1-year ahead	(2) 2-year ahead	(3) 3-year ahead	(4) 4-year ahead	(5) 5-year ahead
Reserves/Loans	0.18***	-0.06***	-0.18***	-0.23***	-0.26***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Bank fixed effects	✓	✓	✓	✓	✓
R^2	0.02	0.00	0.02	0.03	0.04
Observations	292448	292448	292448	292448	292448

where $k = 1, ..., 5$. The results are presented in Table 12 and show that there is a positive correlation between provisioning and one-year ahead charge-offs, which however turns negative in year two and remains significantly negative until year five. Reserves made for future loan losses are high when realized future loan losses are low. And probably even more problematic, when reserves for loan losses are low, realized future loan losses are high. In Table B2.11 and Table B2.12 in the appendix, we show that the patterns presented in the previous two tables are robust when we include in the regressions a set of control variables and year fixed effects.

Bank's provisioning behavior is characterized by predictable reversals. Provisions in the balance sheet are adjusted in response to realized past charge-offs. At the same time, reserves for loan losses made in the balance sheet forecast future loan losses negatively for horizons of more than one year. Hence, past-dependent provisioning for loan losses seems to lead to a failure of adequate provisioning for future loan losses over windows longer than one year.

This pattern is in line with models where expectations are past dependent (Bordalo et al., 2018; Greenwood et al., 2018). However, this extrapolation does not necessarily have to be a behavioral bias at the part of bank management. Automated screening and pricing processes as part of credit risk management in banks may generate the same pattern, as soon as credit risk models are adjusted to match recent data. Furthermore, bankers might have incentives to chose a level of provisions that is not aligned with their actual loan loss expectations. The next section will therefore show that similar reversals can also be found in the long-run macro panel data.

6. Profitability and financial crises

Measures of credit expansion are a strong indicator of financial instability risk and followed by macroeconomic underperformance (Mian et al., 2017a; Schularick and Taylor, 2012). We show that bank profitability tends to lead these credit expansions. A natural next step is to ask whether profitability also helps to understand the transition from boom to bust. We start by documenting stylized facts on the dynamics of bank profitability around systemic banking crises in the first subsection and analyze the data more systematically in the second subsection. The dates of systemic financial crises are taken from Jordà et al. (2017b). In this chronology, systemic financial crises events are defined as years when a significant part of the banking system failed or had to be rescued through government intervention.

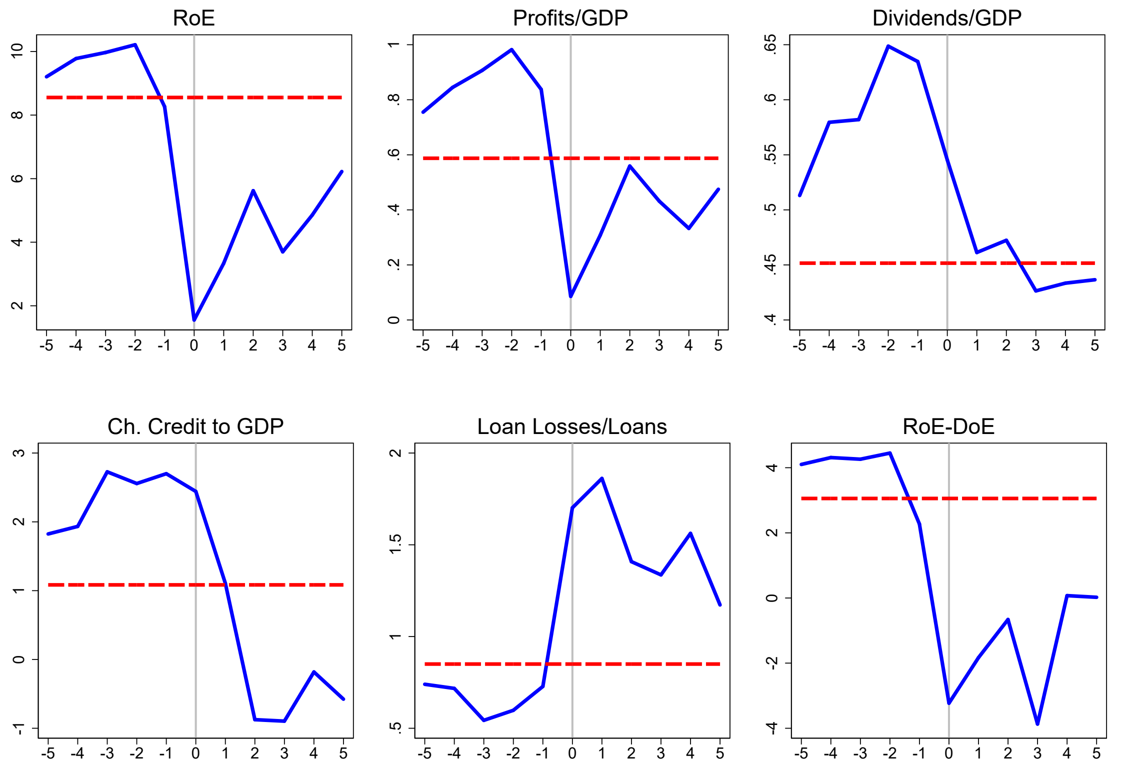
6.1. Stylized facts

Figure 8 displays the mean evolution of credit and profit variables in the years around financial crises, where -5 on the horizontal axis indicates an observation 5 years prior to a crisis observation in our data and 5 an observation 5 years after the crisis started. Blue lines always display the mean of a variable around financial crises, while red dashed lines correspond to the sample mean of the respective variable. A number of key facts stand out:

First, banking sector profits are high before a crisis (upper left panel of Figure 8). Banks' RoE is substantially above the sample mean during the run-up to crises and peaks at roughly 2 percentage points above the sample mean two years before the start. Alternative profitability series such as profits relative to GDP or dividends to GDP are also surging before crises (upper middle and upper left panels of Figure 8). Similar to RoE, these measures peak at more than 40% above their sample average two years before a crisis. The reason for bank profitability bein high, is that loan losses are exceptionally low before financial crises. For the smaller subset of financial crises where we were able to collect data on the ratio of loan losses relative to loans outstanding, it can be seen that loan losses are below the sample average in the years before a financial crisis.

Second, decreasing profitability heralds the end of the credit boom and the start of financial distress. Profitability levels are falling to levels close to the sample mean already one year prior to the crisis, that is between the years -2 and -1. Hence, weak fundamentals in the banking system already manifest themselves one year before the start of the full blown crisis. A similar pattern is also identified in Baron et al. (2018) for bank stock index returns and here in panel one for profits to GDP and dividends to GDP. Once the crisis hits,

Figure 8: *Profit variables around financial crisis dates*



Notes: These figures display the evolution of credit and profit variables around a financial crisis, i.e. 0 refers to a year in which a financial crisis starts. Blue (solid) lines display the mean of a variable in the years prior to and after a financial crisis date. Red (dashed) lines present the sample average for the respective variable. All variables are expressed in percentage points.

profits decrease even more and are on average almost 6% lower in the year of a crisis. This development is largely driven by loan losses. Loan losses rise significantly in the first year of a crisis and remain elevated for the following five years. Visual inspection of the lower left panel of Figure 8 reveals that yearly mean changes in the credit-to-GDP ratio are high and increasing before a financial crisis and, unlike RoE they keep rising up until the start of the crisis. This result is in line with the idea that financial crises are often a credit boom gone bust (Schularick and Taylor, 2012).

Third, retained earnings bolster bank capital in the run-up, while dividend smoothing drains capital during crises. The lower right panel of Figure 8 shows the difference between RoE and DoE - retained earnings relative to equity - around crises. This difference shows whether additional bank profits before the crises are retained in the bank or paid out to shareholders. Even though dividend payments relative to GDP rise 30% above their sample mean before crises (see top right panel of Figure 8), the rise in overall bank profitability is so pronounced that banks are able to retain a substantial share of their additional profits.

Banks retain on average around 4% of equity in the years prior to a crisis. This result might be part of the explanation for the finding in Jordà et al. (2017a) that low bank capitalization does not predict financial crises. The additional retained earnings seem to boost bank capital and dampen the build up of leverage during the credit boom. During a crisis, dividend payments to bank shareholders exceed profits. The fall in retained earnings is largely driven by a sluggish and limited reaction of bank dividend payments relative to earnings during the crisis. The top right panel of Figure 8 shows that dividends only fall to the sample mean, while all other profitability measures decrease substantially below their long-run averages.

The key patterns described above are not driven by specific crises episodes or subsamples of our data. Figure B4.4 and Figure B4.5 show windows around banking crises before and after 1945. All major facts are present in both subsamples.

6.2. Crisis prediction

We will now explore these relationships econometrically using prediction models that relate bank profitability and loan losses to the likelihood of financial crises. Specifically, we estimate a probabilistic logit model, that specifies the log-odds ratio of a financial crisis starting in country i in year t, denoted by the binary variable $S_{i,t}$, as a linear function of lagged changes in our profitability variables:

$$\log\left(\frac{Pr[S_{i,t}=1|X_{i,t}]}{Pr[S_{i,t}=0|X_{i,t}]}\right) = \alpha_i + \beta X_{i,t} + \epsilon_{i,t}\,. \tag{20}$$

Here $X_{i,t}$ includes five lags of changes in return on equity (RoE) or loan losses over loans (LoL), which we standardize to have mean zero and standard deviation one. β 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 probability to experience crises.

Columns (1) and (2) of Table 13 report the results, where $X_{i,t}$ includes five lags of changes in RoE. Two features stand out: a sequence of increases in RoE predicts a financial crisis. The likelihood of financial crises increases when profitability increases. This result becomes even stronger when we add five lags of changes in credit to GDP ratios to control for the relationship between credit and financial crises (Schularick and Taylor, 2012). However, the sign of the coefficient on RoE reverses in the year prior to the crisis. Financial crises are preceded by a year of decreasing profitability. In Columns (3) and (4) we show that

Table 13: *Predicting banking crises*

	Change in RoE		Change in LoL	
	(1)	(2)	(3)	(4)
Lag 1	-0.23***	-0.18*	0.14	0.03
	(0.08)	(0.10)	(0.15)	(0.25)
Lag 2	0.23**	0.31**	0.17	-0.03
	(0.12)	(0.12)	(0.20)	(0.18)
Lag 3	0.14*	0.22***	-0.31**	-0.54*
	(0.08)	(0.08)	(0.15)	(0.28)
Lag 4	0.11	0.15*	-0.22**	-0.37**
	(0.07)	(0.08)	(0.09)	(0.18)
Lag 5	0.14**	0.17***	-0.34**	-0.43***
	(0.06)	(0.06)	(0.17)	(0.15)
Credit Growth		✓		✓
AUROC	0.69	0.74	0.65	0.75
Number of Crises	64	64	35	35
Observations	1935	1935	907	907

the predictive nature of banking sector income variables also extends to loan losses. A sequence of falling loan losses is associated with a heightened probability to experience a financial crisis a few years later. Again, this is also the case when we control for changes in credit to GDP in column (4).

Taken together, our findings imply that the run-up to banking crises is characterized by high bank profitability and low loan losses. As we have shown before, decreases in loan losses are associated with subsequent credit expansions. The credit booms that eventually end in financial crises seem to be no exception. The documented evolution of credit losses shares the key characteristics of behavioral credit cycle models (Greenwood et al., 2018). The findings also mirror previous evidence in the empirical literature. Krishnamurthy and Muir (2017) argue that credit spreads are too low prior to financial crises. This mispricing may reflect the decrease in observed loan losses. The "calm before the storm" can also observed in the volatility of equities (Danielsson et al., 2018). The cycle turns when loan losses increase slightly and profitability starts to fall.

6.3. Return predictability

Increases in profitability predict crisis risk. Using data on total bank equity index excess returns kindly shared by Baron and Xiong (2017), we now ask whether bank shareholders are compensated for taking this risk. Shareholders who are aware of increased crisis

Table 14: *Predicting excess returns: RoE levels*

	Dependent variable: bank equity index excess returns					
	(1) 1-year	(2) 2-year	(3) 3-year	(4) 4-year	(5) 5-year	(6) 6-year
$RoE_{i,t-1}$	-0.02	-0.02	-0.05*	-0.11***	-0.12***	-0.11***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
$\Delta_3 Loans/GDP_{i,t-1}$	-0.05**	-0.08***	-0.09**	-0.09**	-0.08	-0.06
	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
R^2	0.026	0.035	0.051	0.071	0.066	0.045
Country fixed effects	✓	✓	✓	✓	✓	✓
Observations	886	854	825	800	775	752

Notes: This table reports estimates for a panel regression of bank equity index excess returns on profitability and credit expansion. The dependent variable is log excess total returns cumulated over h years, where h is specified in the column header. 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.

likelihood a few years after an increase in bank profitability would require higher expected returns to be compensated for holding bank stocks during a high risk period. Whether this is the case can be analysed with a predictive regression of cumulative excess returns (h years ahead) of the bank equity index on measures of past profitability

$$r_{i,t+h} - r^f_{i,t+h} = \alpha_{h,i} + \beta^h Profitability_{i,t} + \epsilon_{i,t+h}, \tag{21}$$

for $h = 1,...,6$. Motivated by the idea that increases in profitability mark the beginning of a credit expansion that is followed by a reversal a few years later, we extend the horizon compared to Baron and Xiong (2017) and look at horizons of up to six years. The results are presented in Table 14, where we include in addition the three-year change in bank loans/GDP.

To account for cross-country differences in the variance of profitability and credit expansions, we standardize our predictor variables at the country level. The results for the three-year credit expansion variable are close to the estimates in Baron and Xiong (2017) at horizons up to three years. RoE forecasts negative but barely significant excess returns over the first three years. However, consistent with the idea that elevated profits first trigger a period of overoptimism that is a few years later followed by a predictable reversal, we find that profitability forecasts signisficantly lower excess returns after three years. Put differently, bank shareholders are systematically disappointed a few years after an increase in profitability. Put differntly, expected and realized stock returns differ systematically after a period of high bank profitability. Table B4.15 presents corresponding results for changes in profitability.

7. Conclusion

According to Minsky (1977) the credit cycle starts with a displacement – a new profit opportunity. This profit opportunity breeds optimism and a boom in credit markets, but also crisis risk down the road. How is it possible that favorable economic fundamentals can sow the seeds for a crisis? In this paper, we set out to study the boom in credit markets, to make sense of the bust.

We establish a new robust fact: bank profitability leads the credit cycle. Credit expands following innovations in profitability. Decomposing profitability, we find that loan losses play an important role for the relationship between profits and credit aggregates. Our results are consistent with a recent theoretical literature on the role of behavioral forces in shaping the credit cycle. When 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 the provisioning behavior of US banks and the earnings expectations of CFOs align with such a channel.

The relationship between profits and credit helps to understand the transition from boom to bust. Measures of bank profits relative to aggregate income spike two years before a crisis. The reversal in profits and loan losses marks the turning point of the credit cycle and is often followed by a banking crisis with severe credit contractions.

Taken together, the evidence presented in this paper suggests that return extrapolation can have important macroeconomic consequences through its effects on credit supply and thereby on financial stability risks in the economy.

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A. Data

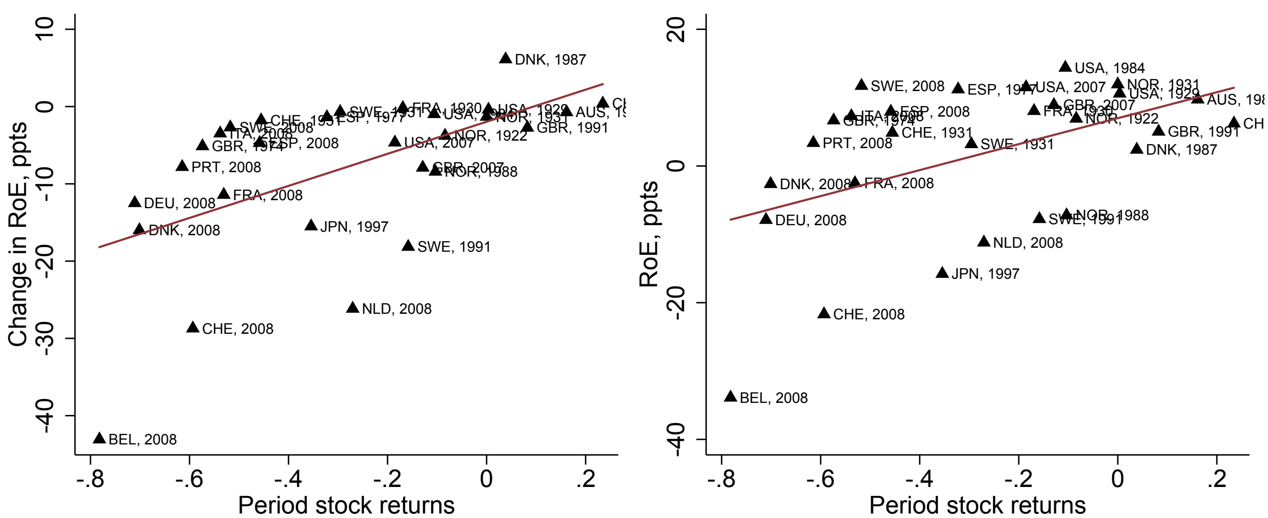
A1. Summary statistics

Table A1.1: *Summary Statistics*

	Obs.	Mean	S.D.	Min	Max
Return on Equity	2215	8.40	6.51	-113.77	33.44
Return on Assets	2205	0.89	0.87	-8.57	6.37
Δ_3 RoE	2145	-0.08	7.78	-111.70	130.79
Δ_3 RoA	2133	-0.05	0.63	-9.49	8.99
Dividends over Equity	1273	5.38	2.26	-4.28	20.88
Retained Earnings over Equity	1260	2.96	6.49	-113.93	30.95
Capital Ratio	2232	10.37	7.48	0.85	46.86
Credit to GDP	2257	56.40	35.38	0.47	204.52
Δ_3 Credit to GDP	2173	2.27	8.71	-56.09	53.08

Note: All variables in percentage points.

Figure A1.1: *Cross-crises correlations of banking sector profitability and equity market returns*



Notes: Correlation of banking sector profitability and banking sector equity returns during systemic banking crises.

A2. Systemic banking crises

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

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. Additional results

B1. Robustness: main result

Table B1.1: *Alternative dependent variable – real private credit per capita*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t-1}$	0.28^{***}	0.20^{***}	0.21^{***}			
	(0.08)	(0.07)	(0.07)			
$RoE_{i,t-1}$				0.40^{***}	0.32^{***}	0.34^{***}
				(0.10)	(0.11)	(0.12)
$Capital\ Ratio_{i,t-1}$			0.00			0.00
			(0.35)			(0.35)
$\Delta_3(Capital/GDP)_{i,t-1}$			-1.03			-1.20
			(0.87)			(0.88)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.03	0.10	0.12	0.04	0.11	0.13
Observations	1617	1469	1445	1651	1496	1468

Notes: This table reports regressions of real private credit per capita changes from t to $t+3$ on RoE_{it-1} and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of real private credit per capita changes. Columns (2) and (5) add the vector of macroeconomic control variables described in the text. Columns (3) and (6) additionally control for net-worth channel 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 B1.2: *Alternative dependent variable – bank assets/GDP*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t-1}$	0.31^{***}	0.31^{***}	0.30^{**}			
	(0.11)	(0.11)	(0.12)			
$RoE_{i,t-1}$				0.53^{***}	0.57^{***}	0.56^{***}
				(0.16)	(0.18)	(0.18)
$Capital\ Ratio_{i,t-1}$			0.30			0.31^{*}
			(0.19)			(0.18)
$\Delta_3(Capital/GDP)_{i,t-1}$			1.37			1.15
			(1.39)			(1.37)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.03	0.10	0.11	0.05	0.12	0.13
Observations	1628	1486	1486	1654	1510	1509

Notes: This table reports regressions of assets-to-GDP changes from t to $t+3$ on RoE_{it-1} and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of assets-to-GDP changes. Columns (2) and (5) add the vector of macroeconomic control variables described in the text. Columns (3) and (6) additionally control for net-worth channel 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 B1.3: *Alternative dependent variable – non-loan bank assets/GDP*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t-1}$	0.12	0.17*	0.17*			
	(0.09)	(0.09)	(0.09)			
$RoE_{i,t-1}$				0.24*	0.30**	0.29**
				(0.13)	(0.15)	(0.14)
$Capital\ Ratio_{i,t-1}$			0.02			0.05
			(0.22)			(0.21)
$\Delta_3(Capital/GDP)_{i,t-1}$			0.68			0.48
			(1.06)			(1.06)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.02	0.09	0.09	0.03	0.09	0.10
Observations	1566	1427	1427	1592	1451	1450

Notes: This table reports regressions of non-loan bank assets/GDP changes from t to $t+3$ on RoE_{it-1} and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of non-loan bank assets/GDP changes. Columns (2) and (5) add the vector of macroeconomic control variables described in the text. Columns (3) and (6) additionally control for net-worth channel 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 B1.4: *Alternative dependent variable – loan-to-deposit ratio*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t-1}$	0.22***	0.16***	0.17***			
	(0.04)	(0.02)	(0.03)			
$RoE_{i,t-1}$				0.34***	0.25***	0.25***
				(0.10)	(0.09)	(0.09)
$Capital\ Ratio_{i,t-1}$			-0.13			-0.11
			(0.13)			(0.13)
$\Delta_3(Capital/GDP)_{i,t-1}$			0.17			0.01
			(0.27)			(0.29)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.04	0.11	0.11	0.05	0.12	0.12
Observations	1602	1461	1459	1629	1485	1482

Notes: This table reports regressions of loan/deposit ratio changes from t to $t+3$ on RoE_{it-1} and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of loan/deposit ratio changes. Columns (2) and (5) add the vector of macroeconomic control variables described in the text. Columns (3) and (6) additionally control for net-worth channel 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 B1.5: *Alternative profitability measure – return on assets*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoA_{i,t-1}$	2.59^{***}	2.05^{***}	2.02^{***}			
	(0.52)	(0.62)	(0.61)			
$RoA_{i,t-1}$				1.40^{*}	2.39^{***}	2.67^{***}
				(0.74)	(0.73)	(0.76)
$Capital\ Ratio_{i,t-1}$			0.24^{**}			0.04
			(0.10)			(0.10)
$\Delta_3 (Capital/GDP)_{i,t-1}$			0.02			0.06
			(0.24)			(0.26)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.05	0.11	0.12	0.03	0.12	0.12
Observations	1611	1470	1445	1641	1494	1468

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on RoA_{it-1} and $\Delta_3 RoA_{i,t-1}$. All specifications control for three lags of credit-to-GDP changes. Columns (2) and (5) add the vector of macroeconomic control variables described in the text. Columns (3) and (6) additionally control for net-worth channel 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 B1.6: *Alternative profitability measure – log real profits per capita*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 Real\ profits\ per\ capita_{i,t-1}$	0.03***	0.03***	0.03***			
	(0.00)	(0.00)	(0.00)			
$Real\ profits\ per\ capita_{i,t-1}$				0.01***	0.02***	0.02***
				(0.00)	(0.01)	(0.01)
$Capital\ Ratio_{i,t-1}$			0.20**			0.11
			(0.10)			(0.11)
$\Delta_3(Capital/GDP)_{i,t-1}$			-0.24			-0.18
			(0.25)			(0.27)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.06	0.11	0.12	0.05	0.10	0.10
Observations	1484	1347	1347	1552	1412	1405

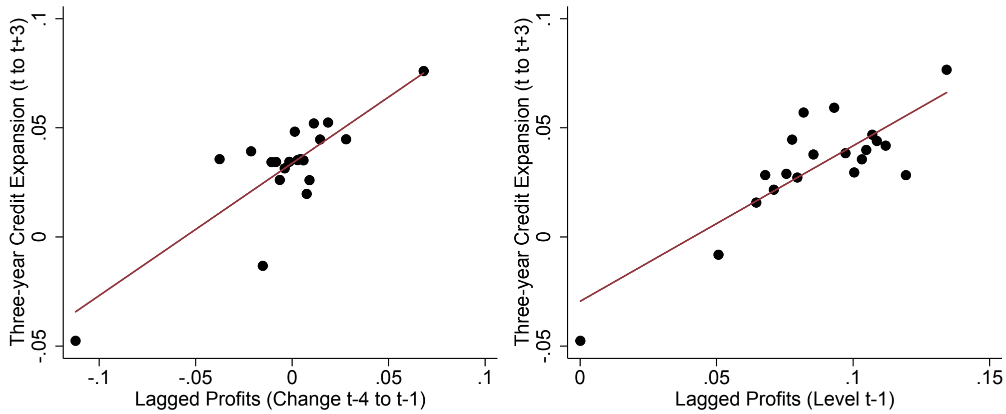
Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $log(profits)_{it-1}$ and $\Delta_3 log(profits)_{i,t-1}$. All specifications control for three lags of credit-to-GDP changes. Columns (2) and (5) add the vector of macroeconomic control variables described in the text. Columns (3) and (6) additionally control for net-worth channel 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 B1.7: *Alternative profitability measure – profits/GDP*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 Profits-to-GDP_{i,t-1}$	2.91^{***}	2.51^{***}	2.43^{***}			
	(0.75)	(0.70)	(0.70)			
$Profits-to-GDP_{i,t-1}$				2.99^{***}	2.60^{***}	2.43^{***}
				(0.79)	(0.76)	(0.78)
$Capital\ Ratio_{i,t-1}$			0.23^{**}			0.15
			(0.11)			(0.11)
$\Delta_3(Capital/GDP)_{i,t-1}$			-0.09			-0.09
			(0.23)			(0.24)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.07	0.12	0.13	0.06	0.12	0.12
Observations	1584	1445	1445	1617	1475	1468

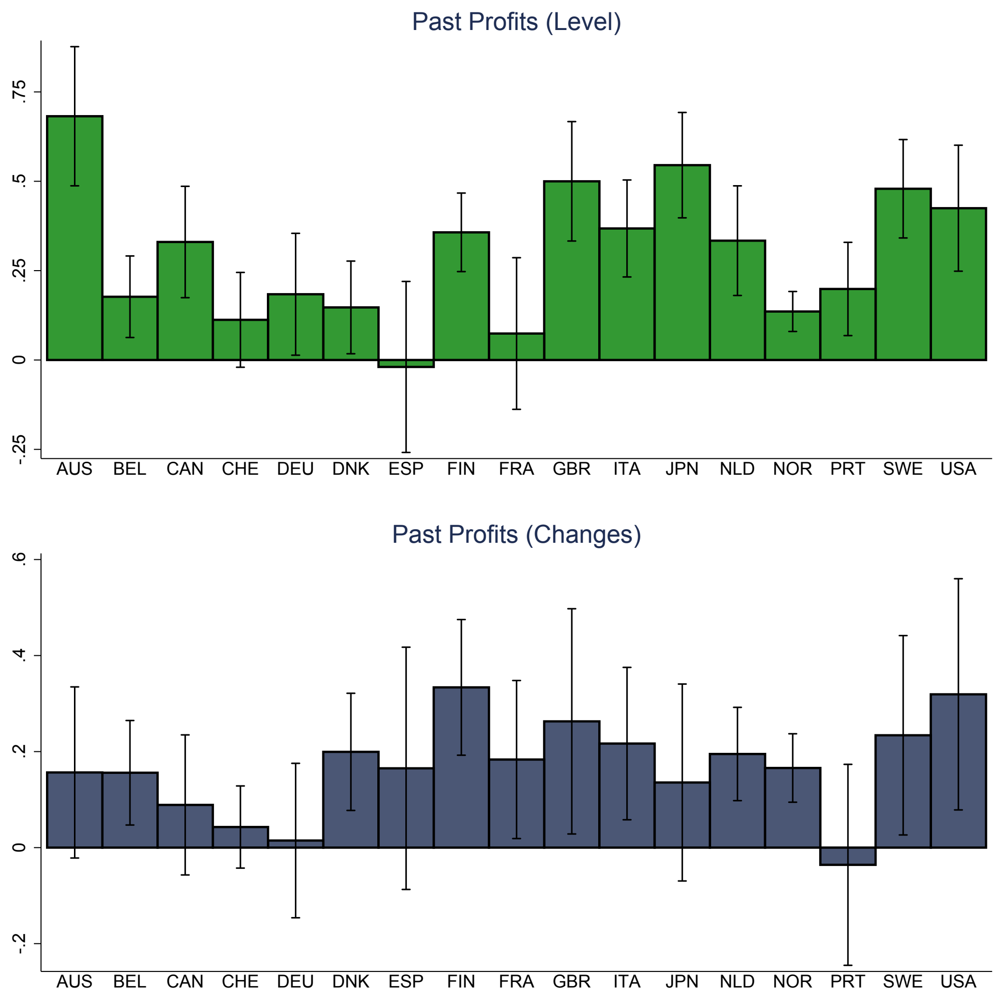
Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $Profits-to-GDP_{it-1}$ and $\Delta_3 Profits-to-GDP_{i,t-1}$. All specifications control for three lags of credit-to-GDP changes. Columns (2) and (5) add the vector of macroeconomic control variables described in the text. Columns (3) and (6) additionally control for net-worth channel 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 B1.1: *Scatterplots for the Global Cycle*



Notes: The figure relates bank profitability and subsequent credit growth for yearly sample averages. Observations are collapsed into 20 equal sized bins according to their profitability. Each point represents group specific profitability and credit growth means after controlling for the covarates from the regressions. Fitted regression lines illustrate the correlation between bank profitability and subsequent credit growth.

Figure B1.2: *Country-level regression coefficients*



Notes: The figure presents coefficients and 90% confidence intervals from individual country regressions. The specifications are $\Delta_3 y_{t+3} = \alpha + \beta^{RoE} RoE_{t-1} + u_{t+3}$ and $\Delta_3 y_{t+3} = \alpha + \beta^{\Delta RoE} \Delta_3 RoE_{t-1} + u_{t+3}$ estimated on individual country samples. Variables have been standardized by country for comparability of coefficients.

Table B1.8: *Subsamples and time effects for loan losses*

	Dependent variable: $\Delta_3 y_{it+3}$				
	(1) Post-1973	(2) Pre-2000	(3) Non-overlap	(4) No-crisis	(5) Year effects
$\Delta_3(LoanLoss/Equity)_{i,t-1}$	-0.05*	-0.12***	-0.16***	-0.07***	-0.04
	(0.03)	(0.04)	(0.06)	(0.02)	(0.03)
Country fixed effects	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓
Exclude 5-year window around crises				✓	
Year effects					✓
R^2	0.23	0.17	0.23	0.15	0.41
Observations	476	573	245	582	737

	Dependent variable: $\Delta_3 y_{it+3}$				
	(1) Post-1973	(2) Pre-2000	(3) Non-overlap	(4) No-crisis	(5) Year effects
$(LoanLoss/Equity)_{i,t-1}$	-0.16***	-0.26***	-0.20***	-0.14***	-0.12**
	(0.05)	(0.05)	(0.06)	(0.03)	(0.06)
Country fixed effects	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓
Exclude 5-year window around crises				✓	
Year effects					✓
R^2	0.25	0.21	0.26	0.18	0.43
Observations	515	609	259	621	776

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $RoE_{i,t-1}$ and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of credit-to-GDP changes and the vector of macroeconomic control variables described in the text. Column (1) uses only post-1973 data. Column (2) uses only pre-2000 data. Column (3) uses non-overlapping windows of three-year credit expansion. Column (4) excludes centered 5-year windows around financial crises. Column (5) includes year-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 B1.9: *Predicting changes in RoE with lagged profitability and bank equity index excess returns*

	(1) ΔRoE_{it}
$RoE_{i,t-1}$	-0.46***
	(0.11)
$\Delta RoE_{i,t-1}$	-0.06
	(0.06)
$\Delta RoE_{i,t-2}$	-0.12**
	(0.05)
$\Delta RoE_{i,t-3}$	-0.03
	(0.05)
Bank equity index excess $return_{it-1}$	0.03***
	(0.01)
Bank equity index excess $return_{it-2}$	0.01
	(0.01)
Bank equity index excess $return_{it-3}$	0.01
	(0.01)
R^2	0.206
Observations	876

Table B1.10: *Credit expansion following surprises in bank profitability*

	(1) Full	(2) Full	(3) No Crises
Residual ΔRoE_{it-1}	0.20***	0.13**	0.08**
	(0.06)	(0.06)	(0.03)
Country fixed effects	✓	✓	✓
Distributed lag in Δy	✓	✓	✓
Control variables		✓	✓
R^2	0.08	0.15	0.16
Observations	759	750	637

Notes: This table reestimates Equation 6 using residuals from a predictive regression. The regression coefficients of the first stage are reported in appendix Table B1.9. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

B2. Robustness: bank level analysis

Table B2.11: *Losses and future reserves*

	Chargeoffs				
	(1) 1-year ahead	(2) 2-year ahead	(3) 3-year ahead	(4) 4-year ahead	(5) 5-year ahead
Losses/Loans	0.10***	0.11***	0.10***	0.08***	0.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bank fixed effects	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
R^2	0.51	0.26	0.14	0.11	0.10
Observations	181240	181240	181240	181240	181240

Notes: This table reports regression results from estimating variants of Equation 18 using US Call Report data. The dependent variable is Net chargeoffs/Loans. All variables are winsorized at the 2.5% level. All specifications include bank 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.

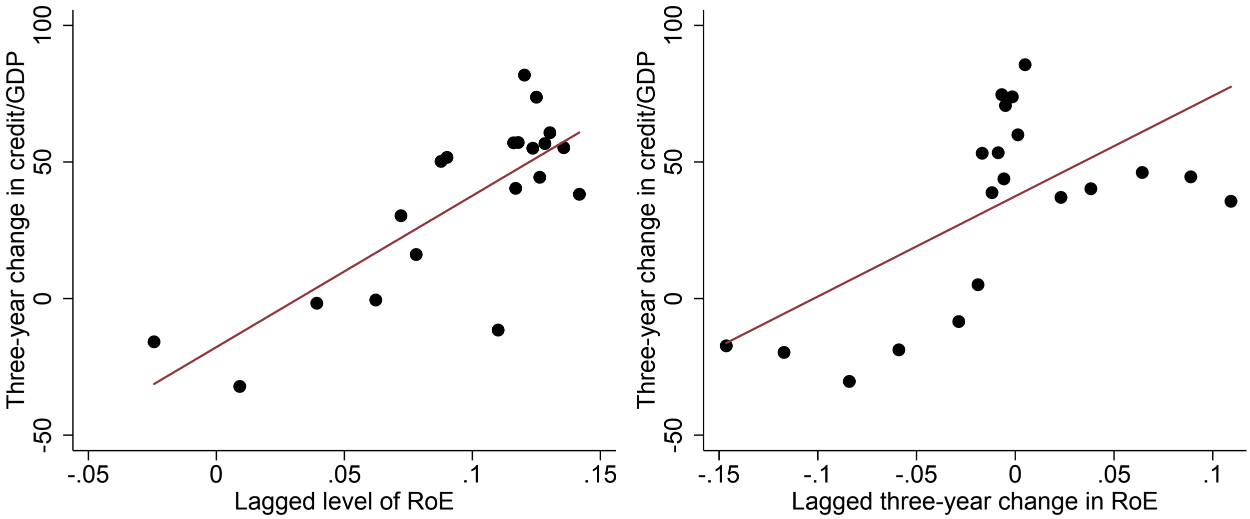
Table B2.12: *Loss reserves and future losses*

	Chargeoffs				
	(1) 1-year ahead	(2) 2-year ahead	(3) 3-year ahead	(4) 4-year ahead	(5) 5-year ahead
Reserves/Loans	0.12***	-0.06***	-0.09***	-0.08***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Bank fixed effects	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
R^2	0.27	0.16	0.11	0.10	0.10
Observations	181240	181240	181240	181240	181240

Notes: This table reports regression results from estimating variants of Equation 18 using US Call Report data. The dependent variable is Net chargeoffs/Loans. All variables are winsorized at the 2.5% level. All specifications include bank 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.

B3. Robustness: survey on earnings expectations

Figure B3.3: *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.

Table B3.13: *CFO expectations: excluding 2007 and 2008*

	RoE_{t+4}		$E_t(RoE_{t+4})$		$RoE_{t+4} - E_t(RoE_{t+4})$	
	(1)	(2)	(3)	(4)	(5)	(6)
RoE_t	0.72***	0.54***	1.15***	1.19***	-0.43***	-0.65***
	(0.07)	(0.05)	(0.03)	(0.03)	(0.05)	(0.03)
$\Delta_4 Loans/GDP_t$		0.00		-0.00***		0.00*
		(0.00)		(0.00)		(0.00)
GDP Growth_t		0.26*		-0.34***		0.59***
		(0.15)		(0.12)		(0.18)
NBER recession		-0.01		-0.01***		0.00
		(0.01)		(0.00)		(0.01)
Fed Funds Rate_t		-0.00***		-0.00*		-0.00
		(0.00)		(0.00)		(0.00)
5-year Traesury Rate_t		0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)
Capital Ratio_t		-1.20***		-0.35***		-0.85***
		(0.21)		(0.07)		(0.18)
dlev		-1.36*		1.06*		-2.42***
		(0.80)		(0.63)		(0.61)
R^2	0.87	0.95	0.98	0.99	0.72	0.82
Observations	63	63	63	63	63	63

Notes: RoE: Sum of net operating income $t-3$ to t divided by bank capital in t . Expected RoE is computed by combining earnings growth expectations from the survey with actual bank earnings and dividing it by capital in t . Actual RoE is defined as next years earnings divided by capital in t . Error = Actual RoE - Expected RoE. CFO Survey question: Relative to the previous 12 months, what will be your company's percentage earnings change during the next 12 months? Newey-West standard errors in parentheses are computed with the automatic lag selection procedure in Newey and West (1994). *, **, ***: Significant at 10%, 5% and 1% levels respectively.

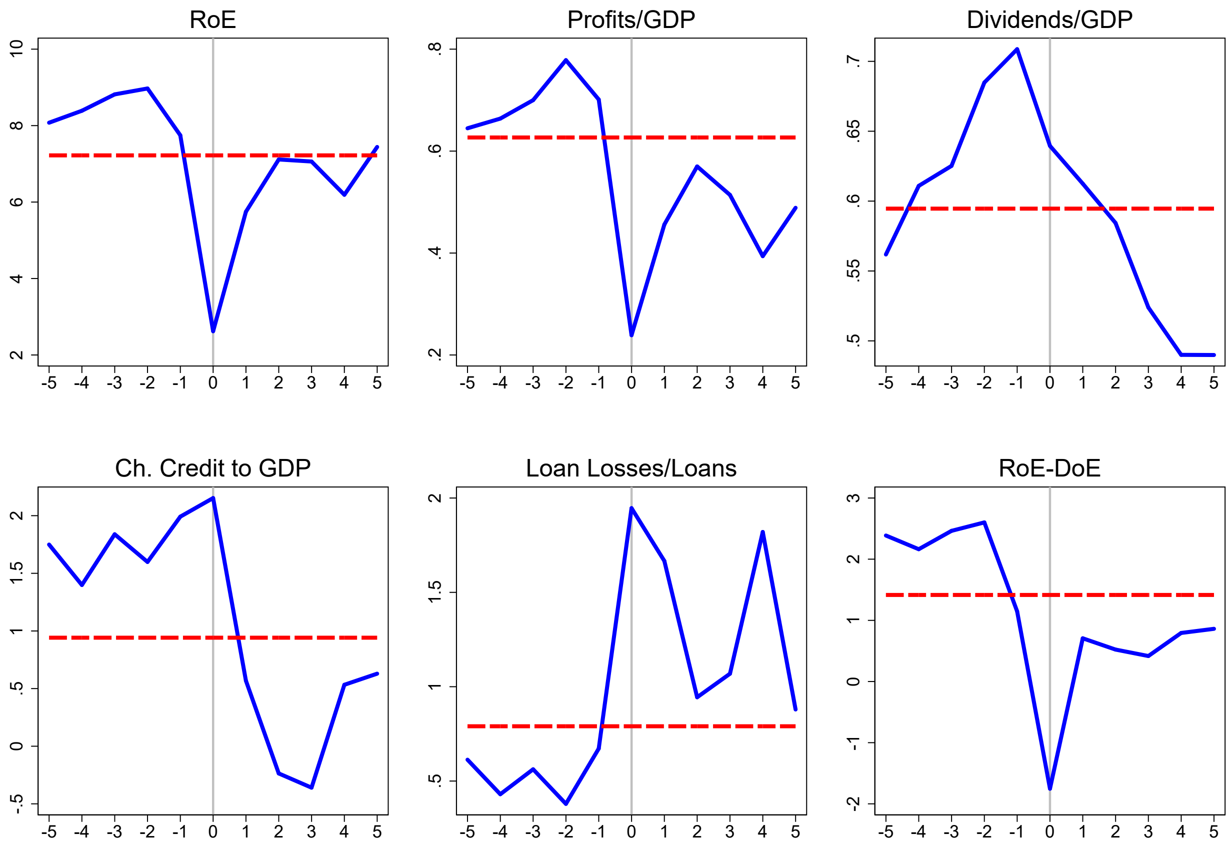
Table B3.14: *CFO expectations and credit growth: excluding 2007 and 2008*

	Credit Growth (Net loans and leases$_{t+1}$/Net loans and leases$_t$)			
	(1)	(2)	(3)	(4)
RoE$_t$	19.07***			
	(2.64)			
DoE$_t$		18.40**		
		(7.44)		
REToE$_t$		17.46***		
		(4.72)		
E$_t$ (RoE$_{t+4}$)			14.60***	
			(2.84)	
RoE$_{t+4}$ - E$_t$ (RoE$_{t+4}$)				-22.50***
				(7.98)
R^2	0.44	0.44	0.42	0.35
Controls	✓	✓	✓	✓
Observations	66	66	66	63

Notes: Predictive regressions of future credit growth. Credit growth is defined as the change in net loans and leases between t and t+1. For a definition of the other variables see notes in the above panel. Newey-West standard errors in parentheses are computed with the automatic lag selection procedure in Newey and West (1994). *, **, ***: Significant at 10%, 5% and 1% levels respectively.

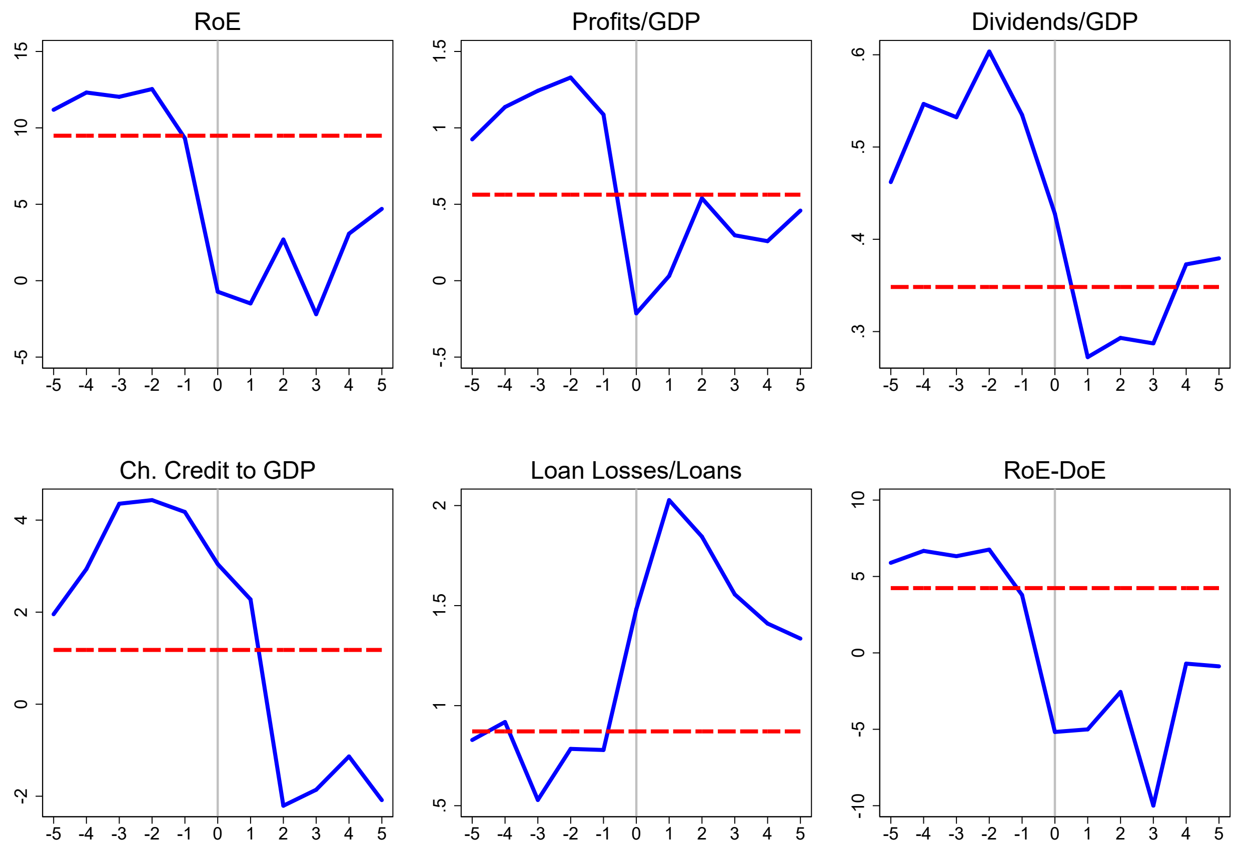
B4. Robustness: profitability around financial crises

Figure B4.4: *Mean of variables around crises – Pre WW2 sample*



Notes: These figures display the evolution of credit and profit variables around a financial crisis, i.e. 0 refers to a year in which a financial crisis starts. Blue (solid) lines display the mean of a variable in the years prior to and after a financial crisis date. Red (dashed) lines present the sample average for the respective variable. All variables are expressed in percentage points.

Figure B4.5: *Mean of variables around crises – Post WW2 sample*



Notes: These figures display the evolution of credit and profit variables around a financial crisis, i.e. 0 refers to a year in which a financial crisis starts. Blue (solid) lines display the mean of a variable in the years prior to and after a financial crisis date. Red (dashed) lines present the sample average for the respective variable. All variables are expressed in percentage points.

Table B4.15: *Predicting excess returns: RoE changes*

	Dependent variable: bank equity index excess returns					
	(1) 1-year	(2) 2-year	(3) 3-year	(4) 4-year	(5) 5-year	(6) 6-year
$\Delta_3 RoE_{i,t-1}$	-0.01	-0.01	-0.05*	-0.09***	-0.09**	-0.07**
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
$\Delta_3 Loans/GDP_{i,t-1}$	-0.05***	-0.08***	-0.11***	-0.12**	-0.11**	-0.09
	(0.02)	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)
R^2	0.024	0.034	0.049	0.059	0.049	0.030
Country fixed effects	✓	✓	✓	✓	✓	✓
Observations	872	841	812	787	762	739

Notes: This table reports estimates for a panel regression of bank equity index excess returns on profitability and credit expansion. The dependent variable is log excess total returns cumulated over h years, where h is specified in the column header. 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.