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WHY DOES FAST LOAN GROWTH PREDICT POOR PERFORMANCE FOR BANKS?

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ABSTRACT

From 1973 to 2014, the common stock of U.S. banks with loan growth in the top quartile of banks over a three-year period significantly underperforms the common stock of banks with loan growth in the bottom quartile over the next three years. The benchmark-adjusted cumulative difference in performance over three years exceeds twelve percentage points. The high growth banks also have significantly higher crash risk over the three-year period. This poor performance is explained by fast loan growth as asset growth separate from loan growth is not followed by poor performance. These banks reserve less for loan losses when their loans grow quickly than other banks. Subsequently, they have a lower return on assets and increase their loan loss reserves. The poorer performance of the fast growing banks is not explained by merger activity and loan growth through mergers is not accompanied by the same poor loan performance. The evidence is consistent with fast-growing banks, analysts, and investors failing to properly appreciate the extent to which the fast loan growth results from making riskier loans and failing to charge for these risks correctly.

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1. Introduction

Many recent papers show that credit booms generally end poorly and are followed by poor economic performance (e.g., Baron and Xiong (2015), Jordà, Schularick, and Taylor (2013), Reinhart and Rogoff (2009), or Schularick and Taylor (2012)). Such a result could be explained by macroeconomic phenomena. With this view, banks would rationally be making more loans because of good lending opportunities without taking more risk, but the economy would unexpectedly experience a shock which would end the credit boom and cause poor performance.[1] Hence, a credit boom would be followed by slow growth. The recent evidence by Krishnamurthy and Muir (2015) that credit spreads are low before crises is consistent with this possibility if markets are efficient, as it indicates that investors' expectations of credit losses are low immediately before crises.

Alternatively, however, it could be that the end of the credit boom is the result of poor performance of weak loans made during the credit boom. With this view, bank lending increases because banks fail to fully realize the risks of new loans and make loans that are riskier than they think. As the risks of these loans materialize, poorly performing loans weaken the banks, reduce the credit supply, and lead to poor economic performance.[2] Country-level analyses such as Reinhart and Rogoff (2009) or Schularick and Taylor (2012) do not make it possible to discriminate between the two explanations for why credit booms end poorly.

In this paper, we undertake a bank-level analysis that allows us to assess whether banks that experience fast loan growth make poorer loans. We find that banks that grow quickly make loans that perform worse than the loans of other banks, that investors and equity analysts do not anticipate this

[1] Mian and Sufi (2010) argue that such a view is consistent with the real business cycle literature which associates credit expansions with positive productivity or technology shocks (e.g., Bernanke and Gertler (1989) or Kiyotaki and Moore (1997)). When asset values fall, firms have lower net worth and less collateral, restricting their borrowing and leading to lower credit growth and lower economic activity. Mian and Sufi (2009) show that this view was also prevalent at least at the onset of the recent crisis. They refer to testimony of Alan Greenspan and Ben Bernanke during the credit expansion, in which Greenspan and Bernanke attributed the growth in mortgage credit and housing prices to fundamental economic improvements such as productivity and income gains. Kahle and Stulz (2013) find evidence that a demand shock can explain both a decrease in corporate investment and the end of the corporate credit boom during the recent crisis.

[2] Brunnermeier (2009) provides an overview of different mechanisms that led to the financial crisis, including the lending supply channel mechanism. Gorton (2010) argues that it was not only a bank lending supply channel but more generally a credit supply channel that contributed to the crisis. Shleifer and Vishny (2010) and Gennaioli, Shleifer, and Vishny (2012) develop models in which financial innovation and investor sentiment lead to a fragile banking sector.

poorer performance, and that these banks fail to set aside enough reserves for these loans, which is consistent with the hypothesis that they underappreciate the risk of these loans.

A bank can grow quickly by underpricing its loans. As a result, it will face a large loan demand and its lending will increase if it has enough capital to support more loans. In the short-run, investors will generally not be able to assess whether the bank's lending is increasing because it is underpricing loans. Eventually however, riskier loans will have a higher default rate and it will become apparent that a bank grew by making riskier loans. Such a bank will experience increases in loan loss provisions relative to other banks. A bank that underprices loans may be doing so because it is overoptimistic about borrowers' future performance, in which case its concurrent loan provisions will be smaller and will not reflect that it is making riskier loans. If a bank chooses to grow its loan portfolio by making riskier loans and properly reserves for the greater risk, its loan loss provisions should be higher and should reflect the greater risk of the new loans.

We analyze a panel of U.S. publicly listed banks between 1972 and 2014. We first examine whether high bank asset growth predicts poor future bank stock returns, following the methodology of Baron and Xiong's (2015) country level analysis. If banks grow quickly because they make risky loans, they will experience higher loan losses following a period of high growth. If the banks and their investors properly understood that the high growth was the result of riskier loans, the stock price should correctly reflect the expectation of higher loan losses, so that high loan growth should not predict lower performance. By analyzing a panel of banks, we focus on variation in growth across banks and eliminate the effects of economic conditions because they are common across banks. We first examine the relation between past loan growth measured over one and three years and future returns measured over one, two, and three years in pooled time-series cross-sectional regressions with year-fixed effects. Dividing banks in quartiles of loan growth, we find that banks in the top quartile of three-year loan growth have significantly lower returns than banks in the bottom quartile for one, two, and three-year returns. We find some evidence of underperformance when we use one-year loan growth, but it is weaker. Unlike loan growth, non-loan asset growth does not predict future returns. Our evidence is robust to alternative econometric approaches. The evidence is slightly stronger when we use bank fixed effects. The same results hold for returns adjusted using a characteristic-based benchmark return as in Daniels et al. (1997) constructed either using all firms or only banks. Importantly, our results hold even if we exclude all recession years from the sample, so that our evidence cannot be attributed to macroeconomic shocks. We also explore whether our evidence could be attributed to regional shocks, but conclude that this is not the case.

We turn next to whether banks that grow faster make poorer loans. We first investigate the evolution of the return on assets. We find that the fast-growing banks have much higher ROA than the banks in the quartile with lowest growth in the formation year. However, by year 3 after formation, the order is reversed and the banks in the fastest growing quartile have a significantly lower ROA than the banks in the lowest growth quartile. The difference is economically important as it corresponds to roughly one-fifth of the sample mean of ROA. Fast-growing banks experience a decrease in ROA relative to the banks in the lowest growth quartile each year for the three years after formation.

Examining loss provision levels, we find that banks with high growth have lower loan loss provisions than banks with low growth in the formation year. Again, the order reverses over the next three years, so that by year 3 after formation, the high-growth banks have significantly higher loan loss provisions than the low-growth banks. The loan loss provisions of the high-growth banks increase significantly relative to the loan loss provisions of the low-growth banks every year over the next three years following formation.

Our evidence is consistent with the view that banks that grow quickly through loan growth do not appear to believe that they are making poorer loans than the banks that grow slowly. If they thought they were making riskier loans and provisioned properly, they would have greater loan loss provisions in the formation year than the banks that grow slowly, which is not the case. Using the methodology of La Porta (1996), we also find evidence that analysts are surprised by the poorer performance of the high-growth banks after formation, in that their forecasts are too optimistic for high-growth banks relative to low-growth banks.

One way for banks to grow quickly is to acquire other banks. We know from the literature that there is evidence, albeit not unanimous, that long-run abnormal returns following acquisitions are negative (e.g., Rau and Vermaelen (1998), Loughran and Vijh (1997), or Moeller, Schlingemann, and Stulz

(2005)). Consequently, it could be that our evidence simply reflects that banks that grow more merge more and hence have lower returns because of mergers. This turns out not to be the case. First, we show that high organic growth by itself leads to worse performance. Second, we show that the merger effect holds separately from the organic growth effect. Lastly and most importantly for our conclusion that fast-growing banks make riskier loans, we find that when we distinguish between organic loan growth and loan growth through acquisitions, the evidence of riskier loans is primarily driven by organic loan growth. In other words, high-growth banks do not appear to acquire banks with riskier loans, they make those riskier loans on their own.

Overall, our evidence is consistent with banks not fully appreciating the risk of the loans they are making when they grow quickly. Such an outcome could arise because a bank is excessively optimistic about the prospect of its loans. However, other explanations are possible as well. First, it could be that in their push for growth, a bank's executives set incentives that lead loan officers to make riskier loans along dimensions that are not directly observable by the executives who monitor the risk of the loans. Second, executives could be fully cognizant of the higher risk of the loans they are making, but might attempt to hide that risk for better performance in the short run. While we cannot completely distinguish between these three different explanations, the conclusions that can be drawn from our paper remain valid: Banks do not provision enough for poorer loans after periods of strong organic credit growth, and bank investors and analysts alike fail to understand the perils of fast loan growth.

The asset pricing literature has provided evidence that firms that grow more have poorer returns (e.g., Cooper, Gulen, and Schill (2008), Hou, Xue, and Zhang (2014), Polk and Sapienza (2009), or Titman, Wei, and Xie (2004)). Our evidence is distinct but related to that literature. First, our evidence is not related to investment in the conventional sense. It does not involve capital expenditures that have diminishing marginal returns. Second, though our evidence does not involve investment in production, we are able to show that banks that grow fast make loans that have poorer performance. Third, our evidence suggests that banks that grow fast may not know that their loans are weaker.

Our paper is related to the strand of the literature that examines whether financial institutions made poorer loans during the recent credit crisis. Papers documenting reduced credit quality during credit expansions and subsequent bad economic outcomes prior to and during the recent crisis include Dell'Ariccia et al. (2009), Demyanyk and van Hemert (2011), Keys et al. (2010), and Mian and Sufi (2009) for mortgage lending and Axelson et al. (2013) for leveraged loans prior to the recent crisis. Except for Dell'Ariccia et al. (2009), these papers generally emphasize the importance of securitization in the decline in loan quality. Securitization plays no role in our analysis because we focus on loans that banks keep on their books. Also contrary to these papers, we examine the loan growth of bank holding companies and its relation to future stock returns using a time series of 40 years and not periods immediately preceding a crisis. Greenwood and Hanson (2013) show evidence of deteriorating credit quality during boom times for the corporate bond market over the last century. López-Salido, Stein, and Zakrajšek (2015) show that when credit risk is aggressively priced, it tends to be followed by a subsequent widening of credit spreads and a contraction in economic activity. Their results are also consistent with the credit supply channel but they focus on the role of credit-market sentiment and examine aggregate output.

Several papers examine why banks appear at times to choose to lower their standards in making loans. Rajan (1994) focuses on the implications of short-term incentives of bank managers. With such incentives, managers might want to show that a bank is profitable by booking fees associated with loans at the expense of future credit quality. Dell'Ariccia and Marquez (2006) show that increases in the demand for loans can lead to a decrease in credit standards when screening becomes less valuable. Berger and Udell (2004) propose an "institutional memory" hypothesis which predicts that banks decrease their lending standards as bank personnel starts forgetting the most recent period of credit stress and loses the loan restructuring skills acquired during that period. Examining commercial loans made by banks between 1980 and 2000, they find support for their hypothesis and show that a bank's commercial loan growth increases as time passes since the bank's last loan bust. These potential explanations for fast loan growth associated with a decrease in credit standards can help understand fast loan growth at some banks, but we show importantly that banks, investors, and analysts alike do not appear to understand the increased riskiness of the loans made during a period of sharp loan growth.

Finally, our paper is also related to Baron and Xiong (2015) who examine bank credit expansion at the country level for a set of 20 developed countries between 1920 and 2012. They show that bank credit expansion predicts poor returns in stock market and bank indices. Our study focuses on one country instead and examines the credit growth of individual banks and its relation to loan quality and future returns. Baron and Xiong (2015) conjecture that credit may flow to borrowers with poor credit quality during a large expansion of bank credit but cannot test this at the country level. Our incremental contribution is to test this conjecture using bank-level data and to abstract from the general economic environment by focusing on high growth banks relative to low growth banks at any given point in time.

Our paper proceeds as follows. In Section 2, we explain how we construct our sample, how we form asset and loan growth quartiles, and present summary statistics. In Section 3, we show that high growth banks have lower stock returns after formation. In Section 4, we investigate the hypothesis that these banks make poorer loans. In Section 5, we show that our evidence cannot be explained by merger activity. In Section 6, we examine the robustness of our main results, and we conclude in Section 7.

2. Sample construction, data, and summary statistics

We now describe our sample construction, data sources, and define and summarize key independent and dependent variables used in the analysis.

2.1. Sample construction

The sample includes all depository credit institutions and bank holding companies for which data are available in both the Financial Services format of Standard and Poor's Compustat as well as in the monthly security file of the Center for Research in Security Prices (CRSP). A large number of banks are added to the CRSP tapes in December 1972; few banks are available before that date. Consequently, our sample period is 1972 to 2013.

We construct our sample as follows. We search the CRSP database for all firms that have an SIC code between 6020 and 6079 (Commercial Banks, Savings Institutions, and Credit Unions) or from 6710 through 6712 (Offices of Bank Holding Companies) at some point in the firm's history. We then eliminate all American Depositary Receipts (ADRs) and firms incorporated in a foreign country. We exclude non-depository credit institutions, brokerages, and investment banks because we are interested in asset and loan growth in the traditional banking industry. We also drop observations with a nominal stock price of less than one dollar. We manually inspect the list in a final step and eliminate firms that are not depository banks or bank holding companies (e.g. American Express, Berkshire Hathaway, GEICO, Mellon Financial Corp, State Street).

Some firms consistently have an SIC code outside the included range up to a certain point in time and then switch to consistently having an included SIC code. For example, before December 2007, Countrywide Financial is classified as a non-depository credit institution with SIC code 6162 (Mortgage Bankers & Loan Correspondents). Afterwards, the classification changes to SIC code 6035 (Savings Institutions). Similarly, Morgan Stanley and Goldman Sachs are investment banks before September 2008, but then become bank holding companies. For such firms, we include data only for the time period during which they are depository institutions or bank holding companies.[3]

CRSP SIC codes sometimes oscillate between two classifications. In addition, CRSP can be slow to update the SIC classification when a change in a firm's business occurs. To improve precision in the above classifications, we use EDGAR searches and read firms' business descriptions in their 10-K filings. We use Google searches for observations that predate EDGAR. Prior to 1990, some savings & loan associations are classified in CRSP as having SIC code 6120-6123, a code range that does not currently exist in the SIC manual. We include these observations in our sample.

Compustat added financial data for a large number of small banks in fiscal year 1993. Cross-sectional differences among small banks are unlikely to affect overall credit supply beyond the local level. In addition, including these banks would cause a structural break in our data. We examine the Compustat data and find that the spike in observations in 1993 disappears once we exclude banks with less than $2 billion in total assets (measured in 2013 US dollars). We therefore use $2 billion in total assets as a cutoff point for inclusion in our sample. Overall, we have 664 unique banks in our sample, with the average bank having 12 bank-year observations.

[3] We follow the same approach for firms that switch from an included to an excluded SIC code at some point. For example, Ocwen Financial Corp was a Savings Institution until June 2005. After that point, the company sold its bank branches and specialized on providing servicing and origination processing solutions to the loan industry.

Our empirical tests in the following sections link past loan and asset growth to subsequent one-, two-, or three-year returns and loan-loss provisions. When a bank drops out of the sample due to a non-merger related delisting, we drop the observations as soon as we can no longer calculate the future return. If a bank is the target in an acquisition, we drop the target as soon as there is no complete subsequent return available. If a bank is the acquirer, we take the past loan and asset growth of the acquirer and match it with the returns for the surviving entity, even if the acquirer takes on the name of the target. We make an exception to the above rules for Citigroup. In 1998, Citicorp was acquired by Travelers Group, an insurance company, to form Citigroup. Because Citigroup is a systemically important bank, we wish to record an uninterrupted history for this institution. Therefore, we create one unified record for Citigroup, using Citicorp data before the merger and Citigroup data after the merger.

Table 1 shows the number of sample banks by year. Our sample contains 131 banks in 1972 and increases to a maximum of 223 banks in 1988. Between 1989 and the onset of the recent financial crisis, there are about 200 banks each year in our sample. The number of banks reduces to 175 towards the end of our sample period.

2.2. Data sources

We obtain accounting information from Standard and Poor's Compustat and stock price information from CRSP. We obtain data on earnings per share (EPS) and analyst forecasts from the Institutional Brokers' Estimate System (I/B/E/S). Our subsequent analysis requires us to separate organic growth from growth via mergers and acquisitions. We use the Chicago Fed M&A database to obtain information on bank mergers and acquisitions. We use the link table from the regulatory identification numbers (RSSD ID) to CRSP's permanent company numbers (PERMCO) provided by the New York Fed to link the Chicago Fed M&A database with the CRSP data. For PERMCOs not covered in the New York Fed's file we find the corresponding bank in the National Information Center. We use Call Reports (FFIEC031) or FR-Y-9C data to find information on the loan portfolio and assets of targets in mergers and acquisitions. We obtain information on failed banks from the FDIC.

2.3. Summary statistics

Table 2 shows summary statistics for our sample. For each bank in each fiscal year *t*, we calculate subsequent one-, two-, and three-year returns by creating total return indices from the CRSP monthly security file over the corresponding time horizon. If returns are missing for a certain month, we set them to zero for that month. For example, for a bank whose fiscal year ends in December, for fiscal year 1984 the one-year return is defined as the total return index as of December 1985 divided by the total return index as of December 1984 minus one. Thus, if a bank ceases to be traded in March of 1985, then the one-year return for fiscal 1984 cannot be calculated. Two- and three-year returns are annualized. We calculate non-overlapping returns to avoid problems regarding standard errors in the cross-sectional regressions. The table shows that median returns for the sample banks are about 13% per annum.

Loan growth is calculated using data on total loans to customers (Compustat item LCUACU). One-year and three-year loan growth refers to a bank's total loan growth from years *t-1* and *t-3* to year *t*, respectively. For example, one-year loan growth for the same observation as above is calculated as the bank's total loans as of December 1984 divided by total loans as of December 1983 minus one. Three-year loan growth is annualized. Average loan growth is 13.7% at the 1-year horizon, and 13.3% at the 3-year horizon. Median 1-year (3-year) loan growth is 10.3% (11.8%). Asset growth is calculated in the same way as loan growth. The average bank has an asset growth of about 12.6% per year, and the median bank has a one-year asset growth of 9% and a three-year asset growth of 11%. The year *t* return on assets (ROA) is expressed as a percentage and is defined as net income divided by total assets multiplied by 100. The average (median) bank has an ROA of 0.77% (0.85%). Loan loss provisions are also expressed in percentage terms and are calculated as provisions for credit losses (PCL) divided by total gross loans multiplied by 100. Total gross loans are defined as total loans to customers plus reserves for credit losses (RCL). The median bank sets aside 0.44% percent of gross loans as loan loss provisions each year.

Our analysis also requires calculating analyst forecast errors and revisions. We follow La Porta (1996) and Livnat and Mendenhall (2006) and calculate one-, two-, and three-year standardized unexpected earnings (SUE) as the difference between actual EPS as reported in years *t+1*, *t+2*, and *t+3*, respectively, and the current median analyst forecast EPS, divided by the current stock price. To make sure that analysts have information on fiscal year t data when making their forecasts, we take current analyst forecasts and stock prices as of four months after the end of fiscal year t. For the above example observation from December 1984, the one-year SUE is calculated as the difference between 1985 actual EPS minus the April 1985 median analyst forecast divided by the April 1985 stock price. Table 2 shows that average SUEs at all horizons are slightly negative; i.e. analyst forecasts for banks tend to be too optimistic by about 2.5-3% of the stock price. The one-year analyst revision is defined as the difference between the $t+1$ EPS forecast for year $t+2$ and the year t forecast for year $t+2$, divided by the year t stock price. In the above example, this would be the difference between the April 1986 forecast for year 1986 minus the April 1985 forecast for year 1986, divided by the April 1985 stock price. The two-year analyst revision is defined as the difference between the $t+2$ forecast for year $t+3$ and the year t forecast for year $t+3$, divided by the year t stock price. Analyst forecast revisions are on average negative; the average analyst revises her forecast down by 1.2% of the stock price over a one-year horizon and 1.8% over a two-year horizon. Our final variable is analyst growth expectation, defined as the median analyst long-term growth expectation as recorded in I/B/E/S. “Long-term” in this case refers to five-year earnings growth forecasts (La Porta (1996)).

All variables on forecast errors and revisions are calculated using adjusted I/B/E/S data. Diether, Malloy, and Scherbina (2002) and Payne and Thomas (2003) show that adjusted I/B/E/S data are subject to rounding errors, which could affect inference in studies using zero forecast errors as a threshold or using the dispersion of forecast errors. An alternative to using adjusted I/B/E/S data is to use unadjusted actual EPS as well as unadjusted forecasts and adjusting these using CRSP adjustment factors as of the earnings announcement date as well as the forecast date. Performing these adjustments, we find a correlation coefficient between the adjusted I/B/E/S data and the CRSP-adjusted unadjusted I/B/E/S data of 0.998 for the sample banks. Since the additional matching results in a loss of observations and since we are not specifically interested in studying forecast errors of exactly zero, we report results using adjusted I/B/E/S data.

We winsorize loan growth, asset growth, ROA, loan loss provisions, as well as analyst forecast errors and revisions at the 1st and 99th percentile, respectively, to reduce the impact of outliers in our regression analyses. The distributions of analyst forecast errors and revisions continue to exhibit significant skewness with large outliers. We address the issue in Section 4. While we do not winsorize stock returns, we note that results are quantitatively and qualitatively similar if we do so.

2.4. Low growth and high growth banks

We analyze performance and loan loss provisions of banks with different growth rates in our main regressions. We create growth quartiles for loan and asset growth to do so, for two reasons. First, this approach would capture non-linearities in the relation between loan growth and performance without a priori assumptions. Second, we also estimate a portfolio approach for which it is natural to form portfolios based on quartiles. We also show results using loan and asset growth as continuous variables.

Figure 1 shows the median three-year loan growth for two groups of banks from 1972 to 2013. Each year, we split the sample by past three-year loan growth into quartiles. The solid blue line shows the median loan growth for the banks in the lowest growth quartile, and the dashed red line shows the median loan growth for the banks in the highest growth quartile. Several interesting observations can be derived from the figure. First, the differences between the median growth in low and high growth quartile banks are substantial and range from a low of about 10% in the late seventies to a high of 33% in the late nineties. Second, the consolidation of the U.S. banking sector, with a large number of interstate bank mergers in the late nineties is evident from the figure as the median loan growth in the top quartile approaches 40%, which is unlikely to completely stem from organic growth. We address the point that bank growth in the high growth quartile could be mostly driven by merger activity in section 5, where we also calculate a measure of organic growth. Third, the recessions of the early 1990s and early 2000s show up in the figure as decreases in the median growth rates for both groups of banks. Finally, the recent financial crisis pushed median loan growth rates for low growth banks below zero and also substantially decreased median three-year loan growth for the fastest growing banks to below 20%.

3. Loan and asset growth and subsequent returns

Figure 2 shows a plot of the time-series evolution of the average three-year subsequent non-overlapping returns for two groups of banks over our sample period. The solid blue line shows the average three-year subsequent stock return for banks in the lowest quartile of loan growth. The dashed red line shows the average three-year subsequent stock return for banks in the highest quartile of loan growth. The figure shows that for the vast majority of sample years, subsequent returns for low-growth banks were higher than for high-growth banks, with the exception of a brief episode in the late 1990s / early 2000s.

We now estimate more formal regressions of subsequent returns on loan growth. In Table 3, we follow Baron and Xiong (2015) and estimate

$$r_{i,t+k} = \beta_2 \times I_{\text{loan growth}_{i,t} \in Q_2} + \beta_3 \times I_{\text{loan growth}_{i,t} \in Q_3} + \beta_4 \times I_{\text{loan growth}_{i,t} \in Q_4} + \delta_t + \varepsilon_{i,t} \quad (1)$$

as well as

$$r_{i,t+k} = \alpha_i + \beta_2 \times I_{\text{loan growth}_{i,t} \in Q_2} + \beta_3 \times I_{\text{loan growth}_{i,t} \in Q_3} + \beta_4 \times I_{\text{loan growth}_{i,t} \in Q_4} + \delta_t + \varepsilon_{i,t} \quad (2)$$

where $r_{i,t+k}$ is the k-year ahead stock return of bank I, $I_{\text{loan growth}_{i,t} \in Q_j}$ is an indicator variable equal to 1 if the one-year loan growth of bank i is in the j^th loan growth quartile of all banks in year t, and zero otherwise, and the difference between equation (1) and (2) is that equation (2) contains bank fixed effects α_i. We estimate these regressions for subsequent 1-year, 2-year, and 3-year returns, and estimate similar regressions for three-year loan growth and one- and three-year asset growth. We also include year-fixed effects δ_t in our regressions. Hence, any effects we observe are conditional on controlling for the general economic environment for banks in each year. Note that while we always use non-overlapping returns for k = 2 or 3, we have observations in every year due to new entrants into the sample. For example, for three-year non-overlapping returns, for each bank we use the first three-year return we have available for that bank, then the fourth one, the seventh one, and so on.[4]

[4] An alternative is to align all returns on the same time line. For example, for three-year non-overlapping returns, one could limit the sample to all available observations that start in 1972, 1975, 1978, 1981, and so on. Results are quantitatively and qualitatively similar using this alternative approach.

Table 3 shows results. In each of the panels, Columns 1, 3, and 5 show results for the pooled time-series and cross-sectional OLS regressions, and Columns 2, 4, and 6 show results from specification (2) with bank-fixed effects. In Panel A, we see that one-year loan growth has little predictive power for 1-year or 2-year subsequent returns. We find some predictability at the three-year subsequent return level. Column 6 shows that in years in which banks are in the highest growth quartile relative to years in which they are in the lowest quartile, their subsequent returns are 5.98% lower. Note that these regressions include bank-fixed effects, i.e. effects are identified from banks that switch quartile assignments at least once. There is sufficient time-series variation in banks' assignments to growth quartiles. Out of the 627 (596) banks that enter the one-year (three-year) loan growth regressions, 549 (481) switch the growth quartile at least once, and 395 (256) banks are at least once in the first and fourth growth quartile while in the sample.

Panel B shows the main result of the paper. The return predictability becomes much stronger once we use three-year loan growth to predict subsequent returns. Now, we observe strong return predictability for one-, two-, and three-year ahead returns in both the pooled and fixed effects regressions. For all six specifications, we see that the returns are monotonically decreasing across the growth quartiles. The higher past three-year loan growth, the worse are the returns. The effects are economically and statistically large. For example, for the two-year subsequent returns, we observe that a bank in the highest growth quartile has a 5.52% lower return per year than a bank in the lowest growth quartile. The within effect is even larger with -9.11%. For three-year subsequent returns, we find in the cross-sectional regressions reported in Column 5 that banks in the highest loan growth quartiles have 7.43% lower returns than banks in the lowest growth quartile. Note that these returns are annualized. At the three-year horizon, high loan growth banks therefore have more than 22% lower returns than low loan growth banks.

Loan growth is likely correlated with asset growth for banks. Consequently, it could be that banks perform poorly following high asset growth and loan growth just proxies for asset growth. Panels C and D repeat the same analysis but uses asset growth instead of loan growth. We observe very similar patterns. The return predictability is significantly higher for three-year asset growth (Panel D) than for one-year asset growth (Panel C). Three-year asset growth has a significantly negative correlation with subsequent returns at the one-year, two-year, and three-year horizon. The effect is monotonically decreasing in growth quartiles, and economically significant. At the three-year horizon, we observe that banks in the highest growth quartile have 6.1% lower returns per year (i.e., almost 20% for the three years) than banks in the lowest growth quartile. Results are even stronger when including bank-fixed effects.

To better understand whether our results are due to loan growth or any asset growth including asset growth unrelated to loan growth, we now analyze whether the non-loan asset growth portion has incremental predictive power for future returns. These non-traditional business activities of banks have regularly come under scrutiny, most recently during the financial crisis of 2007 and 2008. Many commentators have argued that, e.g., the Gramm-Leach-Bliley Act, which repealed central provisions of the Glass-Steagall act and allowed banks to affiliate with securities and insurance firms, contributed to the recent crisis. In Panel E, we estimate regressions of bank stock returns on a bank's loan growth and non-loan asset growth during the previous three years. We sort banks into quartiles for loan and non-loan asset growth, respectively, with the lowest growth quartile serving as the base group for the regressions. The loan growth sort and the non-loan asset growth sort are performed independently of each other. We find that, in these regressions, the return predictability only stems from the high loan growth quartiles. The highest non-loan asset growth quartile has coefficients of 0.0079, 0.0064, and 0.0072 at the one-year, two-year, and three-year horizon, and is never close to being statistically significant. The estimates of Panel E are inconsistent with the alternative hypothesis that the results in Panels A and B are driven by asset growth rather than loan growth.

The table also reports R^2s. The R^2s are large because of the time-fixed effects in our regressions. Without those, the R^2 are significantly lower (varying between 0.0029 and 0.0068 in Panel D) and more comparable to other cross-sectional return predictability studies (e.g., Goyal and Welch (2008)).

One possible explanation of the performance difference between high-growth and low-growth banks is that high-growth and low-growth banks have different risks or styles. Researchers have identified several characteristics that explain differences in realized returns. We therefore follow the strategy of Daniel et al. (1997) and calculate portfolio returns with characteristics-adjusted benchmarks.

Portfolio returns are calculated as follows. For one-year holding period returns, at the end of June of each year *t*, banks are sorted into growth quartiles based on their loan growth for the previous three fiscal years. Monthly equally-weighted returns are calculated for each growth portfolio from July of year *t* until June of year *t+1*, when portfolios are re-sorted. We calculate adjusted returns by subtracting a characteristic-based benchmark return from each bank's stock return. Benchmark portfolios are constructed following Daniel et al. (1997) (DGTW) by first sorting all stocks in the CRSP/Compustat Merged universe into size quintiles based on CRSP breakpoints.[5] Within each size quintile, we sort stocks into quintiles based on their industry-adjusted book-to-market ratios using the Fama-French 49 industry classifications. Within each of the resulting 25 portfolios, we then sort stocks into momentum quintiles. We determine which of the 125 portfolios each bank belongs to and subtract that portfolio's value-weighted return from the bank's stock return. We also consider adjusted returns for which the benchmark portfolios only include banks. That is, we subtract from a bank's return the value-weighted average of the returns of all other banks (excluding the bank itself) that are in the same size/book-to-market/momentum portfolio. The quintile cutoffs for these bank-only benchmark portfolios are the same as for the benchmark that includes nonfinancial firms. For the 8.7% observations in the sample for which there is no other bank in the same benchmark portfolio, banks are matched to the nearest benchmark portfolio, relaxing first the momentum criterion, then book-to-market, then size. Among the initially unmatched observations, 73% can be matched to banks that are in the same size quintile, the same book-to-market quintile, and the immediately adjacent momentum quintile.

For two-year and three-year holding period returns, we form portfolios with overlapping holding periods as in Jegadeesh and Titman (1993). For example, in the case of two-year holding period returns for loan growth portfolio number four, at the end of June in year *t* the portfolio buys the stocks of all banks that are in the highest loan growth quartile at that point in time and holds these stocks for two years. Stocks bought at the end of June of year *t*-1 continue to be held through June of year *t*+1. Stocks

[5] We use CRSP breakpoints since our sample is limited to years in which Nasdaq stocks are covered in CRSP and thus CRSP breakpoints should be comparable across years. Results are quantitatively and qualitatively similar when using NYSE breakpoints.

bought at the end of June of year t-2 are sold in June of year t. The resulting portfolios are rebalanced monthly to maintain equal weights.

Table 4 shows the results. The first four columns show returns for the different loan growth quartiles, and the last column shows the returns to a strategy that goes long the highest loan growth quartile banks and short the lowest loan growth quartile banks. There are three panels, one each for one-year, two-year, and three-year holding period returns. Within each panel, the first row shows raw returns, the second row DGTW-adjusted returns, and the third row DGTW-adjusted returns when the universe is restricted to banks. All three panels show that the highest growth quartile bank portfolio has significantly lower adjusted returns than the lowest growth quartile. The results get stronger the longer the holding period. Focusing on Panel C which looks at the 3-year holding period returns, we find that the DGTW-adjusted long-short portfolio generates statistically significantly negative returns of 45 basis points per month. In other words, a portfolio of banks in the highest loan growth quartile underperforms a portfolio of banks in the lowest loan growth quartile by 5.4% annually. If we carry out the DGTW adjustment using banks only, we find statistically stronger, but economically slightly lower results. A portfolio of aggressively growing banks underperforms a portfolio of slow growth banks by 36 basis points per month (4.3% annually). Overall, our conclusions from Table 3 remain robust after using characteristic-based benchmarks to adjust returns. High growth banks significantly underperform low-growth banks.

We have so far sorted banks into groups by quartiles of growth. A valid question is whether we can observe the same or perhaps even stronger patterns if we make use of all the information in the growth distribution. In Table 5, we re-estimate the three-year growth regressions of Panels B, D, and E of Table 3, but use loan growth, asset growth, and non-loan asset growth as continuous variables instead of the quartile indicator variables. In Panels A and B, we find that three-year loan or asset growth is significantly negatively related to subsequent returns at all examined horizons. The economic magnitude of the pooled regressions can be gauged as follows: The cross-sectional standard deviation of 3-year annualized loan growth (asset growth) is equal to 0.1266 (0.1098). Hence, a one standard deviation increase in loan growth is predicting a 0.1266 x (-0.139) = 1.76% lower one-year return. At the 3-year horizon, we observe a 0.1266 x (-0.2016) = 2.55% lower annualized return. The within bank standard deviation of loan growth is equal to 0.1060. A one standard deviation lower loan growth is predicting a 0.1060 x (-0.3184) = 3.4% lower return per year for the three-year return window. The economic magnitudes are similar for asset growth. The effects in Table 3 are economically larger than those in Table 5. Figure 1, which we discussed before, shows why this is the case. The difference between the average growth rate of the fourth quartile and the average growth rate of the first quartile is more than one standard deviation. In Panel C of Table 5, we use as our explanatory variables three-year loan growth and three-year non-loan asset growth. We find that the coefficients on three-year non-loan asset growth are never significant. These results support our conclusion that the relation between loan growth and poor bank performance is not due to loan growth proxying for asset growth.

Baron and Xiong (2015) in their country analysis also ask whether aggregate bank credit expansion predicts an increase in the crash risk of banking and equity market indices in subsequent quarters. We also want to understand whether, at the individual bank level, high loan growth predicts subsequent dramatic deterioration in a bank's market capitalization. To this end, we estimate a linear probability model and predict the probability of a subsequent return below the fifth percentile of the sample distribution using the bank's three-year loan growth as a predictor. The dependent variable equals one if the bank experiences a return below the fifth percentile over the subsequent 1-, 2-, or 3-year period, respectively, and zero otherwise. The fifth percentiles are -45.7%, -38.1%, and -30.3% for 1-, 2-, and 3-year annualized returns, respectively. We use the same specification as in Table 3 and sort banks into quartiles based on loan growth during the previous three years, respectively. All regressions include time-fixed effects to control for the aggregate economic environment. Table 6 shows the results. There is no predictability of high loan growth for left-tail risk at the 1-year horizon. At the two- and three-year horizon, we observe in Columns 3 and 5 that banks that are in the fourth and highest loan growth quartile have an approximately 4.6%-5.75% higher probability of experiencing a significant negative shock to their market capitalization in the two or three subsequent years relative to low growth banks. The bank-fixed effects regressions in Columns 4 and 6 allow the same conclusion, but now also banks in the second and third growth quartile experience a higher crash risk relative to the time periods in which they were in the low growth quartile. The increases in probability range from 2.25% to 5.8%. To summarize, three-year aggressive loan growth not only predicts negative returns but also the chance of an extremely large shock to a bank's market capitalization.

4. Do high growth banks make poorer loans?

In this section, we seek to understand the cause of the poor subsequent returns. Our analysis is similar in spirit to, e.g., Demyanyk and van Hemert (2011) or Mian and Sufi (2009) who examine whether financial institutions made poorer loans prior to the recent credit crisis. Both papers document that banks made lower quality mortgage loans prior to the recent crisis which led to significantly higher defaults during the crisis. Mian and Sufi (2009) show for example that mortgage credit growth and borrower income growth were negatively correlated in high subprime ZIP codes. López-Salido, Stein, and Zakrajšek (2015) show that when credit risk is aggressively priced, it tends to be followed by a subsequent widening of credit spreads and a contraction in economic output.

The granularity of our analysis is in between those two studies. While we do not have information on individual bank loans, we analyze the loan portfolios, accounting returns, and loan loss provisions of individual banks over a time horizon of 40 years. An important additional distinction of our paper compared to Demyanyk and van Hemert (2011) and Mian and Sufi (2009) is that our analysis deals with loans that are retained on a bank's books and thus cannot be explained by misaligned incentives relative to an originate to distribute securitization model.

4.1. Accounting returns and loan loss provisions of high growth banks

Table 7 presents regressions of the return on assets and loan loss provisions on banks' loan growth. As before, banks are sorted into quartiles based on loan growth during the previous three years. Panels A and B of Table 7 analyze levels and changes in return on assets, defined as net income / total assets, and expressed in percent. Panel A shows that high growth banks have high concurrent accounting returns. Relative to the low loan growth quartile banks, banks with a higher average three-year growth have about 0.21% higher profitability. The economic magnitude can be gauged by comparing the 0.21% with the average sample ROA of 0.77%. Column 2 shows results from the bank-fixed effects regression and comes to a similar conclusion. Compared to periods of low growth for the same bank, the concurrent

ROA is significantly higher after high growth episodes. Panel A shows that the positive ROA effect reverses over the next three years. By year *t*+3, the high growth quartile banks have a significantly lower return on assets, both in pooled (-0.16%) and fixed effects (-0.17%) regressions. Panel B shows the year-over-year changes in ROA by growth quartile, with the lowest growth quartile as the reference group. The performance of high growth banks deteriorates quickly after the high growth episodes. Column 1 shows that the ROA already goes down in the year following the formation period. It decreases for all three growth quartiles, with the highest drop in growth quartile 4 at -0.097%, or 12.6% relative to the sample mean. From year *t*+1 to *t*+2 as well as from year *t*+2 to *t*+3 relative to the formation period, we again observe large changes in the ROA for all three growth quartiles relative to the low growth base group. Column 7 shows the total change in ROA from year *t* to year *t*+3. In this regression, we drop overlapping observations to address concerns about standard errors, similar to the return regressions in Table 3. Over the three post-formation years, the total drop in ROA for the highest growth quartile relative to the lowest quartile is -0.32%, or 41.6% relative to the sample mean. Growth quartiles 2 and 3 also experience a reduction in ROA relative to the lowest growth quartile and the drop in ROA is monotonic in the amount of growth. Overall, the evidence of Panels A and B of Table 7 suggests that higher growing banks make new loans that lead to losses that materialize almost immediately after the periods of high growth and last for up to three years.

The ROA regressions show the ex-post outcome of investments made during the aggressive growth period. But were banks aware of the fact that they were making riskier loans? Panels C and D of Table 7 examine the question and analyze loan loss provisions expressed as percent and defined as loan loss provisions divided by total gross loans and multiplied by 100. The loan loss provision should increase immediately in period *t* if the bank is aware that it grew quickly by making riskier loans.

Panels C and D of Table 7 show results, with Panel C showing loan loss provision levels and Panel D year-over-year changes. It is apparent from Panel C that high growth banks had significantly lower loan loss provisions in year *t* than low growth banks. The effects are economically meaningful. The coefficient of -0.381% for the top loan growth quartile in Column 1 can be compared with the average loan loss provision of 0.68%. Hence, relative to the sample average, a high growth bank has 56% lower loan loss provisions. The evidence is not consistent with high growth banks being aware that their growth came from riskier loans. Column 7 of Panel C shows that the picture looks very different three years after the formation period. The high growth quartile banks have 0.174% higher loan loss provisions at that time (or on a relative basis, 25.6%). The bank fixed effects regressions in Columns 2, 4, 6, and 8 provide similar evidence from within bank effects. The same banks have lower loan loss provisions after high periods of growth relative to their own periods of low growth, and the effect reverses three years after the formation period. Panel D shows that the loan loss provisions increase very quickly after the formation period. For the high loan growth quartile banks relative to the low loan growth quartile banks, the change from year *t* to year *t*+1 is 0.23%, from year *t*+1 to year *t*+2 0.18%, and from year *t*+2 to *t*+3 0.12%, all statistically significant. Growth quartiles 2 and 3 experience similar year-over-year increases in loan loss provisions for two years after the formation period. Column 7 shows the total change in loan loss provisions from year *t* to year *t*+3. In this regression, we again drop overlapping observations. Over the three post-formation years, the total increase in loan loss provisions for the highest growth quartile relative to the lowest quartile is 0.49%, or 72.1% relative to the sample mean. Growth quartiles 2 and 3 also experience an increase relative to the lowest growth quartile and the increase in loan loss provisions is monotonic in the amount of growth. Again, the evidence from firm-fixed effects regressions paints a similar picture.

Overall, our evidence in Table 7 shows that at the height of the high loan growth, at the beginning of the formation period, high growth banks had high ROA and low loan loss provisions. After periods of high growth, the ROA of banks significantly and quickly deteriorates and loan loss provisions increase substantially. An explanation for the ROA and loan loss provision results in period *t* and their evolution is that high growth banks took riskier loans not charging fully for the greater risk. These actions would temporarily lead to more profit and lower loan loss provisions with subsequent reversals. The evidence is not consistent with banks keeping risk constant and charging less, as that would cause ROA to fall immediately. A potential explanation of the ROA results combined with the loan loss provision results is that executives in these banks did not understand that they were making riskier loans.

4.2. Do equity analysts understand high loan growth banks?

A natural question that arises from our analysis is why investors do not seem to incorporate bank credit cycles into their valuation of banks. From the literature we reviewed in the introduction, these patterns appear to be recurring and could easily be identified. In this section, to shed light on the question, we follow the empirical design of La Porta (1996) who examines whether systematic errors in analyst expectations can help explain the high returns earned by value stocks. La Porta (1996) creates measures of systematic analyst earnings per share (EPS) forecast errors using I/B/E/S data on analysts' earnings forecasts. He finds that analyst expectations about future growth in earnings are too extreme and can be profitably traded upon.

We calculate three measures of analyst forecast errors. We first calculate standardized unexpected earnings for the year $t+x$ (SUE_{t+x}) as the difference between actual earnings for fiscal year $t+x$ and the time t median analyst forecast for fiscal year $t+x$ earnings, divided by the stock price as of the day of the time t forecast. To allow analysts to incorporate all information from fiscal year t, the time t forecast is the median analyst earnings forecast as of the fourth month after the conclusion of fiscal year t, taken from I/B/E/S. Our second measure is analyst forecast revisions. $Revision_{t+1}$ is the difference between the time $t+1$ forecast for fiscal year $t+2$ and the time t forecast for fiscal year $t+2$, divided by the stock price as of the time t forecast. $Revision_{t+2}$ is the difference between the time $t+2$ forecast for fiscal year $t+3$ and the time t forecast for fiscal year $t+3$, divided by the stock price as of the time t forecast. Finally, we analyze not only the earnings per share forecast revision, but also the level and revision of the long-term earnings growth rate, $E_{t+x}(g)$. The earnings growth rate $E_{t+x}(g)$ measured at time t is defined as the median analyst's expectation as of time $t+x$ for the long-term growth rate of the bank's earnings.

The calculation procedure for SUEs and revisions produces many large outliers (see, e.g., Livnat and Mendenhall (2006)). In Panel A, we remedy the issue by estimating median regressions. In such a regression, we minimize the sum of the absolute residuals and not the sum of the squared residuals, putting less emphasis on outliers. *T*-statistics for the median regressions are estimated using bootstrapped standard errors. The bootstrap was performed using 500 replications each for firm clustering, time clustering and no clustering. The double-clustered variance-covariance matrix (VCV) is calculated by subtracting the unclustered VCV from the sum of the firm-clustered plus the time-clustered VCV.[6]

Table 8 shows the results. The first 6 columns of Panel A of Table 8 show the standardized unexpected earnings and indicate that equity analysts systematically overestimate future earnings per share for high growth banks, with coefficients of -0.0013, -0.0039, and -0.0050 for the one-year, two-year and three-year horizons, respectively. The economic magnitude of the coefficients can be gauged by comparing the coefficients with the median analyst SUEs reported in Table 2, i.e. -0.0004 for the one-year horizon, -0.0030 for the two-year horizon, and -0.010 for the three-year horizon. The results are strongest statistically for the *t*+1 and *t*+2 horizons, but at least part of the reason is that few analysts give three-year EPS forecasts (the number of observations decreases from 5,662 at the one-year horizon to 878 at the three-year horizon). Interestingly, the bank-fixed effects regressions show even stronger results, i.e. the same analysts give systematically too high EPS forecasts for the same banks when they grew a lot compared to when they grew little.[7] The last four columns of Panel A show that for the bank-fixed effects regressions, analysts had to systematically revise their EPS forecasts downward for high-growth quartile banks. The bottom four rows of Panel A show how many of the bootstrap replications used to calculate standard errors were successful at each step. Unsuccessful replications either did not converge or encountered a variance-covariance matrix that could not be calculated due to a lack of observations.

Panels B and C show regression results for analysts' long-term growth rate by bank loan growth quartile and the revisions from one year to the next of this long-term growth rate. Results for the long-term growth rate in Panels B and C are estimated using ordinary least squares and allowing for standard error clustering at the bank and time levels.

Analysts believe that bank growth is very persistent. No matter whether we estimate cross-sectional or fixed-effects regressions, we find that analysts expect long-term earnings growth in all three loan growth quartiles to be higher than earnings growth of banks in the lowest growth quartile, for up to three

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[6] See Cameron et al. (2008) and Gow et al. (2010) for additional discussions of this procedure. Code that implements the procedure can be found on the website of Daniel Taylor at Wharton Business School.

[7] Median regressions with bank-fixed effects frequently fail to convergence when including banks that have few observations. To remedy this issue, we require a bank to have at least five observations available to be included in the regressions with bank-fixed effects. Regressions without bank-fixed effects include all banks.

years post formation period. For growth quartile 4, analysts believe that banks can maintain 1.9% extra long-term growth over the first quartile banks in the formation year. In the following year, long-term growth estimates are still 1.7% higher than for low growth banks, and even in year *t*+3, when stock returns have already significantly suffered, analysts still believe that long-term earnings growth will be 1.2% higher. It is evident from these numbers that the long-term earnings growth forecasts are being revised downward. This is more formally confirmed in Panel C, in which we observe strong negative revisions of long-term growth forecasts for banks in the highest loan growth quartile relative to banks in the lowest quartile for one-, two-, and three-year revisions in the panel regressions.

Overall, the results in Table 8 suggest that analysts have difficulty understanding the loan growth patterns of sample banks. They systematically overestimate earnings as well as long-term growth rates of earnings for banks that have grown quickly over the past three years. Our result may help explain the negative stock returns we documented earlier. If even security market experts like analysts are unable to correctly assess the growth potential of banks, perhaps it is not too surprising that market participants think as well that bank growth of high growth banks is persistent and profitable.

5. Organic growth vs. growth through M&A activity

We next analyze whether our results can be explained by the M&A activities of managers of high growth banks. There is some evidence in the literature that managers of growth firms carry out acquisitions with negative long-term abnormal returns. For example, Rau and Vermaelen (1998) find that companies with low book-to-market ratios have lower long-term abnormal returns. They attribute their findings to managers who overestimate their own ability to manage these acquisitions (cf. Roll (1986)).[8] Hence, our evidence could simply reflect that banks that grow more merge more and experience lower returns because of mergers. We separate the loan growth of sample banks into organic loan growth and loan growth via mergers and analyze whether organic growth by itself leads to worse future stock

[8] The question of whether long-term abnormal returns to M&A activity are in fact on average negative has not yet been settled in the literature. For an overview, see Betton, Eckbo, and Thorburn (2008).

performance. We also reexamine the ROA and loan loss provision results distinguishing between organic loan growth and loan growth through acquisitions.

We first need to create a reliable sample of the total assets and total loans of targets in M&A transactions by sample banks to be able to calculate organic growth and growth through M&A activity. We obtain data on mergers and acquisitions of sample banks from the M&A database of the Federal Reserve Bank of Chicago.[9] Having identified target firms, we obtain asset and loan data for the target firms from several sources (call reports for commercial banks, FR-Y-9C reports for bank holding companies, an FDIC list for failed banks, and 10-Ks for other sample firms). We then calculate organic loan growth by adjusting total loan growth for the effect of mergers in the following way. For each of our sample firms, we calculate the sum of all loans acquired in each fiscal year and calculate the organic loan growth as $\frac{\text{Total loans}_t\text{-Loans acquired}_t}{\text{Total loans}_{t\text{-}1}} - 1$. Appendix A of the paper provides details on the matching and calculations, including a description of how to merge the different databases and of all assumptions we made. Because the Chicago Fed's M&A database only starts in 1976 and we require three years of loan data to calculate growth, our sample period for the following tests is restricted to the period 1978 to 2014.

Table 9 presents regression results of bank stock returns on banks' organic and M&A related loan growth, respectively, during the previous three years. As in Table 3, we provide both pooled results as well as bank-fixed effects results. Banks are sorted into quartiles for organic growth, with the lowest growth quartile serving as the base group for the regressions. For merger growth, all banks without a merger in a given three-year period are included in one group which acts as the base group. The remaining banks are sorted into terciles labeled low/medium/high merger growth. The organic growth sort and the merger growth sort are performed independently of each other. Table 9 shows that we continue to find strong return predictability even when we focus on organic growth. For all six specifications in Panel A of Table 9, returns are monotonically decreasing across the organic loan growth quartiles at all horizons. The higher past three year organic loan growth, the worse are the returns. The effects are economically and statistically large in organic growth quartiles 2, 3, and 4. For the three-year

[9] The data are accessible online at the following address: https://www.chicagofed.org/banking/financial-institution-reports/merger-data

subsequent returns, we observe that a bank in the highest organic loan growth quartile has a 6.4% lower return per year than a bank in the lowest organic growth quartile. The within effect – comparing the same bank when it was in the high organic loan growth quartile relative to the low growth quartile – is even larger with an annualized return spread of -9.8%. We also observe return predictability after aggressive external growth, but the effects appear weaker. Relative to the base group of no merger activity in the past three years, we find that only the high merger growth group consistently exhibits lower future returns. At the three year horizon, we observe that high merger growth banks have -3.7% lower annualized returns relative to the no merger banks (-6.1% within effect).

Overall, Table 9 shows that M&A activity alone cannot explain the long-term lower returns of high growth sample banks. We find economically and statistically strong negative subsequent returns for banks that have high organic growth rates. In unreported regressions, we also re-estimate the benchmark adjusted returns using the Daniel et al. (1997) portfolio approach of Table 4 with organic loan growth instead of total loan growth. For both 2-year and 3-year holding period returns, we find that the characteristics-adjusted returns (using either all firms or banks only) of the highest organic growth quartile are significantly lower than those of the lowest organic growth quartile. At the three-year horizon, the difference is -0.42% per month for DGTW-adjusted returns, and -0.36% per month when using only banks for the DGTW adjustment.

We next ask whether the evidence of poorer loans in high growth banks we documented in Table 6 stems from organic loan growth or external loan growth. We seek to understand whether high-growth banks acquire banks with poorer loans, or whether they make those poorer loans on their own.

Table 10 shows results for regressions of ROA and loan loss provision levels on organic loan growth quartiles and merger growth groups. We omit the panels documenting changes in the dependent variables for brevity. The results of Panel A for ROA levels and growth quartiles are very similar to Table 6. In the year in which we measure high three-year organic loan growth, high growth banks have significantly higher ROAs than low-growth banks, and the same holds across all merger growth terciles relative to the no merger growth base group. We find that for the banks with the highest organic loan growth, the level of ROA deteriorates in the following years until in year t+3 after formation period, high growth quartile banks have significantly lower returns on assets than the base group. Their ROA decreases from 0.25% in year t to -0.18% in year t+3. We do not observe the same pattern after years of high merger growth.

Panel B of Table 10 shows the evolution of the loan loss provisions by organic loan growth quartiles and merger growth groups. We show that in the year in which we assign growth quartiles, higher loan growth banks have fewer loan loss provisions, i.e. they either have made better loans or do not recognize that the loans that they have made are potentially riskier. The results are economically and statistically stronger for organic growth than growth via mergers. The economic magnitude of the effect is large. Average loan loss provisions are -0.68%. Relative to the lowest organic growth quartile, banks in the highest organic growth quartile have -0.44% lower loan loss provisions. The effect slowly reverses through time so that at the end of year 3 after formation, high organic loan growth banks have significantly higher loan loss provisions (0.17%) than low organic growth banks.

Overall, Table 10 provides evidence that it is indeed the loans quickly growing banks make on their own rather than the loans they acquire which are responsible for the increase in loan loss provisions and the poorer accounting returns.[10]

6. Robustness of our main results

Our analysis suggests that fast loan growth is associated with making poor loans. Because our results hold in the cross-section, it is less likely that they can be explained by aggregate demand-side productivity shocks. Under such an explanation, banks would be making good loans, but the economy would unexpectedly experience slow growth which would end the credit boom and cause poor performance. We provide two robustness checks that help further alleviate this concern. First, we repeat our analysis but remove recession years. We obtain NBER recession indicators from the St. Louis FRED database and, for each return regression, exclude all returns where at least part of that return occurs during a recession. For example, one recession lasted from August 1990 to March 1991. For one-year returns, we drop the returns for 1990 and 1991. For two-year returns, we drop the returns for 1989-1990, 1990-1991,

[10] In unreported regressions, we repeat the analyses in Table 10 for asset growth and find quantitatively and qualitatively similar results.

1991-1992. For three-year returns, we drop the returns for 1988-1990, 1989-1991, 1990-1992, and 1991-1993.

Our results continue to hold in regressions that are similar to those in Table 3. We find that banks in the highest loan growth quartile have 4.1% lower returns at the 1-year horizon, 5.0% lower annualized returns at the two-year horizon, and 4.8% lower annualized returns at the three-year horizon than banks in the lowest growth quartile. These effects are statistically significant at the 12% level for the one-year horizon and at the 5% level for the two- and three-year horizons.

Second, one potential concern with our results and the above test is whether they could still be driven by *local* demand shocks. If most or all of the banks in the top growth quartile in each formation period were from the same region, local demand shocks (e.g., impact of shale extraction innovation), could explain our results. We test and alleviate such a concern by examining the distribution of the annual bank loan growth across the four US census regions in unreported robustness checks.

We determine a bank's location using headquarters information from Call Reports and FR-Y-9C reports. If the location of a bank holding company is unavailable, we take the location of the largest individual bank held by the BHC. If neither is available, we use the Compustat header location. We assign each bank to a US census region based on its headquarters. We then examine what percentage of banks in a certain census region is in each of the four growth quartiles in each year. If growth and geography were completely uncorrelated, all the percentages would equal 25%. If a local demand shock hypothesis was the main driver of our results, we should observe that the banks in the top growth quartile in a given year mostly are from the same census region. The average fraction of banks in the top growth quartile across all years is surprisingly even across regions. The South has on average the highest fraction of banks in the top growth quartile (28%), and the Midwest has the lowest fraction with 20.7%. The most uneven distribution of banks in the top growth quartiles happened in 1986-1988, when banks from the Northeast represented 41% to 52% of the highest growth quartile banks, and in 1972-1974, when banks from the South represented 46% of the highest growth quartile banks. We therefore believe that the relatively even distribution of fast growing banks across the United States regions make it unlikely that our results are driven by local demand shocks.

To err on the side of caution, in unreported regressions, we re-estimate the paper's main results from Table 3, Panel B forming all growth quartiles within census regions. For example, to determine which growth quartile a Midwest bank falls into in a given year, its growth in that year is compared only to the growth of other Midwest banks, rather than to the growth of all US banks. Results remain economically and statistically significant. Over the three years after the formation period, annualized returns for the highest growth quartile are lower than those for lowest growth quartile by 5.6%. Compustat added financial data for a large number of small banks in fiscal year 1993 which we excluded in our main regressions because cross-sectional differences among small banks are unlikely to affect overall credit supply beyond the local level and to avoid a structural break in our data. Including these banks in our main regressions of Table 3 weakens the economic significance by approximately 20% but does not change the statistical significance. Estimating the regressions using only those small banks does not yield the same return predictability after periods of large loan growth as in Table 3. Hence, our results are driven by the larger banks with assets in excess of $2 billion.

Table 11 addresses a different issue, survivorship bias. It examines whether a higher incidence of delistings could help explain the return difference between high and low loan growth banks. For Table 3, we required that a bank has returns available for the entire subsequent return period of up to three years, i.e., we require the bank to survive for those three years. If low loan growth banks and high loan growth banks have different probabilities of delisting in these three years, it could be that we introduce a survivorship bias. Suppose for example that low growth banks have a higher probability of delisting in the three years post formation period. Because of the three-year return requirement, these delisted banks would be excluded from the sample. If poor performance causes delistings, we would only include better performing low growth banks, helping to explain our results. Note, however, that the portfolio sorts in Table 4 are not susceptible to this problem since they use monthly returns including delisting returns. Nevertheless, in Panel A of Table 11, we examine whether it is in fact true that low loan growth banks have a higher incidence of delisting and in Panel B of Table 11, we test whether our results are robust to a different definition of future returns. In Panel B of Table 11, we define subsequent returns as follows. If a bank only survives for two years, the three-year return equals the two-year gross return plus delisting return, annualized to three years. The number of observations therefore increases because the delisted banks now stay in the sample.

Panel A of Table 11 shows that high growth banks indeed have a lower probability of delisting than low growth banks. It is important to note, however, that banks rarely delist due to bankruptcies. Only 22 of the sample banks delist due to bankruptcy or liquidation. Most of the delistings are due to mergers (387 banks). Though some banks in the sample are taken over due to poor performance (e.g., Countrywide Financial and Wachovia), this is not the typical case. In any case, Panel B of the table shows that our results are very robust to the different definition of future returns. All our main results continue to hold after we include more banks and their delisting returns. High loan growth banks continue to significantly underperform low loan growth banks.

Our final robustness check deals with the M&A results. In Table 9, we separated loan growth into organic growth and merger growth. One of the sample selection criteria was to exclude all bank-year observations for which target loan data for any of the bank's merger targets were unavailable. This excluded 541 observations. We have re-estimated the regressions of Table 9 by including these bank-years and setting target loan data to zero. Our results are unaffected by these changes.

7. Conclusion

We show that U.S. banks with loan growth in the top quartile of banks over a three-year period significantly underperform banks with loan growth in the bottom quartile over the next three years. The effects are economically large and robust to different estimation techniques. A potential explanation for the poor stock performance is that quickly growing banks make loans that perform worse than the loans of banks that grow slowly. We find evidence in favor of this explanation. The effects are not driven by M&A growth.

Several recent papers show that credit booms end poorly and are followed by poor economic outcomes. Our paper analyzes a panel of banks located in the same country and shows that even for individual banks periods of high growth are followed by lower future returns than periods of low growth. Neither equity analysts nor shareholders seem to recognize these patterns. Banks themselves appear too optimistic about the loans they make during high growth periods as their returns on assets decrease in the following years and their loan loss provisions increase.

Appendix A. Procedures for matching the Chicago Fed M&A database to the CRSP/Compustat database and for calculating organic asset and loan growth

The appendix provides detailed information on how we matched the Chicago FED M&A database to the CRSP/Compustat data and how we calculate organic growth, i.e. growth that does not stem from merger activity, for sample banks.

A. Linking mergers in the Chicago Fed M&A database to CRSP/Compustat:

1) Extract both the individual bank mergers and holding company mergers from the database

2) Eliminate "mergers" that are not actually mergers
   The Chicago Fed M&A database contains many mergers that are really just restructurings within the same bank, such as a holding company absorbing its subsidiary or merging two of its subsidiaries. We eliminate these non-mergers by excluding:
   a. Entries where the buyer and the target are held by the same holding company
   b. Entries where the buyer is identical to the target's bank holding company

3) Match the acquirer to CRSP Permcos using the New York Fed's link table
   a. Match acquirer RSSD ID to Permco
   b. Match acquirer's high holder ID to Permco
   c. For mergers before 1990, an older version of the NY Fed's link table has to be used because the most recent version does not provide Permco links before 1990
   d. For Permcos that are missing in the NY Fed's table, hand-collect RSSD IDs from the National Information Center, then perform steps a. and b. above.

B. Obtain asset and loan data for the target firms

We obtain these data from several sources. Commercial banks file call reports. Holding companies file FR-Y-9C reports. Finance companies and other entities file 10-Ks if they are registered with the SEC.

1) Call report data for individual banks
   a. Total assets are in RCFD2170. We divide all Call Report data by 1000 to get millions as in Compustat.
   b. The relevant variable for loans is RCFD2125 "Total Loans and Leases, Net", which is net of unearned income and loan loss allowances. The definition coincides with the definition of LCUACU ("Loans/Claims/Advances - Customer – Total") from Compustat.
   c. When RCFD2125 is not filled, we calculate it as RCFD2122 – RCFDF3123 – RCFD3128

2) FR-Y-9C data for holding companies
   a. Use the same procedure outlined above using the BHCK data series
   b. FR-Y-9C data are available only from September 1986 onwards. For earlier mergers, we use asset and loan data for the individual banks held by the holding company (see point C.4 for this procedure).

3) FDIC List of failed banks
   a. The list reports total assets at the time of failure for all failed banks. Obtaining this data is important as there are hundreds of failed S&Ls for which asset data cannot be found otherwise. Data on the failed bank's loans are unavailable.

4) Compustat data
    a. If none of the above databases has asset data for the target, we obtain data from the financial services view of Compustat, where possible.
    b. This step helps match publicly traded institutions registered as S&Ls, S&L holding companies, Federal Savings Banks, Other Domestic Entities as well as some Bank Holding Companies that do not file the FR-Y-9C

<u>C. Match asset and loan data to the merger data and purge duplicate mergers</u>

1) Pull asset and loan data from the target's most recent Call Report or FR-Y-9C
2) For commercial banks and holding companies, pull high holder ID from Call Reports/FR-Y-9C
3) Eliminate mergers where the high holder is identical to the survivor or the survivor's high holder
4) If an acquirer buys a bank holding company together with its subsidiary bank, the Chicago Fed's database will list both transactions as mergers. Without adjusting for this fact, we would double count the bank's assets. Adjustment procedure:
    a. Using high holder IDs, match each individual bank merger to its holding company merger where applicable
    b. If holding company asset data is available, drop the individual bank merger data
    c. If the holding company's asset data is unavailable, but the individual bank's asset data is available, drop the holding company merger data
    d. If a holding company is owned by another holding company and both are acquired, keep only the high holder observation.
5) For entities that are neither commercial banks nor BHCs, high holder IDs cannot be pulled from call reports/holding company reports. Procedure for eliminating non-mergers and duplicates:
    a. Search for the target entity in the FDIC's National Information Center (NIC)
    b. Find high holder ID in the NIC and flag and drop the merger as a non-merger if the high holder ID is identical with the acquirer or the acquirer's high holder
    c. Flag and drop the merger as a duplicate if the high holder is being acquired by the same buyer at the same time
6) Match asset data from FDIC list of failed banks to the merger data
    a. The merger data does not contain CERT numbers and the FDIC data does not contain RSSD ID, so we have to manually match on name and location.
    b. Of the 366 failed banks for which data is otherwise unavailable, we are able to match 360 banks to the FDIC list.
7) Match Compustat data on target assets and loans to the merger data
    a. Find the last available financial statement for each financial institution in Compustat
    b. Require the last available financial statement to be within two years before the merger date and do not allow it to be after the merger date.
    c. Perform lenient name match requiring city to be identical in both databases and manually inspect.
    d. Perform strict name match without requiring city to be identical and manually inspect. Name match has to be very close and the city in one database has to be a subsection/suburb of the city in the other database.
    e. Name matches also identify some mergers involving both a high holder and a subsidiary. Drop the subsidiary data.

<u>D. Calculate organic loan growth and organic asset growth</u>

1) For each of our sample firms, we calculate the sum of all assets/loans acquired in each fiscal year

2) If a merger involves multiple acquirers (e.g. FDIC split up a failed bank), assume that each of the n acquirers buys *1/n* of the bank's assets/loans
3) Calculate adjusted loan growth for year *t* as

$$\frac{\text{Total loans}_t - \text{Loans acquired}_t}{\text{Total loans}_{t-1}} - 1$$

4) Calculate adjusted asset growth the same way

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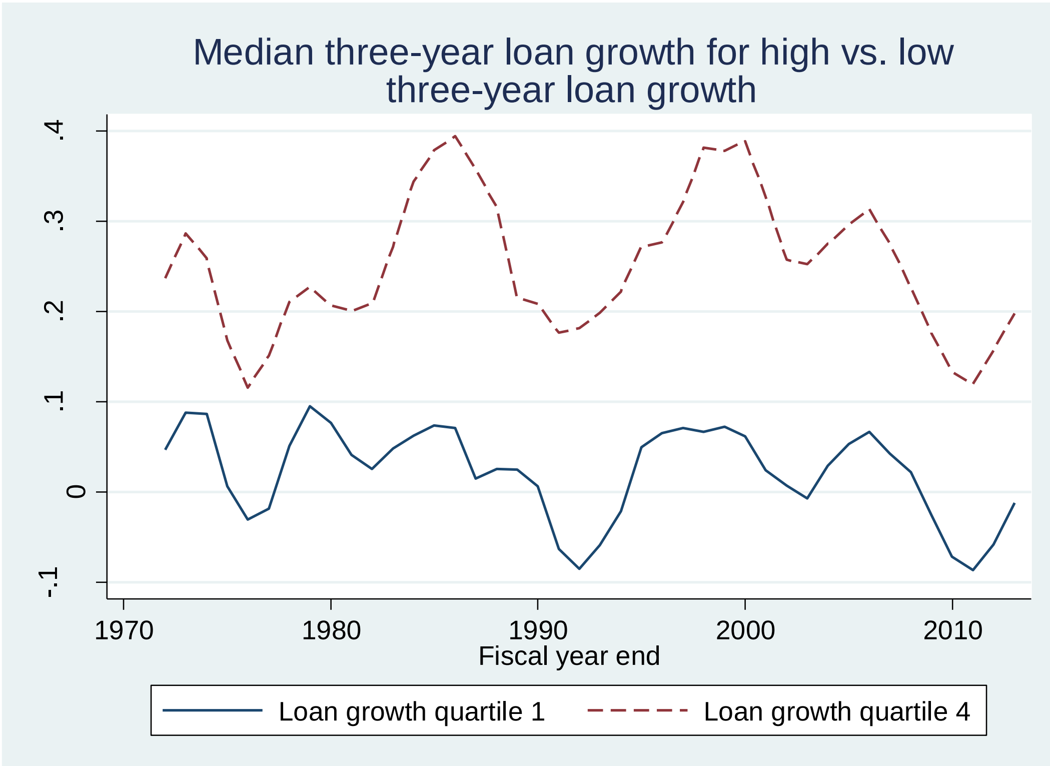

Figure 1. The figure shows the time-series evolution of the median three-year loan growth for two groups of banks. Every year, we classify banks into four groups based on loan growth quartiles. The solid blue line shows the median three-year asset growth for banks in the lowest quartile of loan growth. The dashed red line shows the median three-year loan growth for banks in the highest quartile of loan growth. Our sample period is 1972 – 2013.

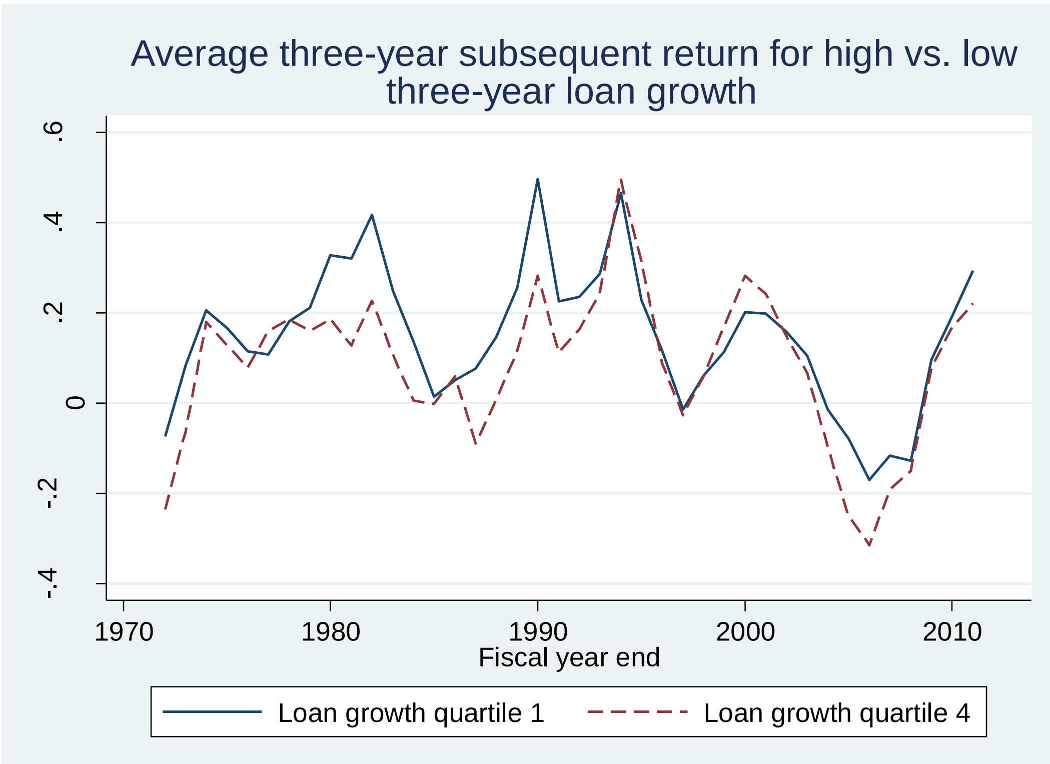

Figure 2. The figure shows the time-series evolution of the average three-year subsequent returns for two groups of banks. Every year, we classify banks into four groups based on loan growth quartiles. The solid blue line shows the average three-year subsequent stock return for banks in the lowest quartile of loan growth. The dashed red line shows the average three-year subsequent stock return for banks in the highest quartile of loan growth. Our sample period is 1972 – 2013.

Table 1: Number of banks per year

The table shows the number of banks that are in the sample each year. Section 2 contains a detailed description of our sample selection procedure. A bank has to have real assets in excess of $2 billion in order to be in the sample. Real assets are calculated as total assets in 2013 dollars using the Bureau of Labor Statistics' Consumer Price Index for all urban consumers.

	# Sample Banks
1972	131
1973	134
1974	143
1975	144
1976	143
1977	148
1978	164
1979	168
1980	171
1981	177
1982	182
1983	187
1984	185
1985	183
1986	183
1987	182
1988	223
1989	211
1990	212
1991	206
1992	205
1993	216
1994	216
1995	200
1996	201
1997	193
1998	212
1999	210
2000	207
2001	205
2002	215
2003	202
2004	211
2005	214
2006	218
2007	207
2008	198
2009	189
2010	180
2011	183
2012	180
2013	175

Table 2: Summary statistics

The table shows sample summary statistics. The first seven rows show summary statistics for 1-year, 2-year, and 3-year subsequent returns as well as asset growth and loan growth over the past one and three years, respectively. For two- and three-year returns, only non-overlapping returns are used. All multi-year returns as well as 3-year loan growth and asset growth are annualized. The table also shows summary statistics for the return on assets (ROA), defined as net income divided by total assets multiplied by 100, as well as loan loss provisions, defined as loan loss provisions divided by total gross loans multiplied by 100. In addition, the table shows summary statistics for several variables related to analyst forecasts: 1-year, 2-year, and 3-year SUE are standardized unexpected earnings for the three subsequent fiscal years, respectively, calculated as the difference between actual earnings per share (EPS) and the current median analyst forecast EPS, divided by the current stock price. Analyst revision$_{t+1}$ is the difference between the current median analyst forecast and the median analyst forecast 12 months later, divided by the current stock price. Analyst revision$_{t+2}$ is the difference between the current median analyst forecast and the median analyst forecast 24 months later, divided by the current stock price. Analyst growth expectation is the current median analyst expected long-term (five year) EPS growth rate. To allow the current fiscal year data to become known to analysts, the current analyst forecast is taken as of the fourth month after the current fiscal year end date (for example, for firms with a fiscal year end date of December 31, we use the median analyst forecast as of April). Loan growth, asset growth, ROA, loan loss provisions, as well as analyst forecast errors and revisions are winsorized at the 1st and 99th percentile, respectively.

	Observations	Mean	St. Dev.	Min.	25th perc.	Median	75th perc.	Max.
1-year return	7914	0.1550	0.3933	-0.9848	-0.0560	0.1290	0.3495	4.2973
2-year return	3728	0.1255	0.2900	-0.9201	-0.0277	0.1270	0.2938	1.7161
3-year return	2365	0.1105	0.2314	-0.8277	-0.0057	0.1309	0.2491	1.0031
1-year loan growth	7330	0.1368	0.1882	-0.2063	0.0308	0.1032	0.1982	1.0081
3-year loan growth	6834	0.1332	0.1266	-0.1418	0.0531	0.1178	0.1925	0.6210
1-year asset growth	7717	0.1266	0.1674	-0.1581	0.0315	0.0932	0.1736	0.9434
3-year asset growth	7185	0.1259	0.1098	-0.1086	0.0569	0.1100	0.1749	0.5655
ROA (%)	7910	0.7747	0.6531	-2.6099	0.5804	0.8549	1.1084	2.0429
Loan loss provisions (%)	7431	0.6779	0.7955	-0.1415	0.2426	0.4380	0.7730	4.6592
1-year SUE	6454	-0.0268	0.1120	-0.7325	-0.0110	-0.0004	0.0050	0.1097
2-year SUE	4790	-0.0316	0.1093	-0.6545	-0.0230	-0.0030	0.0067	0.1266
3-year SUE	906	-0.0242	0.0631	-0.3170	-0.0356	-0.0098	0.0059	0.1390
Analyst revision$_{t+1}$	5209	-0.0124	0.0414	-0.2281	-0.0135	-0.0020	0.0038	0.0610
Analyst revision$_{t+2}$	1025	-0.0181	0.0442	-0.1953	-0.0270	-0.0075	0.0039	0.1000
Analyst growth expectation	4983	10.0350	3.0024	3.0000	8.0000	10.0000	12.0000	22.5000

Table 3: Relationship between loan and asset growth and subsequent returns

Panels A through D present regressions of bank stock returns on a bank's loan growth and asset growth, respectively. Banks are sorted into quartiles based on loan growth and asset growth during the previous one and three years, respectively. Indicator variables representing each quartile are included in the regression with the lowest growth quartile forming the base group. Panel E presents regressions of bank stock returns on a bank's loan growth and non-loan asset growth during the previous three years. Banks are sorted into quartiles for loan and non-loan asset growth, respectively. The loan growth sort and the non-loan asset growth sort are performed independent of each other. The sample period is 1973 – 2014. The regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all banks whose real assets in 2013 dollars are greater than $2 billion. For regressions using subsequent two-year and three-year returns as the dependent variable, overlapping returns are dropped to avoid inflating *t*-statistics due to serial correlation. Standard errors allow for clustering at the bank and time levels. Numbers in parentheses are *t*-statistics. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Panel A: One-year loan growth

	1-year returns		2-year returns		3-year returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Growth quartile 2	0.0106	-0.0037	0.0026	-0.0132	-0.0039	-0.0322**
	(0.72)	(-0.22)	(0.24)	(-1.17)	(-0.31)	(-2.12)
Growth quartile 3	0.0092	-0.0106	-0.0035	-0.0265*	-0.0157	-0.0497**
	(0.58)	(-0.58)	(-0.28)	(-1.90)	(-0.98)	(-2.50)
Growth quartile 4	0.0048	-0.0164	-0.0105	-0.0365*	-0.0261	-0.0598**
	(0.26)	(-0.78)	(-0.62)	(-1.79)	(-1.35)	(-2.39)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Number of observations	7330	7330	3377	3377	2096	2096
R-squared	0.44	0.51	0.54	0.64	0.50	0.67

Panel B: Three-year loan growth

	1-year returns		2-year returns		3-year returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Growth quartile 2	-0.0213	-0.0410**	-0.0152	-0.0403***	-0.0286***	-0.0473***
	(-1.29)	(-2.09)	(-1.61)	(-3.44)	(-3.15)	(-3.75)
Growth quartile 3	-0.0292	-0.0577***	-0.0277**	-0.0576***	-0.0467***	-0.0755***
	(-1.50)	(-2.63)	(-2.27)	(-4.06)	(-3.75)	(-4.75)
Growth quartile 4	-0.0531**	-0.0812***	-0.0552***	-0.0911***	-0.0743***	-0.1088***
	(-2.42)	(-3.15)	(-3.29)	(-4.26)	(-4.32)	(-4.81)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Number of observations	6834	6834	3130	3130	2002	2002
R-squared	0.45	0.51	0.54	0.65	0.52	0.69

Panel C: One-year asset growth

	1-year returns		2-year returns		3-year returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Growth quartile 2	0.0031	-0.0148	-0.0055	-0.0211*	-0.0056	-0.0201
	(0.20)	(-0.98)	(-0.48)	(-1.74)	(-0.44)	(-1.50)
Growth quartile 3	-0.0058	-0.0229	0.0051	-0.0162	-0.0225	-0.0422***
	(-0.31)	(-1.17)	(0.37)	(-1.12)	(-1.64)	(-2.71)
Growth quartile 4	-0.0117	-0.0275	-0.0254	-0.0488***	-0.0350**	-0.0576***
	(-0.57)	(-1.29)	(-1.57)	(-2.71)	(-2.12)	(-2.95)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Number of observations	7717	7717	3534	3534	2179	2179
R-squared	0.43	0.50	0.53	0.64	0.49	0.68

Panel D: Three-year asset growth

	1-year returns		2-year returns		3-year returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Growth quartile 2	-0.0295**	-0.0475***	-0.0207*	-0.0446***	-0.0216**	-0.0514***
	(-2.00)	(-2.88)	(-1.93)	(-3.06)	(-2.23)	(-3.92)
Growth quartile 3	-0.0372**	-0.0614***	-0.0359**	-0.0668***	-0.0469***	-0.0760***
	(-2.03)	(-2.98)	(-2.57)	(-3.95)	(-3.73)	(-4.49)
Growth quartile 4	-0.0575***	-0.0821***	-0.0509***	-0.0794***	-0.0613***	-0.0895***
	(-2.84)	(-3.37)	(-3.54)	(-4.16)	(-4.12)	(-4.64)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Number of observations	7185	7185	3265	3265	2120	2120
R-squared	0.43	0.50	0.52	0.64	0.50	0.68

Panel E: Three-year loan growth vs. non-loan asset growth

	1-year returns		2-year returns		3-year returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Loan growth quartile 2	-0.0218	-0.0409**	-0.0157*	-0.0402***	-0.0288***	-0.0464***
	(-1.31)	(-2.08)	(-1.73)	(-3.48)	(-3.13)	(-3.74)
Loan growth quartile 3	-0.0300	-0.0575***	-0.0286**	-0.0574***	-0.0479***	-0.0746***
	(-1.53)	(-2.62)	(-2.46)	(-4.07)	(-3.74)	(-4.79)
Loan growth quartile 4	-0.0551**	-0.0817***	-0.0568***	-0.0916***	-0.0771***	-0.1084***
	(-2.44)	(-3.19)	(-3.06)	(-4.10)	(-4.03)	(-4.95)
Non-loan asset growth	0.0092	0.0066	0.0077	0.0039	0.0005	-0.0109
quartile 2	(0.82)	(0.56)	(0.79)	(0.28)	(0.06)	(-1.00)
Non-loan asset growth	0.0003	-0.0048	0.0023	-0.0041	0.0048	-0.0041
quartile 3	(0.03)	(-0.40)	(0.23)	(-0.34)	(0.51)	(-0.35)
Non-loan asset growth	0.0079	0.0047	0.0064	0.0031	0.0072	-0.0049
quartile 4	(0.70)	(0.40)	(0.54)	(0.22)	(0.68)	(-0.34)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Number of observations	6834	6834	3130	3130	2002	2002
R-squared	0.45	0.51	0.54	0.65	0.52	0.69

Table 4: Returns to portfolios sorted on three-year loan growth

Banks are sorted into quartiles based on loan growth, respectively, during the previous three years. The table shows average monthly returns (in percent) for the resulting portfolios as well as the difference between Quartile 4 and Quartile 1. The sample period is 1973 – 2014. Adjusted returns are calculated by subtracting a characteristic-based benchmark return from each bank's stock return. Benchmark portfolios are constructed following Daniel et al. (1997) by sorting all stocks in the CRSP/Compustat Merged universe into size, industry-adjusted book-to-market, and momentum quintiles. The table also reports returns adjusted for a characteristic-based benchmark that includes only banks. This benchmark is formed by matching each bank to all other banks (excluding the bank itself) that are in the same size/book-to-market/momentum portfolio. Quintile cutoffs for this bank-only benchmark are the same as for the benchmark that includes nonfinancial firms. For the 8.7% observations in the sample where there is no other bank in the same benchmark portfolio, banks are matched to the nearest benchmark portfolio, relaxing first the momentum criterion, then book-to-market, then size. Among the initially unmatched observations, 73% can be matched to banks that are in the same size quintile, the same book-to-market quintile, and the immediately adjacent momentum quintile. Benchmark portfolio returns are value-weighted based on market capitalization. For holding periods of more than one year, overlapping portfolios are formed as in Jegadeesh and Titman (1993). Numbers in parentheses are t-statistics. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

	Growth quartile				
	1	2	3	4	4-1
		Panel A: 1-year holding period returns (per month)			
Raw returns	1.44***	1.31***	1.22***	0.92***	-0.52
	(5.48)	(5.18)	(4.95)	(3.54)	(-1.40)
Adjusted	0.05	-0.04	-0.12	-0.35**	-0.40*
	(0.38)	(-0.28)	(-0.87)	(-2.20)	(-1.88)
Adjusted	0.13*	0.08	-0.01	-0.17***	-0.29***
(banks only)	(1.83)	(1.30)	(-0.22)	(-2.66)	(-3.15)
		Panel B: 2-year holding period returns (per month)			
Raw returns	1.49***	1.30***	1.18***	0.93***	-0.57
	(5.84)	(5.16)	(4.72)	(3.53)	(-1.54)
Adjusted	0.10	-0.05	-0.14	-0.34**	-0.45**
	(0.76)	(-0.34)	(-1.02)	(-2.23)	(-2.18)
Adjusted	0.19***	0.06	-0.05	-0.15***	-0.34***
(banks only)	(3.09)	(1.07)	(-1.16)	(-2.69)	(-4.10)

Panel C: 3-year holding period returns (per month)

Raw returns	1.50***	1.30***	1.18***	0.93***	-0.56
	(5.97)	(5.14)	(4.68)	(3.50)	(-1.54)
Adjusted	0.11	-0.05	-0.14	-0.34**	-0.45**
	(0.83)	(-0.33)	(-1.03)	(-2.20)	(-2.21)
Adjusted	0.20***	0.05	-0.02	-0.16***	-0.36***
(banks only)	(3.45)	(1.01)	(-0.53)	(-3.01)	(-4.58)

Table 5: Results using loan and asset growth as continuous variables

The table presents regressions of bank stock returns on a bank's loan growth, asset growth, and non-loan asset growth, respectively, as well as time fixed effects and, where indicated, bank fixed effects. The sample period is 1973 – 2014. The sample includes all banks whose real assets in 2013 dollars are greater than $2 billion. For regressions using subsequent two-year and three-year returns as the dependent variable, overlapping returns are dropped to avoid inflating *t*-statistics due to serial correlation. Standard errors allow for clustering at the bank and time levels. Numbers in parentheses are *t*-statistics. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Panel A: Loan growth

	1-year returns		2-year returns		3-year returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Three-year loan growth	-0.1387**	-0.2341***	-0.1394**	-0.2613***	-0.2016***	-0.3184***
	(-2.23)	(-2.89)	(-2.50)	(-3.24)	(-3.20)	(-3.59)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Number of observations	6834	6834	3130	3130	2002	2002
R-squared	0.45	0.51	0.54	0.65	0.52	0.68

Panel B: Asset growth

	1-year returns		2-year returns		3-year returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Three-year asset growth	-0.1621**	-0.2775***	-0.1603***	-0.2919***	-0.2116***	-0.3303***
	(-2.57)	(-3.41)	(-2.96)	(-3.85)	(-3.43)	(-3.78)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Number of observations	7185	7185	3265	3265	2120	2120
R-squared	0.43	0.50	0.52	0.63	0.50	0.68

Panel C: Loan growth vs. non-loan asset growth

	1-year returns		2-year returns		3-year returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Three-year loan growth	-0.1510**	-0.2299**	-0.1501**	-0.2621***	-0.2233***	-0.3371***
	(-2.04)	(-2.55)	(-2.17)	(-2.85)	(-2.85)	(-3.43)
Three-year non-loan	0.0548	-0.0222	0.0479	0.0042	0.1009	0.1011
asset growth	(0.61)	(-0.21)	(0.48)	(0.03)	(0.96)	(0.74)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Number of observations	6834	6834	3130	3130	2002	2002
R-squared	0.45	0.51	0.54	0.65	0.52	0.68

Table 6: Relationship between loan growth and the probability of left tail returns

The table presents results from a linear probability model, predicting the probability of a return below the fifth percentile using a bank's loan growth as well as time fixed effects and, where indicated, bank fixed effects. The dependent variable equals one if the bank experiences a return below the fifth percentile over the subsequent 1-, 2-, or 3-year period, respectively, and zero otherwise. The fifth percentile is -45.7%, -38.1%, and -30.3% for 1-, 2-, and 3-year annualized returns, respectively. Banks are sorted into quartiles based on loan growth during the previous three years, respectively. Indicator variables representing each quartile are included in the regression with the lowest growth quartile forming the base group. The sample period is 1972 – 2014. The sample includes all banks whose real assets in 2013 dollars are greater than $2 billion. For regressions using subsequent two-year and three-year return periods, overlapping periods are dropped to avoid inflating *t*-statistics due to serial correlation. Standard errors allow for clustering at the bank and time levels. Numbers in parentheses are *t*-statistics. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

	1-year returns		2-year returns		3-year returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Growth quartile 2	-0.0069	0.0086	-0.0012	0.0225**	0.0252*	0.0365**
	(-0.88)	(0.89)	(-0.16)	(2.16)	(1.87)	(2.36)
Growth quartile 3	-0.0070	0.0062	0.0008	0.0208	0.0206	0.0347**
	(-0.84)	(0.61)	(0.06)	(1.33)	(1.58)	(2.24)
Growth quartile 4	0.0228	0.0174	0.0464*	0.0540*	0.0575**	0.0580**
	(1.47)	(1.00)	(1.80)	(1.70)	(2.46)	(2.42)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Number of observations	6834	6834	3130	3130	2002	2002
R-squared	0.19	0.36	0.20	0.43	0.15	0.48

Table 7: Relationship between three-year loan growth and profitability / loan loss provisions

The table presents regressions of bank profitability and loan loss provisions, respectively, on a bank's loan growth as well as time fixed effects and, where indicated, bank fixed effects. Banks are sorted into quartiles based on loan growth during the previous three years. Indicator variables representing each quartile are included in the regression with the lowest growth quartile forming the base group. Profitability is defined as the bank's ROA (in percent), calculated as net income divided by total assets multiplied by 100. Loan loss provisions are defined as loan loss provisions divided by total gross loans multiplied by 100. The sample period is 1972 – 2014. The sample includes all banks whose real assets in 2013 dollars are greater than $2 billion. Standard errors allow for clustering at the bank and time levels. Numbers in parentheses are *t*-statistics. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Panel A: ROA levels

	ROA_t		ROA_{t+1}		ROA_{t+2}		ROA_{t+3}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Growth quartile 2	0.2438***	0.1627***	0.1565***	0.0464	0.0451	-0.0757*	-0.0404	-0.1605***
	(5.71)	(5.14)	(4.55)	(1.53)	(1.15)	(-1.96)	(-1.06)	(-4.12)
Growth quartile 3	0.2882***	0.2200***	0.1803***	0.0801**	0.0386	-0.0796*	-0.0366	-0.1632***
	(4.90)	(4.92)	(3.94)	(2.02)	(0.75)	(-1.71)	(-0.57)	(-2.94)
Growth quartile 4	0.2133***	0.2340***	0.1034*	0.0993*	-0.0549	-0.0697	-0.1557***	-0.1739***
	(3.38)	(4.33)	(1.77)	(1.92)	(-0.82)	(-1.05)	(-2.64)	(-2.93)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	6832	6832	6687	6687	6152	6152	5644	5644
R-squared	0.25	0.51	0.24	0.50	0.24	0.51	0.23	0.52

Panel B: ROA changes

	ROA_{t+1} - ROA_t		ROA_{t+2} - ROA_{t+1}		ROA_{t+3} - ROA_{t+2}		ROA_{t+3} - ROA_t	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Growth quartile 2	-0.0845***	-0.1138***	-0.0868***	-0.1089***	-0.0701**	-0.0780**	-0.2181***	-0.2582***
	(-3.14)	(-3.12)	(-3.14)	(-3.37)	(-2.39)	(-2.40)	(-3.39)	(-3.09)
Growth quartile 3	-0.0944***	-0.1238***	-0.1143***	-0.1368***	-0.0784*	-0.0868**	-0.2741***	-0.3471***
	(-2.90)	(-3.00)	(-3.39)	(-3.64)	(-1.78)	(-2.00)	(-3.24)	(-3.19)
Growth quartile 4	-0.0968***	-0.1146**	-0.1252***	-0.1378***	-0.0926**	-0.0891**	-0.3237***	-0.3825***
	(-2.78)	(-2.34)	(-3.08)	(-2.84)	(-2.25)	(-2.10)	(-3.48)	(-2.82)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	6686	6686	6151	6151	5643	5643	1969	1969
R-squared	0.13	0.19	0.13	0.18	0.12	0.19	0.26	0.45

Panel C: Loan loss provision (LLP) levels

	LLP_t		LLP_{t+1}		LLP_{t+2}		LLP_{t+3}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Growth quartile 2	-0.2943***	-0.2275***	-0.1629***	-0.0640	-0.0308	0.0831*	0.0236	0.1354***
	(-5.28)	(-5.27)	(-3.20)	(-1.49)	(-0.63)	(1.71)	(0.52)	(2.77)
Growth quartile 3	-0.3718***	-0.3442***	-0.1672***	-0.0941*	0.0081	0.1118*	0.0725	0.1813***
	(-5.40)	(-6.42)	(-2.81)	(-1.72)	(0.14)	(1.93)	(1.11)	(2.76)
Growth quartile 4	-0.3811***	-0.4233***	-0.1379**	-0.1276*	0.0597	0.1033	0.1739***	0.2272***
	(-5.31)	(-6.36)	(-2.24)	(-1.91)	(0.92)	(1.34)	(2.68)	(3.08)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	6791	6791	6659	6659	6141	6141	5637	5637
R-squared	0.33	0.51	0.31	0.50	0.31	0.51	0.31	0.53

Panel D: Loan loss provision (LLP) changes

	LLP_{t+1} - LLP_t		LLP_{t+2} - LLP_{t+1}		LLP_{t+3} - LLP_{t+2}		LLP_{t+3} - LLP_t	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Growth quartile 2	0.1293***	0.1625***	0.1090***	0.1308***	0.0606	0.0678	0.3142***	0.3704***
	(2.90)	(3.48)	(2.68)	(3.18)	(1.48)	(1.50)	(3.17)	(3.17)
Growth quartile 3	0.1859***	0.2253***	0.1594***	0.1841***	0.0798	0.0823	0.4222***	0.5181***
	(4.22)	(4.70)	(4.06)	(4.60)	(1.49)	(1.39)	(3.39)	(3.28)
Growth quartile 4	0.2293***	0.2696***	0.1795***	0.1987***	0.1186**	0.1156*	0.4936***	0.6117***
	(5.04)	(5.04)	(3.75)	(3.88)	(2.05)	(1.81)	(3.62)	(3.11)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	6641	6641	6127	6127	5634	5634	1954	1954
R-squared	0.24	0.28	0.23	0.27	0.23	0.27	0.37	0.46

Table 8: Are analysts too optimistic about banks with high three-year loan growth?

The table presents regressions of analyst forecast errors and analyst forecast revisions, respectively, on a bank's loan growth as well as time fixed effects and, where indicated, bank fixed effects. Banks are sorted into quartiles based on loan growth during the previous three years, that is fiscal years t-2, t-1, and t. Indicator variables representing each quartile are included in the regression with the lowest growth quartile forming the base group. SUE_{t+x} are standardized unexpected earnings for year t+x, calculated as the difference between actual earnings for fiscal year t+x and the time t forecast for fiscal year t+x earnings, divided by the stock price as of the day of the time t forecast. To allow analysts to incorporate all information from fiscal year t, the time t forecast is the median analyst earnings forecast as of the fourth month after the conclusion of fiscal year t, taken from I/B/E/S. $Revision_{t+1}$ is the difference between the time t+1 forecast for fiscal year t+2 and the time t forecast for fiscal year t+2, divided by the stock price as of the time t forecast. $Revision_{t+2}$ is the difference between the time t+2 forecast for fiscal year t+3 and the time t forecast for fiscal year t+3, divided by the stock price as of the time t forecast. $E_{t+x}(g)$ is the median analyst's expectation as of time t+x for the long-term growth rate of the bank's earnings. The sample period is 1975 – 2014. The sample includes all banks whose real assets in 2013 dollars are greater than $2 billion. The calculation procedure for SUEs and revisions produces many large outliers. In Panel A, we remedy this issue by estimating median regressions. T-statistics for the median regressions are estimated using bootstrapped standard errors. The bootstrap was performed using 500 replications each for firm clustering, time clustering and no clustering. The double-clustered variance-covariance matrix (VCV) is calculated by subtracting the unclustered VCV from the sum of the firm-clustered plus the time-clustered VCV. The table shows how many of the replications were successful at each step. Unsuccessful replications either did not converge or encountered a variance-covariance matrix that could not be calculated due to a lack of observations. Regressions including bank fixed effects in Panel A include only those banks for which a minimum of five observations are available. Results for the long-term growth rate in Panels B and C are estimated using ordinary least squares and allowing for standard error clustering at the bank and time levels. Numbers in parentheses are *t*-statistics. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Panel A: Intermediate term forecast errors and revisions

	SUE_{t+1} (1)	SUE_{t+1} (2)	SUE_{t+2} (3)	SUE_{t+2} (4)	SUE_{t+3} (5)	SUE_{t+3} (6)	$Revision_{t+1}$ (7)	$Revision_{t+1}$ (8)	$Revision_{t+2}$ (9)	$Revision_{t+2}$ (10)
Growth quartile 2	-0.0004	-0.0016**	-0.0013	-0.0032**	-0.0020	-0.0053	-0.0003	-0.0020**	0.0008	-0.0011
	(-0.72)	(-2.44)	(-1.22)	(-2.03)	(-0.54)	(-0.81)	(-0.60)	(-2.25)	(0.38)	(-0.33)
Growth quartile 3	-0.0007	-0.0020**	-0.0026*	-0.0060**	-0.0059	-0.0154*	-0.0003	-0.0027**	-0.0018	-0.0070**
	(-1.15)	(-2.48)	(-1.75)	(-2.48)	(-1.40)	(-1.91)	(-0.55)	(-2.19)	(-0.77)	(-2.39)
Growth quartile 4	-0.0013**	-0.0027***	-0.0039**	-0.0068**	-0.0050	-0.0133	-0.0013	-0.0032**	-0.0018	-0.0065
	(-2.13)	(-3.06)	(-2.23)	(-2.50)	(-1.07)	(-1.20)	(-1.48)	(-2.24)	(-0.65)	(-1.52)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Number of successful bootstrap replications:										
Firm clustering:	500	500	500	500	334	424	500	500	326	413
Time clustering:	500	369	500	412	395	426	500	405	414	423
No clustering:	500	292	500	376	325	337	500	376	327	364
Number of observations	5662	5262	4275	3872	878	529	4670	4239	995	622

Panel B: Long-term growth forecast levels

	$E_t(g)$ (1)	$E_t(g)$ (2)	$E_{t+1}(g)$ (3)	$E_{t+1}(g)$ (4)	$E_{t+2}(g)$ (5)	$E_{t+2}(g)$ (6)	$E_{t+3}(g)$ (7)	$E_{t+3}(g)$ (8)
Growth quartile 2	0.3197**	0.2366**	0.3892***	0.3654***	0.2323*	0.2108*	0.2735*	0.2261*
	(2.32)	(2.20)	(2.58)	(2.66)	(1.73)	(1.81)	(1.86)	(1.73)
Growth quartile 3	0.8629***	0.4211***	0.8408***	0.5071***	0.6273***	0.2235*	0.5489***	0.1770
	(4.40)	(2.95)	(4.46)	(3.66)	(3.49)	(1.75)	(3.12)	(1.20)
Growth quartile 4	1.8904***	0.9190***	1.6707***	0.8285***	1.2683***	0.4064***	1.1744***	0.3781**
	(6.57)	(5.76)	(6.04)	(5.22)	(4.93)	(3.06)	(4.92)	(2.53)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	4458	4458	4019	4019	3573	3573	3195	3195
R-squared	0.20	0.60	0.21	0.60	0.20	0.59	0.21	0.60

Panel C: Revisions of long-term growth forecasts

	$E_{t+1}(g)$- $E_t(g)$		$E_{t+2}(g)$- $E_{t+1}(g)$		$E_{t+3}(g)$- $E_{t+2}(g)$		$E_{t+3}(g)$- $E_t(g)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Growth quartile 2	0.0737	0.1193	-0.1086**	-0.1181	-0.0337	-0.0197	0.1130	0.1558
	(0.97)	(1.18)	(-2.20)	(-1.43)	(-0.37)	(-0.15)	(0.39)	(0.33)
Growth quartile 3	0.0040	0.0606	-0.1702***	-0.1967*	-0.0722	-0.0077	-0.3082	-0.1420
	(0.05)	(0.66)	(-3.09)	(-1.79)	(-0.79)	(-0.06)	(-1.11)	(-0.36)
Growth quartile 4	-0.1621**	-0.0355	-0.3502***	-0.2915***	-0.1510**	-0.0094	-0.7300**	-0.5317
	(-2.46)	(-0.38)	(-4.35)	(-2.95)	(-2.03)	(-0.08)	(-2.39)	(-1.24)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	4019	4019	3479	3479	3092	3092	1112	1112
R-squared	0.06	0.14	0.07	0.13	0.07	0.15	0.12	0.33

Table 9: Organic growth vs. growth through mergers

The table presents regressions of bank stock returns on a bank's loan growth during the previous three years as well as time fixed effects and, where indicated bank fixed effects. The regressions distinguish between organic growth and growth through mergers. The sample period is 1978 - 2014. To determine organic loan growth, mergers and acquisitions from the Chicago Fed's M&A database are matched to our sample and target loans as reported on the most recent Call Report are subtracted from the acquirer's fiscal year end loans in the year in which the merger occurred. Data from the FDIC's list of failed banks and from Compustat are substituted where Call Report data are unavailable. Merger-related loan growth is measured as target loans divided by the acquirer's loans. If a bank acquired one or more institutions over the previous three years for which loan data are unavailable, the observation is dropped from the regressions. Banks are sorted into quartiles for organic growth, with the lowest growth quartile serving as the base group for the regressions. For merger growth, all banks without a merger in a given three-year period are included in one group which acts as the base group. The remaining banks are sorted into terciles labeled low/medium/high merger growth. The organic growth sort and the merger growth sort are performed independent of each other. Standard errors allow for clustering at the firm and time levels. Numbers in parentheses are t-statistics. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

	1-year returns		2-year returns		3-year returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Organic growth quartile 2	-0.0229	-0.0419**	-0.0182	-0.0401**	-0.0202	-0.0434***
	(-1.58)	(-2.23)	(-1.55)	(-2.50)	(-1.43)	(-2.96)
Organic growth quartile 3	-0.0303	-0.0566**	-0.0297*	-0.0641***	-0.0404**	-0.0710***
	(-1.59)	(-2.54)	(-1.80)	(-3.61)	(-2.53)	(-4.32)
Organic growth quartile 4	-0.0388*	-0.0655**	-0.0440**	-0.0808***	-0.0638***	-0.0977***
	(-1.67)	(-2.29)	(-2.07)	(-2.94)	(-3.19)	(-3.34)
Low merger growth	0.0010	-0.0107	0.0132	-0.0045	0.0146**	-0.0030
	(0.08)	(-0.90)	(1.08)	(-0.35)	(2.31)	(-0.21)
Medium merger growth	-0.0171	-0.0384***	-0.0073	-0.0303*	-0.0011	-0.0188
	(-1.33)	(-2.58)	(-0.58)	(-1.91)	(-0.07)	(-0.92)
High merger growth	-0.0369***	-0.0627***	-0.0344**	-0.0623***	-0.0357**	-0.0610***
	(-3.03)	(-3.88)	(-2.57)	(-3.45)	(-2.40)	(-2.71)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Number of observations	5529	5529	2489	2489	1592	1592
R-squared	0.42	0.49	0.50	0.63	0.49	0.68

Table 10: Relationship between organic growth, merger growth, and profitability / loan loss provisions

The table presents regressions of bank profitability and loan loss provisions, respectively, on a bank's three-year organic loan growth, its three-year merger growth, as well as time fixed effects and, where indicated, bank fixed effects. Organic growth and growth through mergers are defined as in Table 9. Banks are sorted into quartiles for organic growth, with the lowest growth quartile serving as the base group for the regressions. For merger growth, all banks without a merger in a given three-year period are included in one group which acts as the base group. The remaining banks are sorted into terciles labeled low/medium/high merger growth. The organic growth sort and the merger growth sort are performed independently. Profitability is defined as the bank's ROA (in percent), calculated as net income divided by total assets multiplied by 100. Loan loss provisions are defined as loan loss provisions divided by total gross loans multiplied by 100. The sample period is 1978 – 2014. The sample includes all banks whose real assets in 2013 dollars are greater than $2 billion. Standard errors allow for clustering at the bank and time levels. Numbers in parentheses are *t*-statistics. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Panel A: ROA levels

	ROA_t		ROA_{t+1}		ROA_{t+2}		ROA_{t+3}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Organic growth quartile 2	0.2267***	0.1546***	0.1798***	0.0744**	0.0493	-0.0761*	-0.0062	-0.1308**
	(4.70)	(3.97)	(3.83)	(1.98)	(1.02)	(-1.86)	(-0.13)	(-2.51)
Organic growth quartile 3	0.2732***	0.2418***	0.1699***	0.0987**	0.0200	-0.0905*	-0.0923	-0.2091***
	(4.50)	(4.24)	(3.32)	(2.03)	(0.36)	(-1.69)	(-1.22)	(-2.86)
Organic growth quartile 4	0.2491***	0.3196***	0.1334**	0.1778***	-0.0659	-0.0555	-0.1795***	-0.1799**
	(3.56)	(4.74)	(2.30)	(3.07)	(-1.01)	(-0.75)	(-2.73)	(-2.53)
Low merger growth	0.1344***	-0.0249	0.1463***	-0.0545	0.1420***	-0.0840*	0.1722***	-0.0311
	(4.31)	(-0.81)	(4.06)	(-1.50)	(3.54)	(-1.86)	(4.31)	(-0.75)
Medium merger growth	0.1226***	-0.0178	0.1052***	-0.0831**	0.1157***	-0.0875*	0.1351***	-0.0326
	(3.92)	(-0.53)	(2.62)	(-2.00)	(2.72)	(-1.90)	(2.91)	(-0.73)
High merger growth	0.0810*	-0.0231	0.0653	-0.0853	-0.0187	-0.1970**	0.0326	-0.1045
	(1.87)	(-0.58)	(0.95)	(-1.41)	(-0.21)	(-2.43)	(0.42)	(-1.58)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	5529	5529	5409	5409	4905	4905	4430	4430
R-squared	0.26	0.52	0.25	0.51	0.24	0.52	0.24	0.52

Panel B: Loan loss provision (LLP) levels

	LLP_t		LLP_{t+1}		LLP_{t+2}		LLP_{t+3}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Organic growth quartile 2	-0.2994***	-0.2325***	-0.1896***	-0.0873**	-0.0461	0.0766	-0.0066	0.1255**
	(-4.68)	(-4.83)	(-3.66)	(-2.08)	(-0.76)	(1.46)	(-0.12)	(1.97)
Organic growth quartile 3	-0.3944***	-0.3688***	-0.2062***	-0.1223**	-0.0178	0.1079	0.0540	0.1921**
	(-5.20)	(-5.95)	(-3.27)	(-2.05)	(-0.25)	(1.57)	(0.63)	(2.16)
Organic growth quartile 4	-0.4382***	-0.5043***	-0.1751***	-0.1715**	0.0511	0.1159	0.1654**	0.2590***
	(-5.03)	(-6.36)	(-2.62)	(-2.41)	(0.70)	(1.28)	(2.06)	(2.60)
Low merger growth	0.0773*	0.0825**	0.0569	0.1004**	0.0225	0.0603	0.0133	0.0201
	(1.65)	(2.06)	(1.04)	(2.12)	(0.38)	(1.16)	(0.22)	(0.40)
Medium merger growth	-0.0150	0.0138	0.0083	0.0923*	-0.0170	0.0538	-0.0359	0.0016
	(-0.41)	(0.35)	(0.18)	(1.92)	(-0.35)	(1.03)	(-0.69)	(0.03)
High merger growth	-0.1048***	-0.0604	-0.0191	0.0820	0.0385	0.1583**	0.0068	0.0933
	(-3.04)	(-1.51)	(-0.34)	(1.43)	(0.54)	(2.26)	(0.09)	(1.31)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	5493	5493	5383	5383	4895	4895	4424	4424
R-squared	0.33	0.53	0.32	0.52	0.31	0.53	0.31	0.54

Table 11: Relationship between loan growth and delistings

Panel A present results from a linear probability model of the probability that a bank will delist within the next one, two or three years, respectively, depending on the bank's loan growth and time fixed effects. Panel B presents regressions of bank stock returns including delisting returns on a bank's loan growth. Banks are sorted into quartiles based on loan growth during the previous three years. Indicator variables representing each quartile are included in the regression with the lowest growth quartile forming the base group. The sample period is 1972 – 2014. The sample includes all banks whose real assets in 2013 dollars are greater than $2 billion. For regressions using subsequent two-year and three-year delistings / returns as the dependent variable, overlapping observations are dropped to avoid inflating *t*-statistics due to serial correlation. Standard errors allow for clustering at the bank and time levels. Numbers in parentheses are *t*-statistics. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Panel A: Probability of delisting

	Delisted within one year		Delisted within two years		Delisted within three years	
	(1)	(2)	(3)	(4)	(5)	(6)
Growth quartile 2	-0.0167**	-0.0162*	-0.0462***	-0.0457***	-0.0366	-0.0318
	(-2.35)	(-1.94)	(-2.73)	(-2.67)	(-1.62)	(-1.25)
Growth quartile 3	-0.0209***	-0.0188**	-0.0391**	-0.0376*	-0.0493*	-0.0440*
	(-2.74)	(-2.07)	(-2.37)	(-1.76)	(-1.91)	(-1.70)
Growth quartile 4	-0.0361***	-0.0468***	-0.0438**	-0.0709***	-0.0474*	-0.0648**
	(-5.04)	(-5.39)	(-2.41)	(-4.10)	(-1.80)	(-2.46)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Number of observations	7090	7090	3548	3548	2428	2428
R-squared	0.03	0.21	0.05	0.36	0.07	0.45

Panel B: Subsequent returns including delisting returns

	1-year returns		2-year returns		3-year returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Growth quartile 2	-0.0105	-0.0310	0.0042	-0.0201	0.0004	-0.0169
	(-0.63)	(-1.59)	(0.23)	(-1.03)	(0.02)	(-0.54)
Growth quartile 3	-0.0243	-0.0515**	-0.0213	-0.0437**	-0.0592**	-0.0874***
	(-1.27)	(-2.34)	(-1.14)	(-2.48)	(-2.54)	(-2.92)
Growth quartile 4	-0.0458**	-0.0712***	-0.0558***	-0.0797***	-0.1202***	-0.1212***
	(-2.28)	(-2.91)	(-2.76)	(-3.36)	(-4.18)	(-3.60)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Number of observations	7088	7088	3459	3459	2341	2341
R-squared	0.43	0.50	0.39	0.56	0.26	0.48