Why Does Fast Loan Growth Predict Poor Performance for Banks?

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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 underperformed the common stock of banks with loan growth in the bottom quartile over the next three years. After the period of high growth, these banks have a lower return on assets and increase their loan loss reserves. The poorer performance of fast-growing banks is not explained by merger activity. The evidence is consistent with banks, analysts, and investors being overoptimistic about the risk of loans extended during bank-level periods of high loan growth. (*JEL* G01, G12, G21)

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Many recent papers have found that credit booms generally end poorly and are followed by poor economic performance (e.g., Baron and Xiong 2017; Jordà, Schularick, and Taylor 2013; Reinhart and Rogoff 2009; Schularick and Taylor 2012). A number of theories have been advanced to explain this phenomenon. Most of the empirical analyses examining these theories have

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focused on country-level evidence. In this paper, we investigate bank-level credit growth and subsequent returns within a single country and ask what the results imply for these theories. We analyze a panel of U.S. publicly listed banks between 1972 and 2014. We find that banks that grow quickly make loans that perform worse than the loans of other banks and that investors and equity analysts do not anticipate the poorer performance. Our evidence is consistent with theories of credit booms that rely on expectation formation mechanisms. According to these theories, banks and investors fail to account fully and in an unbiased way for the risks of loans that banks make during the period of accelerated loan growth.

Macroeconomic rational expectations approaches to explaining why credit booms are followed by poor economic performance rely on shocks to lending opportunities. A positive shock leads banks to lend more as they have better opportunities to lend. Adverse economic shocks then decrease the quality of the loans, are accompanied by poor economic performance, and lead banks to become more fragile and lend less.[1] The recent evidence by Krishnamurthy and Muir (2015) that credit spreads are low before crises and the evidence of López-Salido, Stein, and Zakrajšek (2017) that low credit spreads predict lower economic activity would be consistent with this possibility if markets were efficient because these results indicate that investors' expectations of credit losses are low immediately before crises.

Alternatively, a credit boom could occur because of expectations that fail to take risks correctly into account, so that lenders and market participants become too optimistic about the risks of new lending opportunities (e.g., Kindleberger 1978; Minsky 1977). When the ignored risks are revealed or when the factors that led to overoptimistic expectations are no longer present, investors and bankers reassess the quality of the loans. At that time, reserves are increased, bank stock prices underperform, banks reduce their lending, and analysts are surprised by bank earnings. Bordalo, Gennaioli, and Shleifer (BGS; forthcoming) model credit cycles using what they call "diagnostic expectations," and according to which "agents overweight future outcomes that have become more likely in light of incoming data." They show that a model that uses this expectation formation mechanism can explain why credit booms and periods of low credit spreads are followed by periods of high credit spreads and poor economic performance.[2]

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[1] For example, Bernanke and Gertler (1989) or Kiyotaki and Moore (1997). Mian and Sufi (2009, 2010) argue that this view was 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] 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. A critical component of these models is that investors are assumed to neglect some risk, but its materialization sharply changes their understanding of the distribution of risks.

Both rational expectations and biased expectations theories imply that loans grow quickly before eventually leading to unexpected bank losses. We show that this result holds for our sample of individual banks. But we also provide evidence that the pattern of loan growth and poor subsequent performance for individual banks is not tied to the performance of the economy as a whole or to regional economic performance. The latter results are difficult to reconcile with a purely macroeconomic rational expectations theory of credit booms. That poor bank performance following bank-level credit booms is predictable and that the market and analysts fail to anticipate this fact is difficult to reconcile with the rational expectations theory. Alternatively, the expectation mechanism in BGS starts from a kernel of truth, but excessively extrapolates from it. Hence, at the bank level, we would expect bank loan growth to start from a positive shock, but then the market and the bank would favor loan growth beyond what is supported by the positive shock. That many banks are, at different times, banks with high lending growth and banks with low lending growth in our sample is consistent with that type of expectation mechanism and inconsistent with lasting differences across banks because of business models, ownership, or incentives.

Our evidence shows that high credit growth at the bank level compared to other banks leads to poor performance. The literature shows that high credit growth at the country level leads to poor performance. With the theory of BGS, the two phenomena are related in that high credit growth leads to overly optimistic expectations. Whether investors assess aggregate credit growth or bank-level credit growth, their expectations can become too optimistic. In both cases, they can become too optimistic time after time because each episode has its own narrative (Shiller 2017), and hence they can view each episode as different (see Reinhart and Rogoff 2009). At the bank level, good performance associated with high loan growth can be attributed to new unique factors each time: a new risk management approach, better training for loan officers, new types of mortgages, greater economic prospects, and so on.

We first examine whether high bank loan growth predicts poor future bank stock returns, following the methodology of Baron and Xiong's (2017) country-level analysis. If banks quickly grow because they make risky loans, they will experience higher loan losses following a period of high growth. If the banks and their investors properly understand that high growth is 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 variations 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. Unlike loan growth, nonloan 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. We obtain the same results with returns adjusted by using a characteristic-based benchmark return like in Daniel et al. (1997) that uses either all firms or only banks, as well as when we use the Fama and French (2015) multifactor model. Using a three-year holding period and the Fama and French (2015) model, we find that the monthly alpha for the strategy of going long a low loan growth bank portfolio and short a high loan growth bank portfolio is 0.43% per month for a value-weighted portfolio. The monthly alpha corresponds to a greater than 5% annual return, which is highly economically significant. Since the portfolio is value weighted, the evidence from this alternative approach also indicates that our results are not driven by small banks.

Next, we turn to whether banks that grow faster make poorer loans. We first investigate the evolution of the return on assets (ROA). We find that the fast-growing banks have a much higher ROA than the banks in the quartile with lowest growth in the formation year. However, by year three 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 three after formation, the high-growth banks have significantly higher loan loss provisions than the low-growth banks.

Our evidence suggests 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 reserves 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; 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 demonstrate that high organic growth leads to lower stock returns even after controlling for growth through mergers. 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 decrease in ROA and the increase in loan loss provisions are 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 indicates that banks do not fully appreciate the risk of the loans they are making when they grow quickly. Such an outcome is in line with theories that rely on biased expectations or neglected risks. 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 have incentives to grow their bank's loan portfolio quickly to gain greater compensation in the short run even if doing so is not optimal for the long run and they might attempt to disguise the greater riskiness of the loans. We call these latter two explanations the agency explanations. The first explanation is about agency problems within the firm. The second explanation is about agency problems between managers and shareholders.

Our evidence is more supportive of the biased expectations hypothesis than the agency hypotheses. First, we find that analysts are systematically too optimistic about high loan growth banks, in that they expect these banks to grow much faster over the next five years than other banks and overestimate their profitability. Such a pattern is precisely what is predicted by BGS. Second, with the agency hypotheses, high loan growth banks would be acting suboptimally for their shareholders over a long period of time in the United States in ways that auditors, investors, analysts, boards, and regulators could attempt to discern and correct. For all these parties to fail to do so for more than forty years when they know about the risk seems to be implausible. In addition, since our results involve ordinary bank loans over a long time period, the loan officer agency explanation would require that rank-and-file bankers game their incentives at the beginning of their career, but forget about how they did so once they become executives, or, alternatively, only those bankers who do not game their incentives become executives and they do not learn from their colleagues' activities. Finally, it is also important to note that our results hold for periods that greatly differ in the type of incentive contracts used by banks, as these contracts made use of options mostly in the later years of our sample.

An important issue with our evidence is whether there is something unique about loans. After all, we know from the asset pricing literature that firms that grow more have poorer returns (e.g., Cooper, Gulen, and Schill 2008; Hou, Xue, and Zhang 2015; Polk and Sapienza 2009; Titman, Wei, and Xie 2004). Empirically, we show that our evidence is distinct from the growth anomaly of the asset pricing literature, in that the poor performance of banks that have experienced high relative lending growth cannot be explained by the growth factor used in the asset pricing literature (Hou, Xue, and Zhang 2015). Specifically, we find that a strategy of going long a low-loan growth bank portfolio and short a high-loan growth bank portfolio has an economically significant alpha when using a multifactor model that accounts for the asset growth anomaly. There are good reasons to think that bank loans are different. First, banks produce loans. The loans that are relevant for our study are loans that stay on bank balance sheets. When a manufacturer produces more goods, these goods do not stay on the manufacturer's balance sheet. They are not assets for the manufacturer. As a result, poor performance of loans directly impacts the earnings of a bank by reducing the value of assets of the bank. In contrast, if a manufacturer's products perform poorly, the loss to the manufacturer is indirect. Second, the buyer of a good sold by a manufacturer has strong incentives to make sure that the good meets expectations. In contrast, a bank's borrower has no incentive to tell the bank that its creditworthiness is not as good as assessed by the bank. Third, unless loans have a very short maturity or in fairly extreme circumstances, it will generally take time for outsiders to realize that a bank has been too optimistic about the quality of its loans. Fourth, the performance of the loans may be endogenous to the lending policy of the bank. If a bank grows its book of loans in a specific sector because it believes that this sector has great prospects, it may lend too much to that sector, so that the sector itself grows too much and the loans perform poorly because of oversupply.

There is evidence in the literature of industry booms followed by busts. Credit booms are different from industry booms in general in that they have economy-wide consequences that industry-specific booms generally do not have. One explanation for industry booms in the literature emphasizes competition neglect, namely, that firms do not fully internalize the impact of industry competition on their performance (e.g., Hoberg and Phillips 2010). Such an explanation does not appear to be directly relevant to credit booms, but may be indirectly in that lenders may fail to fully take into account the impact of their lending on the supply of the goods whose production they finance. For instance, a lender might conclude that single-family housing offers good collateral, but might neglect that other lenders think the same, so that there may be an oversupply of such housing. This mechanism still relies on lenders being more optimistic about the performance of loans than they should rationally be. Greenwood and Hanson (2015) explain waves in ship prices by combining competition neglect and extrapolative expectations. Another explanation for booms within an industry is herding. This explanation is pursued by Povel et al. (2016) in a study of booms in the hotel industry. They show that hotels built during local hotel construction booms underperform for decades. They find their evidence to be consistent with information-based herding explanations, where seeing hotels being built leads to more building because it indicates that it is worthwhile to build hotels, but since this is not always the case, as some hotels could be built because of very specific opportunities, hotels built in booms underperform. Our results do not seem to be the result of banks' herding. Our evidence does not appear to reflect local booms involving many lenders. Further, we find that the banks that perform the worst are those that experience the highest lending growth when there is not an aggregate lending boom. However, we cannot exclude that there is herding among borrowers and that the herding then explains the poor performance of loans.

Our paper is related to the strand of the literature that examines whether financial institutions made poorer loans during the recent credit crisis.[3] Papers documenting reduced credit quality during credit expansions and subsequent bad economic outcomes prior to and during the recent crisis include Dell'Ariccia, Igan, and Laeven (2012), 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, Igan, and Laeven (2012), 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.[4] 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 more than forty years and not periods immediately preceding a crisis. Greenwood and Hanson (2013) present evidence of deteriorating credit quality during boom times for the corporate bond market over the last century. López-Salido, Stein, and Zakrajšek (2017) 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. Contrary to our analysis, 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 boost a bank's reported profitability 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

[3] Brunnermeier (2009) provides an overview of mechanisms, including a lending supply channel mechanism, that can help explain the recent financial crisis. 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.

[4] It is possible that during times of crises, some loan growth was the result of unexpectedly high take downs of loan commitments and was thus involuntary. Similarly, during the recent financial crisis, it is possible that some loan growth was the result of loans that a bank intended to securitize but was unable to sell at a reasonable price.

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 find importantly that banks, investors, and analysts alike do not appear to understand the increased riskiness of the loans made during periods of sharp loan growth.

Finally, our paper builds on Baron and Xiong (2017), who examine bank credit expansion at the country level for a set of 20 developed countries between 1920 and 2012. They demonstrate 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 (2017) 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. We 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.

1. Sample Construction, Data, and Summary Statistics

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

1.1 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 and 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. In addition, we need at least one year of subsequent returns to be available. 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 nondepository credit institutions, brokerages, and investment banks because we are interested in loan and asset 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, and 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 nondepository credit institution with SIC code 6162 (mortgage bankers & loan correspondents). Afterward, 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.[5]

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 and loan associations are classified in CRSP with SIC codes between 6120 and 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 the 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.

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 because of a nonmerger 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.[6] 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

[5] 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.

[6] In Section 5, we perform tests to rule out that results are driven by survivorship bias.

Table 1
Number of banks per year

	# 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

The table reports the number of banks in the sample each year. Section 1 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 US dollars using the Bureau of Labor Statistics' Consumer Price Index for all urban consumers.

1989 and the onset of the recent financial crisis, our sample consists of about 200 banks each year. The number of banks decreases to 175 toward the end of our sample period.

1.2 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 merger and acquisition (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 Federal Deposit Insurance Corporation (FDIC).

1.3 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.[7] 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 nonoverlapping 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.[8]

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 one-year horizon, and 13.3% at the three-year horizon. Median one-year (three-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 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

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7 If returns are missing for a certain month, we set them to zero for that month.

8 The mean one-year stock return is 15.50%, whereas the mean annualized stock return over nonoverlapping 3-year periods is 11.05%. This discrepancy is not related to outliers, nonoverlapping intervals, or delisting returns. When we compute log returns, there is no difference between the mean one-year return and the annualized three-year return.

Table 2
Summary statistics

	Observations	Mean	SD	Min.	25th perc.	Median	75th perc.	Max.
1-year return	7,914	0.1550	0.3933	−0.9848	−0.0560	0.1290	0.3495	4.2973
2-year return	3,728	0.1255	0.2900	−0.9201	−0.0277	0.1270	0.2938	1.7161
3-year return	2,365	0.1105	0.2314	−0.8277	−0.0057	0.1309	0.2491	1.0031
1-year loan growth	7,330	0.1368	0.1882	−0.2063	0.0308	0.1032	0.1982	1.0081
3-year loan growth	6,834	0.1332	0.1266	−0.1418	0.0531	0.1178	0.1925	0.6210
1-year asset growth	7,717	0.1266	0.1674	−0.1581	0.0315	0.0932	0.1736	0.9434
3-year asset growth	7,185	0.1259	0.1098	−0.1086	0.0569	0.1100	0.1749	0.5655
ROA (%)	7,910	0.7747	0.6531	−2.6099	0.5804	0.8549	1.1084	2.0429
Loan loss provisions (%)	7,431	0.6779	0.7955	−0.1415	0.2426	0.4380	0.7730	4.6592
1-year SUE	6,454	−0.0268	0.1120	−0.7325	−0.0110	−0.0004	0.0050	0.1097
2-year SUE	4,790	−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 growth expectation	4,983	10.0350	3.0024	3.0000	8.0000	10.0000	12.0000	22.5000
Analyst revision$_{t+1}$	5,209	−0.0124	0.0414	−0.2281	−0.0135	−0.0020	0.0038	0.0610
Analyst revision$_{t+2}$	1,025	−0.0181	0.0442	−0.1953	−0.0270	−0.0075	0.0039	0.1000

The first seven rows show summary statistics for one-, two-, and three-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 nonoverlapping returns are used. All multiyear returns as well as three-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: Analyst growth expectation is the current median analyst expected long-term (five-year) EPS growth rate. One-, two-, and three-year SUE are standardized unexpected earnings for the three subsequent fiscal years, respectively, calculated as the difference between actual 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. 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 (e.g., 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.

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% of gross loans as loan loss provisions each year.

Our analysis also uses analyst growth expectations, defined as the median analyst long-term growth expectations as recorded in I/B/E/S. "Long-term" refers to five-year earnings growth forecasts (La Porta 1996). We also calculate 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 demonstrates that average SUEs at all horizons are slightly negative; that is, 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. 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 that 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 3. We do not winsorize stock returns in this paper, but results are quantitatively and qualitatively similar when we do so (unreported results).

1.4 Low- 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 any nonlinearities in the relation between loan growth and performance without a priori assumptions. Second, in some of our tests we employ a portfolio approach for which it is natural to form portfolios based on quartiles. We also present 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 line corresponds to the median loan growth for the banks in the lowest growth quartile, and the dashed line plots 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

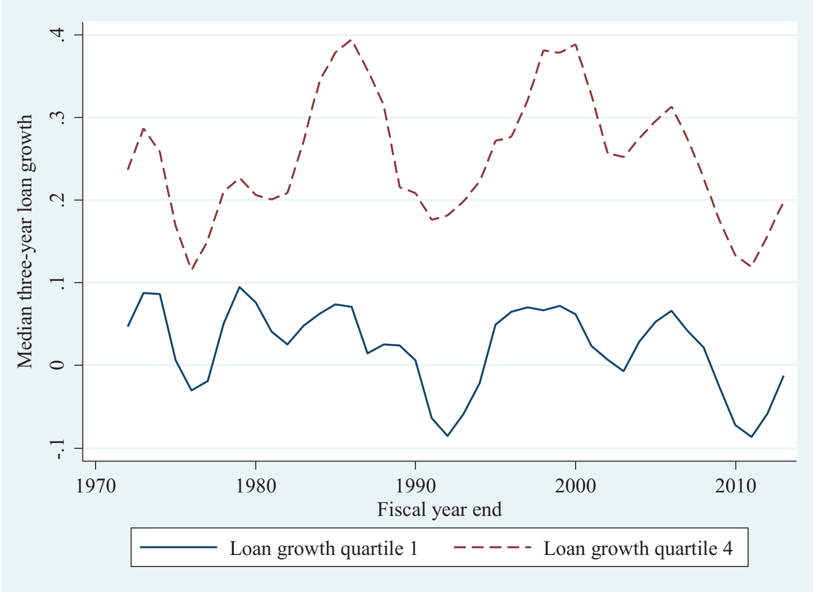

Figure 1
Median three-year loan growth for high versus low three-year loan growth quartiles
The figure shows the time series of the median three-year loan growth rate for two groups of banks. Every year, we classify banks into four groups based on loan growth quartiles. The solid line shows the median three-year loan growth rate for banks in the lowest quartile of loan growth. The dashed line shows the median three-year loan growth rate for banks in the highest quartile of loan growth. The sample period is 1972 to 2013.

from a low of about 10% in the late 1970s to a high of 33% in the late 1990s. 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 4, 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, median loan growth rates for low-growth banks are below zero and median loan growth rates for high-growth banks are below 20% during the recent financial crisis.

Table 3 provides summary statistics of several bank characteristics by growth quartile to get an overview of the differences between the high- and low-growth banks. High- and low-growth banks differ along several characteristics. The economically largest differences are that high-growth banks are larger, have lower book-to-market ratios, are younger, and have higher total capitalization ratios.[9] They perform better, as they have a higher return on assets, a higher

[9] High-growth banks have a lower Tier 1 capital ratio that takes risk-weighted assets into account. Unfortunately, this variable is only available for less than half of our sample period.

Table 3
Summary statistics by loan growth quartile

	Loan growth quartile				
	1	2	3	4	4-1 ($Chi^2(1)$)
Beta	0.8224	0.7272	0.7406	0.7817	−0.0406* (3.06)
log (Market capitalization)	5.9749	6.0917	6.1117	6.2930	0.3181*** (27.86)
Book-to-market	0.9029	0.7774	0.7546	0.7436	−0.1593*** (62.55)
Prior year return	0.1119	0.1269	0.1336	0.1381	0.0195* (3.09)
Prior 3-year return	0.0807	0.1311	0.1377	0.1587	0.0780*** (102.60)
Return on assets	0.7549	0.9046	0.9110	0.8581	0.1032*** (37.19)
Return on equity	11.023	12.485	12.993	12.639	1.617*** (50.74)
Loan loss provisions	0.5542	0.4409	0.4126	0.4121	−0.1420*** (71.20)
Long-term growth forecast	9.00	9.50	10.00	11.00	2.00*** (188.75)
Idiosyncratic volatility	0.0349	0.0316	0.0320	0.0331	−0.0019*** (14.26)
Loans-to-assets	0.5815	0.6066	0.6196	0.6173	0.0357*** (60.94)
Bank age	67.00	72.00	49.00	30.00	−37.00*** (36.45)
Tier 1 capital ratio	10.94	10.89	10.76	10.34	−0.61*** (8.09)
Equity-to-assets ratio (market)	0.0778	0.0982	0.1022	0.0990	0.0212*** (35.54)
Equity-to-assets ratio (book)	0.0696	0.0736	0.0729	0.0704	0.0009 (0.95)

The table shows medians for bank characteristics by loan growth quartile. Beta is estimated using weekly return regressions over the two years prior to the current fiscal year end and idiosyncratic volatility is the root mean squared error from that regression. Market capitalization is defined as the number of common shares outstanding multiplied by the stock price at the end of the current fiscal year. Book-to-market is book equity divided by market capitalization. The prior year return is the bank's stock return from the end of the previous fiscal year until the end of the current fiscal year. The prior three-year return is the bank's annualized stock return from the end of the fiscal year that ended three years ago until the end of the current fiscal year. The return on assets is net income divided by total assets multiplied by 100. The return on equity is net income divided by the book value of common equity multiplied by 100. Loan loss provisions are defined as loan loss provisions divided by total gross loans multiplied by 100. The long-term growth forecast is the median analyst's expectation as of time t for the long-term growth rate of the bank's earnings. 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. Loans-to-assets is total loans to customers divided by total assets. Bank age is the current fiscal year minus the year the bank was established, as recorded in Capital IQ. The Tier 1 capital ratio is obtained from the financial services view of Compustat. The equity-to-assets ratio (market) is defined as market capitalization divided by total assets minus the book value of common equity plus market capitalization. The equity-to-assets ratio (book) is common equity divided by total assets. Book-to-market, return on assets, return on equity, loan loss provisions, and the equity-to-assets ratio are winsorized at the 1st and 99th percentile. The last column shows the results of a chi-square test for a test of difference in medians between quartile 4 and quartile 1.

return on equity, and fewer loan loss provisions. Interestingly, high loan growth banks had significantly higher stock returns during the three years over which we measure the loan growth. The market seems to have appreciated the high loan growth while it was forming.

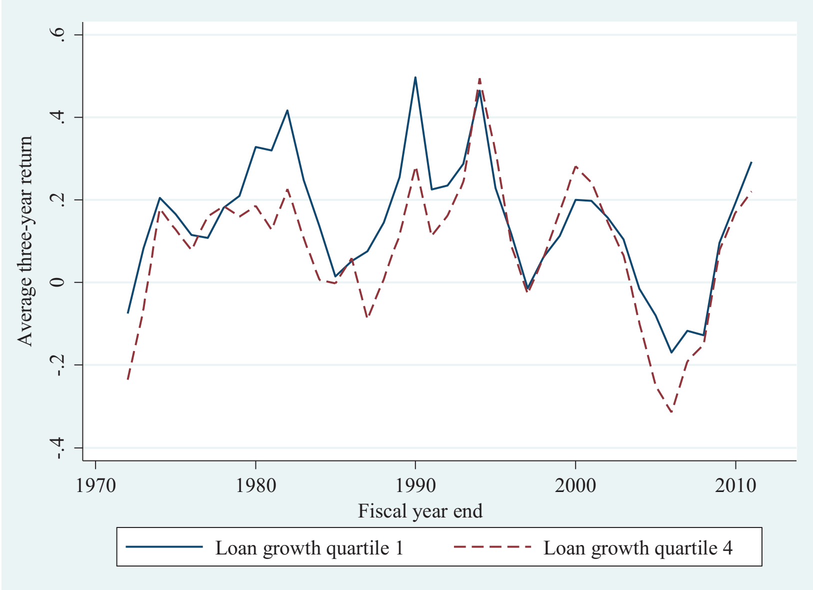

Figure 2
Average three-year subsequent return for high versus low three-year loan growth quartiles
The figure shows the time-series of the average three-year subsequent returns for two groups of banks. Every year, we classify banks into four groups based on loan growth quartiles. The solid line shows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

2. Loan and Asset Growth and Subsequent Returns

Figure 2 presents a plot of the time-series of the average three-year subsequent nonoverlapping returns for two groups of banks over our sample period. The solid line corresponds to the average three-year subsequent stock return for banks in the lowest quartile of loan growth. The dashed line represents the average three-year subsequent stock return for banks in the highest quartile of loan growth. The figure demonstrates 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 and early 2000s.

We now estimate regressions of subsequent returns on loan growth. In Table 3, we follow Baron and Xiong (2017) and estimate

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

and

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

Table 4
Relationship between loan growth and subsequent returns

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 FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Number of observations	7,330	7,330	3,377	3,377	2,096	2,096
R-squared	.44	.51	.54	.64	.50	.67

B. Three-year loan growth

	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 FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Number of observations	6,834	6,834	3,130	3,130	2,002	2,002
R-squared	.45	.51	.54	.65	.52	.69

C. Three-year loan growth, aligning all banks' returns on the same time line

	1	2	3	4	5	6
Growth quartile 2	−0.0213	−0.0410**	−0.0280**	−0.0532***	−0.0269**	−0.0468***
	(−1.29)	(−2.09)	(−2.49)	(−4.26)	(−2.10)	(−2.74)
Growth quartile 3	−0.0292	−0.0577***	−0.0322**	−0.0628***	−0.0352*	−0.0620***
	(−1.50)	(−2.63)	(−2.02)	(−3.72)	(−1.85)	(−2.66)
Growth quartile 4	−0.0531**	−0.0812***	−0.0618***	−0.0923***	−0.0790***	−0.1171***
	(−2.42)	(−3.15)	(−2.69)	(−3.65)	(−3.41)	(−4.03)
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Number of observations	6,834	6,834	3,199	3,199	2,011	2,011
R-squared	.45	.51	.52	.63	.49	.66

(*continued*)

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 jth loan growth quartile of all banks in year t, and zero otherwise. The difference between equation (1) and (2) is that equation (2) contains bank fixed effects α_i. We estimate these regressions for subsequent one-, 2-, 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.

Table 4 presents the results. Each panel in Columns 1, 3, and 5 reports 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. Panel A shows results conditioning on one-year loan growth, and panel B conditions on three-year loan growth. In panel A, we see that one-year loan growth has little

Table 4
Continued

D. Three-year loan growth, Driscoll and Kraay (1998) standard errors

	1-year returns		2-year returns		3-year returns	
	1	2	3	4	5	6
Growth quartile 2	−0.0213	−0.0410*	−0.0206**	−0.0426***	−0.0217**	−0.0434***
	(−1.17)	(−1.81)	(−2.27)	(−3.50)	(−2.63)	(−4.40)
Growth quartile 3	−0.0292	−0.0577**	−0.0322**	−0.0610***	−0.0347***	−0.0648***
	(−1.40)	(−2.44)	(−2.26)	(−3.62)	(−2.94)	(−5.15)
Growth quartile 4	−0.0531*	−0.0812**	−0.0577**	−0.0890***	−0.0601***	−0.0873***
	(−1.96)	(−2.60)	(−2.65)	(−3.62)	(−3.06)	(−4.47)
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Number of observations	6,834	6,834	6,267	6,267	5,738	5,738
R-squared	.45	.51	.50	.61	.49	.64

E. Three-year loan growth, Driscoll and Kraay (1998) standard errors, interaction with macroeconomic growth

	1	2	3	4	5	6
Growth quartile 2	−0.0241*	−0.0456**	−0.0223***	−0.0461***	−0.0231***	−0.0464***
	(−1.71)	(−2.49)	(−2.80)	(−4.18)	(−2.93)	(−4.69)
Growth quartile 3	−0.0322*	−0.0623***	−0.0346***	−0.0653***	−0.0362***	−0.0683***
	(−1.94)	(−3.32)	(−2.77)	(−4.76)	(−3.20)	(−5.83)
Growth quartile 4	−0.0559**	−0.0857***	−0.0592***	−0.0923***	−0.0611***	−0.0900***
	(−2.31)	(−3.41)	(−2.80)	(−4.12)	(−3.13)	(−4.73)
Growth quartile 2 × Δ credit/GDP	0.0325**	0.0387**	0.0128**	0.0200***	0.0072*	0.0136**
	(2.32)	(2.44)	(2.68)	(2.88)	(1.92)	(2.34)
Growth quartile 3 × Δ credit/GDP	0.0356**	0.0426**	0.0204**	0.0299***	0.0088	0.0180**
	(2.03)	(2.34)	(2.39)	(3.14)	(1.35)	(2.50)
Growth quartile 4 × Δ credit/GDP	0.0331	0.0481**	0.0114	0.0269**	0.0049	0.0162**
	(1.53)	(2.25)	(0.89)	(2.32)	(0.58)	(2.11)
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Number of observations	6,834	6,834	6,267	6,267	5,738	5,738
R-squared	.45	.52	.50	.61	.49	.64

The table presents results from regressions of bank stock returns on a bank's loan growth. Banks are sorted into quartiles based on loan 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. The sample period is 1972 to 2013. 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 in panels A and B to avoid inflating t-statistics due to serial correlation. In panel C, we align returns on the same three-year period. For subsequent two-year returns, we use all available observations in 1972, skip 1973, use 1974, skip 1975, and so on. For subsequent three-year returns, we use all available observations in 1972, skip 1973 and 1974, use 1975, skip 1976 and 1977, and so on. In the regressions of panels A–C, standard errors allow for clustering at the bank and time levels. In panels D and E, two- and three-year subsequent returns are overlapping. Those regressions use Driscoll-Kraay (1998) standard errors instead to account for cross-sectional clustering and serial correlation. In panel E, Δ credit/GDP represents the change in total bank credit to the private nonfinancial sector as a percentage of GDP over the past three years, divided by three. Numbers in parentheses are t-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

predictive power for subsequent returns in the regressions without bank fixed effects. We find some predictability for two- and three-year subsequent returns in Columns 4 and 6. Column 6, for example, demonstrates 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. Because these regressions include bank fixed effects, coefficients 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 growth quartile at least once, and 395 (256) banks are at least once in the first and fourth growth quartiles 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.

We always use nonoverlapping returns for 2- and 3-year subsequent returns in panels A and B, but we have observations in every year because of new entrants into the sample. For example, for three-year nonoverlapping 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. An alternative is to align all returns on the same time line. For example, for three-year nonoverlapping returns, one could limit the sample to all available observations that start in 1972, 1975, 1978, 1981, and so on. Panel C of Table 4 shows results. They are qualitatively and quantitatively similar to our main specification in panel B. For example, in the cross-sectional regressions of Column 5 we find that banks in the highest loan growth quartile have 7.9% lower returns than banks in the lowest growth quartile.

An alternative method that avoids inflating test statistics is to adjust the covariance matrix instead of dropping overlapping returns. Driscoll and Kraay (1998) demonstrate that the standard nonparametric time series covariance matrix estimator can be modified such that it is robust to general forms of cross-sectional as well as temporal dependence. Their methodology applies a Newey and West (1987)-type correction to the sequence of cross-sectional averages of the moment conditions. We implement the Driscoll and Kraay (1998) estimator in panel D. We find that our main result is robust to this alternative specification. Banks in the highest growth quartile have 6% lower annualized three-year returns than low-growth banks in the cross-sectional regressions (Column 5), and 8.7% lower returns in the bank fixed effects regressions (Column 6). Both coefficients are statistically significantly different from zero at the 1% level.

The results in panels A through D compare returns of banks with high loan growth to banks with low loan growth. The existing literature shows that high loan growth at the country level is followed by poor returns. These results are distinct, but it is important to investigate how they are related. For this purpose, we interact country-level credit growth with bank loan growth quartiles. Our measure of credit growth is credit/gross domestic product (GDP) in year t minus credit/GDP in year t-3 divided by three to annualize the measure, where credit/GDP is expressed as a percentage.[10] We show in panel E that the interactions are significant and positive for the one- and two-year returns, except for the growth quartile 4, when we do not have bank fixed effects. For the three-year return, the interactions are insignificant when we do not have bank fixed effects and significant when we do. Hence, the interactions dampen the effect we document in the other panels when aggregate credit growth is positive and magnify the effect when aggregate credit growth is negative.

We can gauge the economic magnitude as follows. Our measure of the credit growth averages zero, which means that, on average, credit grows at the same rate as GDP. The interquartile range of our measure of credit growth extends from −0.93 to +1.09. Suppose that credit/GDP increases from 50% to 53.3%. Such an increase is an annual credit growth of 1.09%. Looking at three-year returns, the interaction with credit growth is only significant when we have bank fixed effects. The three-year return is lower for banks in quartile 4 than banks in quartile 1 by 9.00% when credit growth is at the mean (equal to zero), by 7.23% per year $(-0.0900+1.09*0.0162)$ when aggregate credit growth is at its highest in the interquartile range, and by 10.51% $(-0.0900-0.93*0.0162)$ when it is at its lowest. In all cases, the estimate of the return difference is negative. This evidence indicates that the effect we document is weaker when aggregate credit growth is especially strong. Such an outcome could arise if the aggregate effect dominates in periods of strong aggregate credit growth in that most banks are doing well and all bank stock prices are bid up because of optimism about the sector as a whole. When aggregate growth is not strong, investors bid up prices of banks that are doing well in growing credit relative to other banks.

The effect we document is distinct from the negative relation between country-level credit growth and future stock returns, but both effects have in common that high credit growth is bad for future stock returns, be it aggregate growth or bank-level growth. As we discuss in the introduction, our evidence is consistent with models where investors extrapolate good performance associated with high credit growth and are overoptimistic about this performance. Investors can keep making these mistakes at the country and at the bank levels because each episode has unique features that lead to a unique narrative: in other words, to use the title of the book of Reinhart and Rogoff (2009), each time they think that this time is different, because each time is not simply about credit growth but is about why credit growth has different attributes.

[10] Our measure of country-level credit growth is the same as the one used in Baron and Xiong (2017). We obtain total bank credit to the private nonfinancial sector as a percentage of GDP from the Bank of International Settlements.

Table 5
Relationship between asset growth, loan growth, and nonloan asset growth and subsequent returns

A. 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 FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Number of observations	7,717	7,717	3,534	3,534	2,179	2,179
R-squared	.43	.50	.53	.64	.49	.68

B. Three-year asset growth

	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 FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Number of observations	7,185	7,185	3,265	3,265	2,120	2,120
R-squared	.43	.50	.52	.64	.50	.68

C. Three-year loan growth versus three-year nonloan asset growth

	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)
Nonloan asset growth quartile 2	0.0092	0.0066	0.0077	0.0039	0.0005	−0.0109
	(0.82)	(0.56)	(0.79)	(0.28)	(0.06)	(−1.00)
Nonloan asset growth quartile 3	0.0003	−0.0048	0.0023	−0.0041	0.0048	−0.0041
	(0.03)	(−0.40)	(0.23)	(−0.34)	(0.51)	(−0.35)
Nonloan asset growth quartile 4	0.0079	0.0047	0.0064	0.0031	0.0072	−0.0049
	(0.70)	(0.40)	(0.54)	(0.22)	(0.68)	(−0.34)
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Number of observations	6,834	6,834	3,130	3,130	2,002	2,002
R-squared	.45	.51	.54	.65	.52	.69

Panels A and B present results from regressions of bank stock returns on a bank's asset growth. Banks are sorted into quartiles based on 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 C presents regressions of bank stock returns on a bank's loan growth and nonloan asset growth during the previous three years. Banks are sorted into quartiles for loan and nonloan asset growth, respectively. The loan growth sort and the nonloan asset growth sort are performed independent of each other. The sample period is 1972 to 2013. 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 10%, 5%, and 1% level, respectively.

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. Table 5, panels A and B, repeat the same analysis as shown in Table 4, panels A and B, but use asset growth instead of loan growth. We observe very similar patterns. The return predictability is significantly higher for three-year asset growth (panel B) than for one-year asset growth (panel A). Three-year asset growth has a significantly negative correlation with subsequent returns at the one-, two-, 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 (panel B, Column 5). 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 nonloan asset growth portion has incremental predictive power for future returns. In addition to including a bank's liquid assets and investment portfolio, bank nonloan assets also include nontraditional business activities of banks that have regularly come under scrutiny, most recently during the financial crisis of 2007 and 2008. Many commentators have argued that, for example, 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 C, we estimate regressions of bank stock returns on a bank's loan growth and nonloan asset growth during the previous three years. We sort banks into quartiles for loan and nonloan asset growth, respectively, with the lowest growth quartile serving as the base group for the regressions. The loan growth sort and the nonloan asset growth sort are performed independently of each other. We find in these regressions that the return predictability only stems from the high loan growth quartiles. The highest nonloan asset growth quartile has coefficients of 0.0079, 0.0064, and 0.0072 at the one-, two-, and three-year horizon, and is never close to being statistically significant. The estimates of panel C are inconsistent with the alternative hypothesis that the results in panels A and B of Table 4 are driven by asset growth rather than loan growth.

Tables 4 and 5 also report R^2s. The R^2s are large because of the time fixed effects in our regressions. Without those, the R^2s are significantly lower (varying between 0.0029 and 0.0068) 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- and low-growth banks have different risks or styles. Researchers have identified several characteristics that explain differences in realized returns, and we have shown in Table 3 that high-and low-growth banks differ along some of these characteristics. We therefore follow the strategy of Daniel et al. (1997) and calculate portfolio returns with characteristics-adjusted benchmarks.

Three-year holding period returns for the portfolios are calculated using overlapping holding periods like in Jegadeesh and Titman (1993). 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. For example, in the case of 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 three years. Stocks bought at the end of June of years t-2 and t-1 continue to be held through June of year t+1 and t+2, respectively. Stocks bought at the end of June of year t-3 are sold in June of year t. The resulting portfolios are rebalanced monthly to maintain equal weights. Portfolios are re-sorted in June every year.

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. (DGTW; 1997) by first sorting all stocks in the CRSP/Compustat Merged universe into size quintiles based on CRSP breakpoints.[11] 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, and 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.

Table 6 presents the results. The first four columns report 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. The first row presents raw returns, the second row DGTW-adjusted returns, and the third row DGTW-adjusted returns when the universe is restricted to banks. The table shows that the highest growth quartile bank portfolio has significantly lower adjusted returns than the lowest growth quartile. 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. When

[11] 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.

Table 6
Returns to portfolios sorted on three-year loan growth

	Growth quartile				
	1	2	3	4	4-1
Raw returns	1.50***	1.30***	1.18***	0.93***	−0.56***
	(5.62)	(4.58)	(4.28)	(3.00)	(−4.05)
Adjusted	0.11	−0.05	−0.14	−0.34*	−0.45***
	(0.67)	(−0.27)	(−0.88)	(−1.65)	(−3.47)
Adjusted	0.20***	0.05	−0.02	−0.16***	−0.36***
(banks only)	(2.99)	(1.13)	(−0.72)	(−2.62)	(−3.21)

Banks are sorted into quartiles based on loan growth during the previous three years. The table shows average monthly returns (in percent) over a three-year holding period for the resulting portfolios as well as the difference between quartile 4 and quartile 1. Loan growth is measured as of fiscal year end of 1973 through 2013 and returns are measured from July 1974 through December 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 in 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, and 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. We form overlapping portfolios like in Jegadeesh and Titman (1993). Standard errors are adjusted for autocorrelation using the Newey and West (1987) estimator with 12 lags. Numbers in parentheses are t-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

we carry out the DGTW adjustment using banks only, results are economically slightly lower, but continue to be highly statistically significant. A portfolio of fast-growing banks underperforms a portfolio of slow-growth banks by 36 basis points per month (4.3% annually). Results for one- and two-year holding period returns are highly similar and are omitted for brevity. Overall, our conclusions from Table 4 remain robust after using characteristic-based benchmarks to adjust returns. High-growth banks significantly underperform low-growth banks.

The approach of Fama and MacBeth (1973) provides an alternative for taking differences between bank characteristics into account. The basic idea is to project, for each of our 41 cross-sections, the bank returns on the characteristics and then aggregate the estimates in the time dimension. We include the following characteristics: beta, the logarithm of market capitalization, the book-to-market ratio, a capitalization ratio (market value of equity / total assets), the prior year's stock return, the ROA, and idiosyncratic volatility.[12] Table 7 presents the results. In panel A, we use the same specification as panel C of Table 5 that separates loan growth and nonloan asset growth and include indicator variables for each quartile. Columns 1–3 analyze the returns for

12 Beta and idiosyncratic volatility are calculated from weekly returns during the prior two years. We include a capitalization ratio in the regression because Baker and Wurgler (2015) show that there is an anomaly in which lesser-capitalized banks underperform better-capitalized banks.

Table 7
Fama-MacBeth regressions

A. Growth quartiles

Time horizon for return	$[t, t{+}1]$ 1	$[t, t{+}2]$ 2	$[t, t{+}3]$ 3	$[t{+}1, t{+}2]$ 4	$[t{+}2, t{+}3]$ 5
Loan growth quartile 2	−0.0212	−0.0205**	−0.0176*	−0.0206*	−0.0109
	(−1.52)	(−2.17)	(−1.97)	(−1.76)	(−0.78)
Loan growth quartile 3	−0.0192	−0.0221*	−0.0212*	−0.0276*	−0.0268
	(−1.38)	(−1.94)	(−1.82)	(−1.88)	(−1.67)
Loan growth quartile 4	−0.0396**	−0.0419**	−0.0442**	−0.0496***	−0.0515***
	(−2.03)	(−2.19)	(−2.14)	(−2.73)	(−2.76)
Nonloan asset growth quartile 2	0.0065	0.0023	−0.0005	−0.0093	−0.0124
	(0.57)	(0.27)	(−0.07)	(−0.86)	(−1.19)
Nonloan asset growth quartile 3	−0.0050	0.0027	0.0052	0.0028	0.0054
	(−0.37)	(0.33)	(0.74)	(0.30)	(0.40)
Nonloan asset growth quartile 4	0.0134	0.0122	0.0164*	0.0062	0.0203
	(1.03)	(1.27)	(1.70)	(0.51)	(1.36)
Beta	0.0395**	0.0357***	0.0250*	0.0485**	0.0247
	(2.39)	(2.75)	(1.80)	(2.28)	(1.23)
Log (market cap)	−0.0168***	−0.0143***	−0.0115*	−0.0201***	−0.0168**
	(−2.78)	(−2.85)	(−1.94)	(−2.79)	(−2.38)
Book-to-market	0.0139	0.0273	0.0405	0.0473	0.0534
	(0.48)	(1.05)	(1.62)	(1.36)	(1.60)
Prior year stock return	0.0488	0.0658**	0.0350	0.0932**	−0.0421
	(1.47)	(2.33)	(1.28)	(2.66)	(−1.02)
Return on assets	0.1018***	0.0552***	0.0505***	0.0024	0.0254
	(5.74)	(3.02)	(3.08)	(0.11)	(1.31)
Idiosyncratic volatility	−1.4351**	−1.5423**	−1.2953***	−1.0740	0.2628
	(−2.15)	(−2.31)	(−2.78)	(−1.33)	(0.36)
Equity-to-assets ratio (market)	−1.4782***	−0.7646**	−0.4342	−0.2740	−0.1855
	(−4.11)	(−2.61)	(−1.44)	(−0.95)	(−0.49)
Constant	0.3126***	0.2395***	0.1674***	0.2775***	0.1810**
	(4.05)	(3.87)	(3.05)	(3.69)	(2.26)
Number of observations	6,487	5,932	5,412	5,932	5,412
Average R-squared	.25	.29	.30	.23	.21

(*continued*)

the one-, two-, and three-year horizon. We deal with overlapping returns in Columns 2 and 3 by adjusting the standard errors for autocorrelation using the Newey and West (1987) estimator with one and two lags, respectively. We however also report, in Columns 4 and 5, the individual returns for the periods $t{+}1$ to $t{+}2$, and $t{+}2$ to $t{+}3$. Our results continue to show that banks that grow their loan business fastest have the worst future returns. Relative to the omitted group of low loan growth banks, high-growth banks underperform by approximately 4% each year for the following three years. We do not observe differences in returns for banks in different nonloan asset growth quartiles. It is reassuring that these results are economically and statistically close to those reported in Tables 4 to 6 that use different estimation methods. The coefficients on the characteristics show the expected signs: high beta stocks, small stocks, value stocks, and momentum stocks outperform.

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 by making use of all the information in the growth distribution. In Table 7, panel B, we address this point. We reestimate the Fama-MacBeth regressions

Table 7
Continued

B. Continuous measures for growth

Time horizon for return	[t, t+1] 1	[t, t+2] 2	[t, t+3] 3	[t+1, t+2] 4	[t+2, t+3] 5
3-year loan growth	−0.1354**	−0.1468**	−0.1786**	−0.1780***	−0.2414***
	(−2.24)	(−2.23)	(−2.28)	(−2.91)	(−3.11)
3-year nonloan asset growth	0.0938	0.1212	0.1918*	0.1555	0.3184**
	(0.74)	(1.36)	(2.01)	(1.37)	(2.28)
Beta	0.0424**	0.0365***	0.0239*	0.0471**	0.0213
	(2.59)	(2.93)	(1.80)	(2.25)	(1.08)
Log (market cap)	−0.0161***	−0.0127**	−0.0102*	−0.0171**	−0.0162**
	(−2.80)	(−2.51)	(−1.72)	(−2.35)	(−2.35)
Book-to-market	0.0106	0.0238	0.0372	0.0472	0.0574*
	(0.36)	(0.90)	(1.44)	(1.38)	(1.69)
Prior year stock return	0.0505	0.0621**	0.0288	0.0830**	−0.0488
	(1.52)	(2.30)	(1.12)	(2.61)	(−1.20)
Return on assets	0.0994***	0.0516***	0.0505***	−0.0028	0.0281
	(5.74)	(2.86)	(3.14)	(−0.13)	(1.38)
Idiosyncratic volatility	−1.3013*	−1.4768**	−1.1979***	−1.1148	0.2742
	(−1.98)	(−2.33)	(−2.78)	(−1.49)	(0.39)
Equity-to-assets ratio (market)	−1.3773***	−0.6885**	−0.3976	−0.2093	−0.1840
	(−4.12)	(−2.45)	(−1.37)	(−0.73)	(−0.52)
Constant	0.2954***	0.2266***	0.1609***	0.2563***	0.1840**
	(3.95)	(3.66)	(2.98)	(3.43)	(2.36)
Number of observations	6,487	5,932	5,412	5,932	5,412
Average R-squared	.23	.27	.29	.22	.20

The table presents results from Fama-MacBeth regressions of bank stock returns on loan growth and nonloan asset growth over the previous three years as well as beta, the log of market capitalization, the ratio of book equity to market equity, the return during the previous year, the return on assets, and idiosyncratic volatility. In panel A, banks are sorted into quartiles for loan and nonloan asset growth, respectively. Indicator variables representing each quartile are included in the regression with the lowest growth quartile forming the base group. The loan growth sort and the nonloan asset growth sort are performed independent of each other. In panel B, loan growth and nonloan asset growth are used as continuous variables. Beta is estimated by regressing a bank's weekly excess return on the weekly market excess return during the previous two years. Idiosyncratic volatility is the root mean squared error from this regression. The book-to-market ratio and the return on assets are winsorized at the 1st and 99th percentiles. The sample period for loan growth is 1974 to 2013 and returns are measured until 2014. The sample includes all banks whose real assets in 2013 dollars are greater than $2 billion. Column 1 presents results from a regression for the return over the subsequent year. Columns 2 and 3 present results from regressions for the returns over the subsequent two and three years, respectively, with standard errors adjusted for autocorrelation using the Newey and West (1987) estimator with one and two lags, respectively, to address the overlap in returns. Columns 4 and 5 avoid creating overlapping returns by using as the dependent variable the return during the second (third) year after measuring the independent variables. Number of observations indicates the total number of observations in the panel. Average R^2 is the average R^2 of the cross-sectional regressions. Numbers in parentheses are t-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

of panel A but use loan growth and nonloan asset growth as continuous variables instead of the quartile indicator variables. We find that three-year loan growth is significantly negatively related to subsequent returns at all examined horizons. The economic magnitude of the coefficients can be gauged as follows: The cross-sectional standard deviation of 3-year annualized loan growth is equal to 0.1266. Hence, a one standard deviation increase in loan growth is predicting a $0.1266 \times (-0.1354) = 1.71\%$ lower one-year return. At the 3-year horizon, we observe a $0.1266 \times (-0.1786) = 2.26\%$ lower annualized return. The effects using loan growth quartiles are economically larger than those in panel B of Table 7. 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. We also find that the coefficients on three-year nonloan asset growth are never statistically significantly negative. 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 (2017) in their country analysis also ask whether aggregate bank credit expansion predicts an increase in the crash risk for banking and equity market indices in subsequent quarters. Similarly, we want to understand whether, at the individual bank level, high loan growth predicts a 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 one-, two-, or three-year period, respectively, and zero otherwise. The fifth percentiles are -45.7%, -38.1%, and -30.3% for one-, two-, or three-year annualized returns, respectively. We use the same specification used in Table 4 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 8 shows the results. There is no predictability of high loan growth for left-tail risk at the one-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 fast loan growth not only predicts negative returns but also the chance of an extremely large shock to a bank's market capitalization.

3. 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, for example, Demyanyk and van Hemert (2011) or Mian and Sufi (2009), who document that banks made lower quality mortgage loans prior to the recent crisis, which led to significantly higher default rates during the crisis. Mian and Sufi (2009), for example, find that mortgage credit growth and borrower income growth were negatively correlated in high subprime ZIP codes. Unlike these two studies, our analysis deals with loans

Table 8
Relationship between loan growth and the probability of left tail returns

	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 FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Number of observations	6,834	6,834	3,130	3,130	2,002	2,002
R-squared	.19	.36	.20	.43	.15	.48

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 one-, two-, or three-year period, respectively, and zero otherwise. The fifth percentiles are −45.7%, −38.1%, and −30.3% for one-, two-, or three -year annualized returns, respectively. 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 to 2013. 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 10%, 5%, and 1% level, respectively.

that are retained on a bank's books and thus cannot be explained by misaligned incentives relative to an originate-to-distribute securitization model.

On a more aggregate level, López-Salido, Stein, and Zakrajšek (2017) 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 the studies of Mian and Sufi (2009) and López-Salido, Stein, and Zakrajšek (2017). Although 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.

3.1 Accounting returns and loan loss provisions of high-growth banks

Table 9 presents regressions of the ROA 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 9 analyze levels and changes in ROA, defined as net income/total assets, and expressed in percentage. 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

Table 9
Relationship between three-year loan growth and profitability/loan loss provisions

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 FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	6,832	6,832	6,687	6,687	6,152	6,152	5,644	5,644
R-squared	.25	.51	.24	.50	.24	.51	.23	.52

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 FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	6,686	6,686	6,151	6,151	5,643	5,643	1,969	1,969
R-squared	.13	.19	.13	.18	.12	.19	.26	.45

(*continued*)

Table 9
Continued

C. 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 FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	6,791	6,791	6,659	6,659	6,141	6,141	5,637	5,637
R-squared	.33	.51	.31	.50	.31	.51	.31	.53

D. 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 FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	6,641	6,641	6,127	6,127	5,634	5,634	1,954	1,954
R-squared	.24	.28	.23	.27	.23	.27	.37	.46

The table presents results from 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 to 2013. 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. Columns 7 and 8 of panels B and D drop overlapping observations to address concerns about standard errors. Numbers in parentheses are t-statistics. LLP, loan loss provision. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

three years. By year t+3, the high-growth quartile banks have a significantly lower ROA, 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 quickly deteriorates 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 5. 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 9 suggests that faster growing banks make 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? We examine both reserves and loan loss provisions. Though we do not tabulate the results, we investigate whether banks that grow more have different levels of reserves in the formation year and in subsequent years. Note that reserves are a balance sheet item. We define loan loss reserves as reserves for credit losses divided by loans outstanding. We find that banks in the fourth growth quartile have lower reserves than banks in the first growth quartile by 59 basis points. In subsequent years, high-growth banks increase reserves relative to low-growth banks. In panels C and D of Table 9, we show results for loan loss provisions expressed as a percentage and defined as loan loss provisions divided by total gross loans and multiplied by 100. The loan loss provision should be higher in period $t$if the bank is aware that it grew quickly by making riskier loans. Loan loss provisions reduce a bank's income when they are made and increase its loan loss reserves.

Panel C shows 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 consistent with the view that high-growth banks failed to fully understand the risks of the loans they were making. 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. 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 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 9 shows that at the time we measure high loan growth, high-growth banks have high ROA and low loan loss provisions. After the formation period, 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 made 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.

3.2 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 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. First, we analyze the level and revision of the long-term earnings growth rate, $\mathrm{E}_{t+\mathrm{x}}(\mathrm{g})$. The earnings growth rate $\mathrm{E}_{t+\mathrm{x}}(\mathrm{g})$ is defined as the median analyst's expectation as of time $t+x$ for the long-term growth rate of the bank's earnings. Second, we 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 third 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. The calculation procedure for SUEs and revisions produces many large outliers (see, e.g., Livnat and Mendenhall 2006). In panel C of Table 10, 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.[13]

Table 10 shows the results. Panels A and B provide regression results for analysts' long-term growth rate estimates by bank loan growth quartile and the revisions from one year to the next of this long-term growth rate estimate. Results for the long-term growth rate in panels A and B 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 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 declined, analysts still believe that long-term earnings growth will be 1.2% higher. Although the growth forecasts are still high in year t+3, it is evident from these numbers that they are being revised downward. This is more formally confirmed in panel B, 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 regressions without bank fixed effects.

[13] See Cameron, Gelbach, and Miller (2008) and Gow, Ormazabal, and Taylor (2010) for additional discussions of this procedure. Code that implements the procedure can be found on the Web site of Daniel Taylor at Wharton Business School, University of Pennsylvania.

Table 10
Are analysts too optimistic about banks with high three-year loan growth?

A. Long-term growth forecast levels

	E_t(g)		E_{t+1}(g)		E_{t+2}(g)		E_{t+3}(g)	
	1	2	3	4	5	6	7	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 FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	4,458	4,458	4,019	4,019	3,573	3,573	3,195	3,195
R-squared	.20	.60	.21	.60	.20	.59	.21	.60

B. 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 FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	4,019	4,019	3,479	3,479	3,092	3,092	1,112	1,112
R-squared	.06	.14	.07	.13	.07	.15	.12	.33

(*continued*)

Table 10
Continued

C. EPS forecast errors and revisions

	SUE_{t+1}		SUE_{t+2}		SUE_{t+3}		$Revision_{t+1}$		$Revision_{t+2}$	
	1	2	3	4	5	6	7	8	9	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 FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	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	5,662	5,262	4,275	3,872	878	529	4670	4,239	995	622

The table presents results from regressions of analyst growth forecast levels and revisions as well as earnings forecast errors and revisions on a bank's loan growth, 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. $E_{t+x}(g)$ is the median analyst's expectation as of time t+x for the long-term growth rate of the bank's earnings. 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. The sample period is 1975 to 2013. The sample includes all banks whose real assets in 2013 dollars are greater than $2 billion. Results for the long-term growth rate estimates in panels A and B are estimated using ordinary least squares and allowing for standard error clustering at the bank and time levels. The calculation procedure for SUEs and revisions produces many large outliers. In Panel C, 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 because of a lack of observations. Regressions including bank fixed effects in panel C include only those banks for which a minimum of five observations are available. Numbers in parentheses are t-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

The first six columns of panel C of Table 10 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-, two-, 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, that is, -0.0004 for the one-year horizon, -0.0030 for the two-year horizon, and -0.010 for the three-year horizon. For further interpretation, consider that the median sample bank that enters the regressions in panel C of Table 10 has a price/earnings ratio of 12. This implies that analysts overestimate earnings for high-growth banks relative to low-growth banks by 1.6%, 4.7%, and 6.0% of current fiscal year earnings for the one-, two-, and three-year horizons, respectively. 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; that is, the same analysts give systematically too high EPS forecasts for the same banks when they grew a lot compared to when they grew little.[14] The last four columns of panel C show that in the bank fixed effects regressions, analysts had to revise their EPS forecasts downward for high-growth quartile banks. The bottom four rows of panel C list 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 because of a lack of observations.

Overall, the results in Table 10 suggest that analysts are too optimistic about the growth and profitability of the high-loan growth banks. They systematically overestimate long-term growth rates as well as earnings for banks that have grown quickly over the past three years. Our result may help explain the negative stock returns we documented earlier. In the model of BGS, agents have diagnostic expectations which lead them to extrapolate recent growth. Though the model looks at the economy as a whole, the behavior of analysts here is consistent with that type of expectations. Eventually, when growth slows and loans are revealed to be more risky than anticipated, bank performance worsens, reserves increase, and investors stop being overoptimistic, which leads to poor stock returns.

[14] Median regressions with bank fixed effects frequently fail to converge 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.

4. Organic Growth versus Growth through M&A Activity

Next, we 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 (Roll 1986).[15] 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 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 collect data on mergers and acquisitions of sample banks from the M&A database of the Federal Reserve Bank of Chicago. Having identified target firms, we collect 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 $\frac{\text{Total loans}_t - \text{Loans acquired}_t}{\text{Total loans}_{t-1}} - 1$. Appendix A provides details on the matching and calculations, including a description of how to merge the different databases and of all assumptions we make. 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 11 presents regression results of bank stock returns on banks' organic and M&A related loan growth, respectively, during the previous three years. Like in Table 4, 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 11 shows that we continue to find strong return predictability even when

[15] 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).

Table 11
Organic growth versus growth through mergers

	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 FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Number of observations	5,529	5,529	2,489	2,489	1,592	1,592
R-squared	.42	.49	.50	.63	.49	.68

The table presents results from 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 to 2013. 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 when 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 10%, 5%, and 1% level, respectively.

we focus on organic growth. For all six specifications in Table 11, 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 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 11 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 reestimate the benchmark adjusted returns using the Daniel et al. (1997) portfolio approach of Table 6 with organic loan growth instead of total loan growth. For both 2- 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.

Next, we ask whether the evidence of poorer loans in high-growth banks we documented in Table 8 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 12 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 8. 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 12 demonstrates 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; that is, 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 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 12 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.

Table 12
Relationship between organic growth, merger growth, and profitability/loan loss provisions

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 FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	5,529	5,529	5,409	5,409	4,905	4,905	4,430	4,430
R-squared	.26	.52	.25	.51	.24	.52	.24	.52

B. 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 FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	5,493	5,493	5,383	5,383	4,895	4,895	4,424	4,424
R-squared	.33	.53	.32	.52	.31	.53	.31	.54

The table presents results of 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 like in Table 11. 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 to 2013. 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. LLP, loan loss provision. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

5. Robustness of Our Main Results

The summary statistics in Table 3 show that high-loan growth banks are larger than low loan-growth banks. Gandhi and Lustig (2015) find that the largest commercial bank stocks have significantly lower risk-adjusted returns than other bank stocks and argue that this relationship reflects that larger banks benefit from too-big-to-fail subsidies. We now ask whether the fact that larger banks have lower excess returns can rationalize our main finding. Every year, banks are sorted into deciles based on their total assets and the banks in the largest decile are removed from the sample for that year. For example, in 2013, all banks with total assets exceeding $65 billion are removed. We then form groups based on loan growth, and repeat our main analysis of Table 4 of the paper. In unreported regressions, we find that excluding the largest decile of banks does not account for our results. The underperformance of fast-growing banks remains economically and statistically strongly significant.

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 that would end the credit boom and cause poor performance. We provide two robustness checks to examine whether aggregate demand-side shocks could explain our results. 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, 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 4 but exclude recession years. We find that banks in the highest loan growth quartile have 4.1% lower returns at the one-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 miss statistical significance for the one-year horizon (p-value 12%), but are statistically significant 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 U.S. 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 U.S. 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 from 1986 to 1988, when banks from the Northeast represented 41% to 52% of the highest growth quartile banks, and from 1972 to 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 U.S. regions makes it unlikely that our results are driven by local demand shocks.

To err on the side of caution, in unreported regressions, we first reestimate the paper's main results from Table 4, panel B, and include year times census region fixed effects. Our results are robust to this alternative specification. Second, we form 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 U.S. 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 4 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 like in Table 4. Hence, our results are driven by the larger banks with assets in excess of $2 billion.

Table 13 addresses two different issues. First, all our prior evidence stems from regressions that equally weighted all observations. We now provide evidence on both equal- and value-weighted returns. Second, 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 2015; Polk and Sapienza 2009; Titman, Wei, and Xie 2004). Are our results just rediscovering

Table 13
Alphas for a high minus low loan growth portfolio

	Equally weighted returns			Value-weighted returns		
	1	2	3	4	5	6
Alpha	−0.5624***	−0.6145***	−0.6296***	−0.3389**	−0.3526**	−0.4316**
	(−4.05)	(−4.12)	(−4.28)	(−1.99)	(−2.07)	(−2.44)
Mkt-RF		0.0428	0.0434		0.0060	0.0184
		(1.48)	(1.45)		(0.09)	(0.33)
SMB		−0.0002	0.0171		−0.0568	−0.0027
		(−0.01)	(0.52)		(−1.23)	(−0.05)
HML		0.0748*	0.0802		0.0768	0.0483
		(1.78)	(1.55)		(0.95)	(0.39)
RMW			0.0578			0.1955
			(1.02)			(1.32)
CMA			−0.0264			0.0236
			(−0.34)			(0.12)
Number of observations	486	486	486	486	486	486
R-squared	.00	.02	.02	.00	.01	.02

Each June, banks are sorted into quartiles based on loan growth during the preceding three fiscal years. The dependent variables are the monthly equally weighted and value-weighted returns (in percent), respectively, of a portfolio that buys banks in the high loan growth quartile and sells banks in the low loan growth quartile. Stocks bought or sold at the end of June of year t are held until the end of June of year t+3. Overlapping portfolios are formed like in Jegadeesh and Titman (1993). The table shows time series regressions of the high minus low loan growth portfolio returns on the excess market return and the factors small minus big (SMB), high minus low book-to-market (HML), robust minus weak (RMW), and conservative minus aggressive (CMA) from Fama and French (2015). Loan growth is measured as of fiscal year end of 1973 through 2013 and returns are measured from July 1974 through December 2014. Standard errors are adjusted for autocorrelation using the Newey-West (1987) estimator with twelve lags. Numbers in parentheses are t-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

the growth effect for a sample of banks? We follow Fama and French (2015) and estimate their five factor model that includes an investment growth factor (CMA). Each June, banks are sorted into quartiles based on loan growth during the preceding three fiscal years. The dependent variables are the monthly equally weighted and value-weighted returns (in percent), respectively, of a portfolio that buys banks in the high loan growth quartile and sells banks in the low loan growth quartile and holds those positions for three years. As with our other portfolio results, we form overlapping portfolios like in Jegadeesh and Titman (1993). The table shows time series regressions of the high minus low loan growth portfolio returns on the five factors of Fama and French (2015). The main result is featured in Columns 3 and 6. The alpha of the portfolio that buys banks in the high loan growth quartile and sells banks in the low loan growth quartile is persistently negative in the five-factor model, no matter whether we calculate equally weighted or value-weighted returns. The economic magnitude is 63 basis points per month for the equally weighted returns and 43 basis points per month for the value-weighted returns.[16] Further examination reveals that the negative alpha stems from the high loan growth quartile. When we separately estimate these regressions for the first and fourth loan growth quartile banks,

[16] We find economically and statistically similar results when we implement the methodology of Hou, Xue, and Zhang (2015) instead.

we find for the equally weighted regression that the low loan growth banks have a statistically insignificant alpha of +3 basis points. However, for the high loan growth quartile, banks have an alpha of −63 basis points, which is strongly statistically negative. For the value-weighted regressions, the low loan growth quartile banks have a statistically insignificant alpha of −2 basis points, while the high loan growth quartile banks have a statistically significant alpha of −45 basis points. Hence, our evidence at the bank level is reminiscent of the country-wide result of Baron and Xiong (2017). However, we find negative excess returns after accounting for established asset pricing factors, while they find negative excess returns without accounting for risk. Regardless, such results are difficult to explain with standard asset pricing models and are more consistent with a behavioral explanation.

Equally important, we find that the long-short loan growth portfolio does not load at all on the investment growth factor CMA, neither in the equally weighted nor in the value-weighted specification. In other words, the loan-growth effect we document in our paper is decisively different from the investment growth effect uncovered in the asset pricing literature.

In unreported regressions, we address survivorship bias. We examine whether a higher incidence of delistings could help explain the return difference between high and low loan growth banks. For Table 4, we required that a bank has returns available for the entire subsequent return period of up to three years; that is, 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-year 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 Tables 6 and 13 are not susceptible to this problem since they use monthly returns including delisting returns. Nevertheless, we have replicated the regressions of Table 4 with a different definition of future returns. 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. 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.

Another robustness check deals with the M&A results. In Table 11, 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 reestimated the regressions of Table 11 by including these bank-years and setting target loan data to zero. Our results are unaffected by these changes.

In a final robustness check, we address the concern that our results may be affected by some banks mostly staying in the same quartile during the sample period or oscillating between two adjacent growth quartiles. We reestimate our main result in panel B of Table 4 only for those banks that are both in the top and the bottom loan growth quartile at one point in time. Results are quantitatively and qualitatively similar to the results we report in Table 4 for regressions including bank fixed effects.

6. Conclusion

We showed 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. Our evidence shows that it is not only aggregate credit booms that are followed by poor performance but also bank-level credit booms. In our paper, poor performance following bank-level credit booms cannot be attributed to shocks to aggregate or even regional economic activity. Some evidence suggests that the strength of the effect we document is inversely related to aggregate credit growth, suggesting that when aggregate credit growth is very strong, the aggregate effect dominates, as investors become excessively optimistic about the whole banking sector. In contrast, when aggregate credit growth is weaker, investors appear to become more optimistic only about those banks that have strong loan growth.

Our evidence supports the model of BGS, where credit booms start from a kernel of truth, but investors and bankers alike excessively extrapolate from this kernel of truth, so that they believe loans to be less risky and hence more profitable than what is true in reality. Eventually, they learn that their expectations were flawed; bank stocks underperform; and loans have more default losses than expected. These flawed expectations appear to be common to bankers, analysts, and investors. Such expectational errors can recur because each bank-level credit boom is likely to have a different narrative, so that it is never exactly the same story repeating itself.

We used a sample period that exceeds 40 years. Such a long time series has the benefit of enabling us to show that the phenomenon we document is persistent and is not the result of changes in bank regulations or in bank governance.

In future research, it would be helpful to investigate whether the dynamics of bank-level lending booms are similar in foreign countries. In addition, using shorter but more recent sample periods would help in better understanding the dynamics of bank-level lending booms as more data are available. For instance, while we have explained why our results are more supportive of the expectation formation theory than of agency theories, more recent samples would make it possible to use data on bank ownership, managerial incentives, and bank governance to investigate the agency theories more deeply. It is important, however, to note that regardless of the relative importance of agency theories versus expectation formation theories, the conclusions that can be drawn from our paper remain valid: banks do not hold enough provisions for poor loan performance after periods of strong organic growth, and bank investors and analysts alike fail to understand the negative implications of strong growth for risk and profitability.

Appendix A. Procedures for Matching the Chicago Fed M&A Database to the CRSP/Compustat Database and for Calculating Organic 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 loan growth, that is, growth that does not stem from merger activity, for sample banks.

A.1 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 nonmergers 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.

A.2 Obtain 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 1,000 to get millions like 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 loan data for the individual banks held by the holding company (see point C.4 for this procedure).

3. Compustat data

   a. If none of the above databases has 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

A.3 Match Loan Data to the Merger Data and Purge Duplicate Mergers

1. Pull 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 loans. Adjustment procedure:

   a. Using high holder IDs, match each individual bank merger to its holding company merger where applicable
   b. If holding company data is available, drop the individual bank merger data
   c. If the holding company's data is unavailable, but the individual bank's 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 nonmergers 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 nonmerger 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 Compustat data on target 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.

A.4 Calculate Organic Loan Growth

1. For each of our sample firms, we calculate the sum of all 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 loans
3. Calculate organic loan growth for year t as

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

4. Results reported in Table 11 exclude all banks that acquired a bank whose loan data are unavailable. In the robustness test we describe in Section 5, we set organic loan growth equal to organic asset growth when loan data are unavailable and equal to zero when both loan and asset data are unavailable.

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