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MASTER THESIS

Does the market really miss the risk associated with fast loan portfolio growth?

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Declaration of Authorship

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"Quality is more important than quantity. One home run is much better than two doubles."

Steve Jobs

"A sound banker, alas, is not one who foresees danger and avoids it, but one who, when he is ruined, is ruined in a conventional way along with his fellows, so that no one can really blame him"

J.M. Keynes, *The Consequences to the Banks of the Collapse of Money Values (1931)*

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Abstract

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Does the market really miss the risk associated with fast loan portfolio growth?

by Niels J. SCHUURMAN

This thesis provides deeper analysis into the research of Fahlenbrach, Prilmeier, and Stulz (2017). By replicating their database of U.S. listed banks in the period 1972-2013 this thesis investigates if the market really misses the risk associated with fast loan growth. Adding the loan loss provisions, reserves and equity-ratio it shows that the loan growth still has high predictive power. The real estate segment of the loan portfolio seem to be the main driver of the worse subsequent returns. While loan seasoning has an effect on the subsequent returns, banks that grow the fastest over a long period seem to have the worst returns, indicating that a fast growing strategy destroys shareholder value. This result also seems to hold during recessions. The conclusion is thus that the market really misses the risk associated with fast loan growth, confirming the research of Fahlenbrach, Prilmeier, and Stulz. It also shows banking regulation should focus more on loan loss provision, reserves and the value of collateral.

Keywords: Loan growth, bank returns, loan loss provisions, loan loss reserves, segmental loan growth
JEL Codes: G01, G12, G21

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1 Introduction

More than a decade after the start of the financial crisis of 2007 - 2009 there is still debate about how banks should be regulated and how a crisis like that can be averted in the future. The Basel Committee, an international organization with the purpose of enhancing financial stability by improving supervisory knowhow and the quality of banking administration worldwide, has been working on new standards regarding the capital reserves that banks should hold. Their effort resulted in the Basel III standard in 2010 - 2011, though due to changes it will not be fully implemented before 2019. Despite this, the Basel Committee has recently already proposed an even stricter regime with regards to capital constraints.[1]

Just like the regulators, academics (understandably) have also given the financial crisis a lot of attention. Many papers have been attributed to bank lending, more specifically the boom and bust of credit markets (e.g. Stein, 2014; Fahlenbrach, Prilmeier, and Stulz, 2017; Foos, Norden, and Weber, 2010; Bordalo, Gennaioli, and Shleifer, 2016). This research can be reclassified into three different kinds. The first kind takes the highest viewpoint and looks at the macro-economic impact on country aggregate bank lending (e.g. Baron and Xiong, 2016).

There are two main theories on macro-economic level that explain why credit booms are followed by poor economic performance. The *rational expectations* theory, relies on shocks in the economy. A positive shock increases the loan opportunities for banks, then a negative shock in the economy decreases the quality of the loans, which in turn leads to weakened banks, whom will lend less, what will result in a credit crunch (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997).

The other main theory is that of the *biased expectations*. This theory states that banks are too optimistic about their loan opportunities and lend to too many customers, while not provisioning enough. When these bad loans subsequently start to default, the banks have to make huge provisions to increase their reserves. This leads to a dry up of the available for loans, which results in a crunch. These theories are further explained in section 2.1.

[1] The regulators see these new proposed rules as an addition to the Basel III, but banks themselves see it a new set of rules and call them the Basel IV standards. Currently the target implementation date is 2022.

The second kind of research looks at bank-level data and the impact of lending and provisioning (e.g. Laeven and Majnoni, 2003; Foos, Norden, and Weber, 2010; Bikker and Metzemakers, 2005; Keeton, 1999).

The third kind looks at the impact of the banks' behavior on the stock price of the banks (e.g. Wahlen, 1994; Houge and Loughran, 1999). Houge and Loughran (1999) found which banks tend to perform the worst after their IPO. They found that big institutions whose loan portfolio grew fast in the three years before the IPO are the ones that perform the worst over a five-year post-offering holding period. One of the latest papers in this third classification is the paper of Fahlenbrach, Prilmeier, and Stulz (2017) (hereafter: FPS).

The research question (and name of the article) of FPS was "Why does fast loan growth predict poor performance for banks?". FPS convert a paper of the first kind (Baron and Xiong, 2016), to examine 664 publicly listed U.S. banks from 1973 to 2014 and study the effect of the growth of the loan portfolio on the stock performance of these banks. They divide banks in quartiles based on the growth of the loan portfolio over the preceding one- and three-years. Based on these quantiles they look at the subsequent stock returns of these different quantiles over an one-, two- and three-year window.

They found that banks in the top quantile based, on the three-year loan portfolio growth, significantly outperform the stock of the bottom quantile bank during the growth years. After these three growth years, the stocks of the top quantile banks significantly underperform against the stocks of banks in the bottom quantile during the subsequent three years. The high growth banks have the lowest loan loss provisions during the growth period, but this reverses after the three years. This results in lower return on assets and lower stock returns. FPS control for mergers and acquisitions and find that the predictive power of the loan growth is not driven by mergers and acquisitions. They concluded that the banks that have the most organic growth make worse loans than they think, because if they knew that they were making riskier loans, they would have increased their loan loss provisioning during the growth period. Banks, investors and equity analysts all fail to recognize the risk that is associated with the high growth.

FPS also devise a trading strategy on their insight. They find a monthly negative alpha of 56 (34) basis points per month on an equally (value) weighted portfolio, by going long the high growth portfolio and short the low growth portfolio and hold this long-short portfolio for three years. When adding more asset pricing characteristic from Fama and French (2015), their alpha increases to 63 (43) basis points. This is an economically significant result.

One could argue that the fast loan growth is a proxy for the real problem, insufficient provisioning. FPS show that fast growing banks tend to fail to recognize the quality of the loans they are granting. But as Keeton (1999) shows, loan growth does not have to result in a subsequent crash. A bank that grows fast, but recognizes the associated risk and thus makes the required loan loss provisions, would not experience a similar crash like a bank that grows equally fast, but fails to make the required loan loss provisions.

Banks with high loan loss reserves and a big equity buffer can take more unexpected loan losses than a bank that is has almost no reserves and a low solvency ratio. FPS thus show that fast loan growth predict poor subsequent performance, because banks that grow fast *in general* are overoptimistic about the loan opportunities and fail to recognize the associated risk. But does the market really miss the associated risk with fast growing banks? It seems more likely that banks that have insufficiently provisioned in the past are the ones that will experience the worst subsequent performance, as they are not as well guarded against a sudden downturn. If the market incorporates the level of loan loss provisions the bank makes, and the level of loan loss reserves and equity buffer the bank has, does the loan growth than still have such a high explanatory power?

This thesis will try to supplement the paper of FPS by researching if the market really misses the increasing risk of an (abnormal) fast growing loan portfolio. While FPS showed which banks are most likely to under-provision, the market might incorporate the level of protection a bank has against (un)expected loan losses. Just that the fastest growing banks have a tendency to be the least protected banks, does not mean that all fast growing banks will encounter a crash in the future. This should be reflected in an efficient market, but it should also not be missed by the regulators. While FPS show that rapid growing banks should be a red flag for regulators, I try to answer the question if these are the only banks the regulators should look at.

The research question of this thesis is thus as follows:

Does the market really miss the risk associated with fast growing loan portfolio's?

The results show that the market really does miss the risk associated with fast growing loan portfolio's. Even when corrected for buffers against future loan losses do banks with the highest loan growth still experience the worst returns? It seems that banks which have an aggressive growth strategy will destroy shareholder value in the long run. Evidence for this theory is provided by the fact that loan seasoning is present in the data, but higher returns will be achieved when investing based on the three-year loan growth, instead of investing based on the loan growth two- or three-years ago.

This thesis finds evidence that banks that grant loans to a pool of risker borrowers than the existing customers are the banks that will grow the fastest. However, further research is needed to confirm this. The results of FPS also holds during recessions, however, the loan growth of three year prior to the recession will have a less negative (or even positive) effect in a multi-year returns regressions. As nobody can predict how long a recession will last, investors should keep looking at banks that had the most aggressive loan growth strategy and not invest based on loan seasoning.

Splitting the loan portfolio into different segments shows that the real estate segment is the main driver of the worse subsequent returns. This could be because the real estate segment is the biggest segment of the average loan portfolio (around 60%), resulting that the bank with the fastest growing real estate segment is also the bank with the fastest growing total loan portfolio. Yet, this is not always true, indicating that it might be indeed the real estate segment. Banks with more real estate hold less reserves as their loans are secured by the real estate, but the results also suggest that that banks with less reserves have worse returns. If the collateral then turn out to be bad, these banks have no cushion to take the loan losses. Banks seem to provision insufficiently, because they trust (too much) on the value of the collateral. Surprisingly, the portfolio mix itself does not really drive the subsequent returns.

These result thus confirm the findings of FPS and reiterates their warning to shareholders and regulator to look at the risks associated with banks that grow their loan portfolio fast. This thesis thus adds to the research of Fahlenbrach, Prilmeier, and Stulz, but also to e.g. Cavallo and Majnoni (2002), Laeven and Majnoni (2003), Bikker and Metzemakers (2005), and Foos, Norden, and Weber (2010) about bank performance and loan growth, and loan loss provisioning. But it also adds to the research of Ahmed, Takeda, and Thomas (1999) and Cooper, Jackson III, and Patterson (2003), explaining more about the predictive power of several variables in bank stock returns.

This thesis is constructed as follows. Chapter 2 reviews the relevant literature and introduces the hypotheses. Chapter 3 describes how the data is collected and the database is constructed. Chapter 4 explains the variables and formula's in the methodology section. In chapter 5 the results are shown and discussed. Chapter 6 discusses the robustness of these results. Chapter 7 ends this thesis with a conclusion, while also describing the limitations and giving further research recommendations.

2 Literature

In this chapter the relevant literature is reviewed and based on this literature the hypotheses are constructed. This chapter starts with an overview of the literature on the macro-economic and business regarding business cycles, income smoothing and capital management with provisioning, loan seasoning and secured loans. Based on this literature multiple hypotheses are posed.

2.1 Macro-economic lending

Regarding the macro-view research of credit boom and bust, as described in the introduction, there are two main theories. The first is the *rational expectations* approach, which relies on shocks in the economy. A positive shock result in more lending opportunities for the banks, who will grant more loans and thus increase their loan portfolio. Then a negative shock in the economy will decrease the quality of the loans, which decreases the performance of the banks. This in turn will decrease the ability of banks to grant loans, what will decrease the amount of investments in the economy, thus resulting in poor economic performance. Banks do not - or are not able to - grant new loans, either because they have made bad loans in the past and do not have the sufficient funds, or because no good new opportunities exist (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997).

The alternative is the *biased expectation* approach, in which banks fail to recognize the risks associated with the new loans. The banks thus become too optimistic about the new lending opportunities and a credit boom is born (Kindleberger and O'Keefe, 2001; Minsky, 1977; Asea and Blomberg, 1998). Only when the risk associated with these *more-risky-than-anticipated* loans materialize do the banks, followed by their investors, reassess the quality of the loans and the performance of the bank. This is followed by increasing reserves, crashing stock prices and reduced lending.

The main difference between these two theories is that the first approach does not 'blame' the banks for the poor performance. In the view of the *rational expectations* practitioner the under-performance of the granted loans is due to a negative shock to the economy, which cannot be blamed to the banks. From the perspective of the *biased expectations* view, the banks can be blamed. It was their fault for not recognizing the risk associated with the loans.

A new approach is given by Bordalo, Gennaioli, and Shleifer (2016), who combine both approaches into a behavioral model. The growth of the loan portfolio is started by a justifiable positive shock. Yet, the banks (and investors) extrapolate this positive shock too far and let the loan portfolio grow into the territory not justifiable by the positive shock. Their model of *diagnostic expectations* thus starts from the rational expectations theory, but flows over into the biased expectations theory. Regardless of the chosen theory, they all state that after a credit boom there will be a burst during which the banks have to take (unexpected) losses.

2.2 Business Cycles

The problem of macro-economic research on country aggregate-level is that it cannot test the theories. This is because it cannot differentiate whether the poor performance of the economy is due to bad loans or that bad loans are a result of a poor economy. FPS are able to test the theories, because they use bank-level data, which allow for testing the performance of banks with respect to their loans, regardless of the state of the economy. The results of FPS do not reconcile with the rational expectations theory, because they find that fast loan growth is followed by poor economic performance, regardless of the state of the economy. Foos, Norden, and Weber (2010) also find that (abnormal) fast loan growth predicts subsequent poor performance, regardless of country or year. If the rational expectations theory held, the growth of the loan portfolio would not be able to predict the performance of the banks. Instead, all banks (exposed to the same economy) would be hit by the negative shock and the past loan growth would have no influence. Instead the more aggressive the growth in the past, the higehr the losses in the future. If the banks knew they were taking on more risk, they would have increased the loan loss provisions to even out the loss. The research shows they do not. As the banks do not take this approach, banks most likely did not anticipate the risk, which is in line with the biased- and dynamic expectation theories.

FPS do state that explanations could also be found in agency theories. For example it could be that bank executives have (financial) incentives to grow the loan portfolio of the bank. They might agressively grow the loan portfolio so they get greater compensation in the short-run, while hurting the long-run performance of the bank by disguising the risk by pushing it to the future (see also Rajan, 1994).

Why banks start lending in the first place remains open for discussion. Asea and Blomberg (1998) find that during economical upswings banks relax their lending standards and re-tighten it during downturns. During an economic boom, banks are inclined to take on more risk, because of the positive outlook of the economy and expectation that all customers will be able to repay their loans. During downturns however, banks will be very pessimistic as they overstate credit risk (Bouvatier and Lepetit, 2008).

A possible explanation for the misvaluation of credit risk is the *disaster myopia* (Guttentag and Herring, 1984). The disaster myopia focusses on the trend that banks tend to underestimate the probability of low-frequency shocks. Bank managers have the tendency to assign subjective probabilities to the chances of default. When there are no major shocks in the economy, this subjective probability will fall below the actual probability. This will result in lower credit standards and lower default premiums. But this increases the vulnerability of both the lender and the borrower. In this case even a small shock can heavily impact the solvency of the borrower, which could even default, thus impacting the solvency of the lender.

An other reason for the misvaluation of credit risk is *herd behavior* (Rajan, 1994). Herd behavior focuses on the idea that bank managers have a short-term view and will thus set credit policies that will improve their pay and reputation in the short run. Rajan (1994) found evidence for this due to the fact that bank credit policies changed as the conditions of those in demand of credit changed. Banks (or at least their managers) adjust their policies to accomodate the client(s), so they can generate more business right now.

Dell'Ariccia and Marquez (2006) found that when banks obtain more private information about their borrowers and the information asymmetry in the financial system decreases, banks tend to lower their credit standard. This results in an increase in the aggregate credit, but lower loan portfolio quality, which will result in lower profits. This greater credit exposure, which becomes more instable, increases the risk of financial instability.

Berger and Udell (2004) develop the *institutional memory hypothesis*. The institutional memory hypothesis states that loan officers ease credit standard over time. The previous loan bust is not remembered because of loan officer turnover. This effect is most significant at smaller banks, as teams are smaller here and thus the effect of turnover is higher. It is also possible that lager banks have more strict and more long-term pricing and credit standard policies, covering both the credit boom and bust. This is also possible due to changes in the capital requirements of banks (Heuvel, 2002).

Jackson et al. (1999) point out that the quality of banks' assets will deteriorate during a downturn, as the value of the collateral will decrease and customers will have more problems with meeting the payments. As a result, banks will have an increase in risk exposure during the downturn, which will increase their capital requirements, at a moment that new capital becomes expensive. As a consequence, banks will most likely be forced to cut back on their lending.

The reason for the easening of the credit standard is thus unknown, but it does fluctuate over time and has a big impact on the aggregate credit supply and the quality of the loan portfolios of banks.

2.3 Income Smoothing & Capital Management

Loan loss provisions exist so banks take the cost of a loss when it should be realized, but before it is materialized. If a bank expects that 10% of their loans will default, they need to have a reserve of 10% for loan losses. With loan loss provisions banks can adjust their level of reserves to the desired level. This provision will lower their profit, but it will increase the reserves level on the balance sheet. This is the basis for accrual accounting. It shields the bank from suddenly having no money. If banks would not make provisions, a loss would directly result in a decrease of their equity. Reserves are a cushion - filled with provisions - for expected loan losses. Equity will take the hit from unexpected losses.[1]

Provisions thus have an impact on the income statement and the balance sheet. On the balance sheet they impact the level of reserves, which are counted towards regulatory capital.[2] Moyer (1990) finds that bank managers use the loan loss provisions as an instrument to manage the level of the capital ratio's. Beatty, Chamberlain, and Magliolo (1995) also find that the loan loss provisions are used to manage the capital ratio's, but also find that loan loss provisions are not used to smooth earnings. Interestingly, in the same issue of the *Journal of Accounting Research*, Collins, Shackelford, and Wahlen (1995) find that banks do use the loan loss provisions to manage earnings. They do note that the effect is mostly driven by the differences in banks though.

Ahmed, Takeda, and Thomas (1999) use a change in the 1990's bank capital regulation as a natural experiment to see if bank managers use the loan loss provisions

[1] For a more elaborate explanation of how loan loss reserves and the equity cushion work, I highly recommend the appendix from Laeven and Majnoni (2003).

[2] This is a metric used by regulators which states how well guarded a bank is against downturns. This is one the main points of the current discussions regarding the Basel Standards.

to smooth earnings and regulatory capital, but also signal private information about future prospects. The change in the regulation allows less of the reserves to be added to the Tier 1 capital.[3] This means that after the regulatory change, it became less effective to increase the capital ratio's by increasing the level of the reserves through high provisions. It became better to increase the level of the reserves to the max, after that it becomes more effective to not recognize the cost, as this will increase the earnings, which will flow into equity (retained earnings).[4] Ahmed, Takeda, and Thomas find the following: a change in the loan loss provision level does reflect an expected change in the quality of the loan portfolio, banks do use the loan provision to manage capital ratio's, but earnings management and signaling does not determine the loan loss provision.

If you want to smooth earnings, you would increase your provisions during good times (to make the profit go down) and decrease the provisions during bad times (to boost profits). Laeven and Majnoni (2003) document that provisions are indeed increased when profits are high, but that profits are decreased based on the growth of the loan portfolio. This effect is especially strong in the U.S. and Japan. They explain this by stating that banks provision too late.[5]. Most loans are granted during good times, so just before a credit crunch the banks will have their biggest loan portfolio. Then when things go bad, banks have a massive loan portfolio, which is suddenly a very big risk. Banks now need to make additional provisions, which will deteriorate their earnings and erode the bank's capital at a moment that capital is very expensive.

Cavallo and Majnoni (2002) also find a negative relation between loan growth and provisioning levels, which indicates the procyclical effect that banks provision too late. Regarding income smoothing they find that this differs per country. For G10 countries they do find evidence that banks smooth their income, reducing the procyclical effect, but for non-G10 countries they find no income smoothing, which would explain why these countries have a more difficult time to recover from credit crunches.

Bikker and Metzemakers (2005) also find that banks do not provision enough during good times. They find this due to the negative relation between GDP growth and provisioning. The procyclical effect is somewhat mitigated by the income smoothing effect, which increases provisions during (very) profitable times. Interestingly,

[3]The Tier 1 capital ratio is one of the main regulatory capital ratio's that is used by regulators to judge the financial soundness of banks.

[4] Equity is also part of the Tier 1 capital ratio.

[5]Bikker and Metzemakers (2005) and Cavallo and Majnoni (2002) call this a procyclical effect

Bikker and Metzemakers also document a positive relation between loan growth and provisioning. This is in contrast with Laeven and Majnoni (2003), but as they further investigate this contradiction, they find that this is due to data and model differences. The effect of loan growth on the level of provisions thus remains a bit ambiguous. Furthermore, Bikker and Metzemakers document confirmation of the capital management hypothesis. Bouvatier and Lepetit (2008) also document a procyclical effect of provisioning, but notes that this effect is especially strong for poorly capitalized banks.

Foos, Norden, and Weber (2010) state that rapid loan growth is an important driver of increased risk. They also document that abnormal loan growth[6] of two to four years ago have the biggest impact on current loan losses (see also section 2.4). They further document that abnormal loan growth leads to a decline of interest income (see also section 2.5 below). Their third finding is that preceding abnormal loan growth also leads to a decrease of the bank solvency. Their results are robust for M&A-activity.

Cooper, Jackson III, and Patterson (2003) document that the loan loss reserves and leverage (amongst others) are univariately important in the forecast for bank stock returns. An increase in the loan loss reserve level or the leverage predicts a decrease in the stock return. This indicates that the market is weary of banks that increase their risk, either by increasing their leverage or by having a riskier loan portfolio. In a multivariate model, the loan loss reserve variable loses its significance, but leverage remains an important driver. To their surprise firm size, measured as the market cap, has no predictive power.

All this research shows the importance of provisions, reserves and solvency (or leverage) on the performance of banks. While sometimes ambiguous, there is also a link between these variables and loan growth. FPS document the effect of loan growth on the (stock) performance of banks, but do not incorporate these other variables which could explain the performance of banks. Given that the capital management hypothesis seems to hold in all studies, the performance of bank stocks might also be related to the available cushion banks have for bad loans.

Banks who provision more during good times, will have higher reserves during bad times, which means that when the market crashes, these banks do not have to increase their provisioning levels as much and will have sounder earnings. As they won't have to increase their provisioning they also won't have to eat into their equity (through lower/negative retained earnings) to increase the reserves.

[6] They define abnormal loan growth as the percentage of growth of the bank above the country's aggregrate credit growth.

This all leads to the hypothesis 1: *Preceding loan portfolio growth loses its predictive power when loan loss provisions, reserves and equity are added to the equation.*

2.4 Loan Seasoning

Loan seasoning most likely also affects the research of FPS. The concept of loan seasoning is that borrowers usually do no immediately default on their loans. Borrowers can withhold investments or other payments in the first years to make their interest and loan payments. After a few years the borrowers are not able to do this anymore and start to default on their loans (Avery and Gordy, 1998).

Berger and Udell (2004) attribute this to their institutional memory hypothesis, due to loan officer turnover loans made in an credit boom have a higher chance of default as the loan officers do not remember or recognize the associated risk (see also section 2.2).

Foos, Norden, and Weber (2010) show - in line with the loan seasoning concept - that the loans made three years ago have the biggest impact on the current loan losses. The effect of the loan growth two and four years ago also has a significant effect, but less than the three-year effect. This implies that *if* borrowers default on their loans, this is most likely done after three years. Notably the growth of four years ago has quite a small effect, implying that if a borrower 'survives' the first three years, they are good for their money. Salas and Saurina (2002) find a similar result for savings banks in Spain. Hess, Grimes, and Holmes (2009) also find that the effect of the loan growth of two to four years ago has a strong effect on the subsequent loan losses in Australasia.

Combined, this line of research suggest that the exposure to additional loan losses of banks differs according to the moment that the 'abnormal' loan growth was realized.

FPS categorize banks based on the loan growth over the past three years. This seems to contradict the loan seasoning effect. Imagine two banks, A and B. In both cases we start with an initial loan portfolio size of $P_{t,x}$. P represents the size of the loan portfolio, at year t, while x stands for either bank A or B. This portfolio grows each year by $Growth_{t,x}$. The size of the loan portfolio after three years, for the banks is thus:

$$P_3 = P_0 * (1 + Growth_{1,x}) * (1 + Growth_{2,x}) * (1 + Growth_{3,x}) \tag{2.1}$$

The three year growth, the main metric used by FPS, is thus:

$$(P_3/P_0) = 1 * (1 + Growth_{1,x}) * (1 + Growth_{2,x}) * (1 + Growth_{3,x}) \tag{2.2}$$

By using the preceding 3 year loan growth the moment of the growth does not matter, but only the overall growth. This does not align with the research of Foos, Norden, and Weber, and Berger and Udell. By looking at the overall growth over the past 3 years the loan seasoning effect is ignored and the quartiles include both banks that will experience defaults at different moments.

2.4.1 Example

A simple example with numbers. Both bank A and bank B start with an initial loan portfolio of \$100 million. Bank A grows by 20% in year 1 and 5% in year 2 and 3. Bank B grows by 5% in year 1 and 2, but 20% in year 3. At the end of year 3 both banks have a loan portfolio of $\$100 * 1.05 * 1.05 * 1.2 = \$132.3$, which represents a 3-year growth of 32.3%. Both bank A and bank B will be placed in the same quartile, but their *increased exposure* in year four is quite different.

If we assume that it takes indeed three years before loan losses realize, the increased exposure of the loan growth in year 1 realizes in year 4. For bank A this is \$ 20 million, but for bank B this exposure is 'only' \$ 5 million. Based on the study of FPS, banks in the same quartile are equally bad in recognizing the risk of their loans. The default rates for the loans made by bank A en B in year 1 should therefore be the same.

If we multiple the same default rate against the exposure of both banks, the loan losses that bank A needs to take are four times the size of bank B. We can make this example even more extreme if we think of a bank C, that also starts with \$ 100 million, but does not grow in year 1 and 2, but grows 32.3% in year 3. This bank's increased risk would only start to show in year 6. Based on quantiles of three year growth it would be associated with the risks of bank A and B though, despite that the loan loss of bank C will most likely be lower in year 4.

FPS overcome this problem by looking at the 3-year growth and the subsequent 3-year returns. The result of their 3-year returns are statistically much more significant than their 1-year returns, based on the preceding 3-year loan growth. If we assume *ceteris paribus* on banks A, B and C over the years 4, 5 and 6, their overall return over years 4 till 6 should be the same.

Yet, if we want to improve our trading results it would make more sense to look at the growth of three years ago. In a 3-year holding portfolio based on quantiles that are based on the 3-year growth A, B and C would be in the same quantile. Despite that bank A will most likely have the worst performance in year 1 and bank B and C in year 3. Over the same three year holding period one could possibly have a higher return if one would not invest in bank A in year 1 and not invest in banks B and C in year 3.

In table 7 FPS split the stock returns per year. Based on the preceding three-year loan growth (both for quartiles as continuous), the stock return for the top growth banks is the worst from year $t+2$ to $t+3$. In panel A of table 9 they also show that the ROA is the worst in year $t+3$. Interestingly, panel B of table 9 shows that the change in ROA is the highest in the period $t+1$ to $t+2$ and not from $t+2$ to $t+3$.

While it is only in year $t+3$ that these banks have significantly the highest level of loan loss provisions,[7] the change biggest change in their loan loss provisions is during year $t+1$.[8] So while the top growth banks start to realize in year $t+1$ that they have granted bad loans, the ROA decreases the hardest during year $t+2$, after which the stock market drops the most during year $t+3$. This shows that the market did not really anticipate the magnitude of how bad the loans were. If the market noticed that the banks suddenly increased their loan loss provisions and correctly noticed this signal the biggest return drop would have been during the period $t+1$ to $t+2$. In that case the market would have followed the ROA. Now the market only reacts after the banks show at the end of $t+2$ that their ROA is deteriorating, which results in the worst stock performance during the period $t+2$ to $t+3$.

Furthermore, as Keeton (1999) and Salas and Saurina (2002) show, loan growth per sé does not imply something bad. High loan growth in year 3 might be justified due to a positive economic shock, but the same growth in year 1 might be unjustifiable. To give an example, banks that grew a lot in 2007 most likely made a lot of bad loans because they were overoptimistic and had to recognize a lot of loan losses in the years after. Banks that grew by the same percentage in 2010 most likely found either very secure borrowers or had very high loan loss provisions, because they were much more aware of (or took more time assessing) the risks associated with their loans.

This all leads to hypothesis 2: *The performance of three subsequent 1-year holding portfolio's based on loan growth of three years ago performs better than one 3-year holding*

[7] See panel C in table 9.

[8] See panel D in table 9.

portfolio based on the preceding 3-year loan growth.

Hypotheses 2 is driven by two sub-hypotheses.

Sub-hypothesis 2.1: *The 1-year returns are driven by the loan portfolio growth of 3 years ago and not the preceding 3-year loan portfolio growth.*[9]

Sub-hypothesis 2.2 is: *The biggest drop in the ROA will be two years after the loan growth.*[10]

2.5 How do banks grow the fastest?

Banks can increase their market share (and portfolio) mainly in two ways. Lowering interest rates and/or credit standards.

Given the research of FPS that the fastest growing banks are the ones that will perform the worst in the future, it is interesting to see if there is a difference in how these banks achieve this growth. Sinkey and Greenawalt (1991) find that the higher the interest rate, the higher the subsequent non-performance of the loans. This is subject to a form of endogeneity, because it is unsure if the loans failed because of the high interest rate, or that the high interest rate was charged, because it was a high risk loan. On the other hand, Foos, Norden, and Weber (2010) show that fast growing banks grant new loans at a lower interest rate. They find this by looking at the relative drop in the average interest rate after the high growth. They find that the more a bank grows, the lower the average interest rate. If we assume that fast growing banks grant worse (or more risky) loans, but also at a lower interest rate, than the research of Sinkey and Greenawalt must mean that the higher interest rate was the reason for the failure.

The finding of Foos, Norden, and Weber (2010), which later was confirmed for Italy by Crovini, Ossola, and Giovando (2016), that new loans have a lower interest rate, is in contrast with the idea of risk-based loan pricing. If the new loans are indeed worse, these loans would have higher interest rates. With the assumption that the fastest growing banks are indeed the most ignorant, the top quartile banks should have worst interest income.

[9] So the loan growth of period $t-3$ to $t-2$ will have the biggest impact on the stock return of year $t+1$.

[10] So the biggest drop in ROA will be during the period from $t-1$ to t, based on the loan growth of period $t-3$ to $t-2$.

Hypothesis 3: *The drop in the relative interest income will be the highest for the fastest growing banks.*

The other method is lowering credit standards. As mentioned in section 2.2 there are multiple reasons why a bank will lower its credit standard. Though if banks lower their credit standards, they accept the fact that they will take on more risky loans. This would have to result in higher provisions, and thus higher loan loss reserves (Clair, 1992). While FPS show the level of loan loss provisions for different years, they look at the levels for different quartiles based on preceding three-year loan growth. This does not show the incremental change is the loan loss provision (or reserves).

Laeven and Majnoni (2003) do look at the effect of the preceding loan growth on the level of the provisions. The find that the effect differs per region, but for the U.S. they find both significantly positive and negative coefficients, dependent on their model specification. They find that the more US banks grow, the lower the provisioning percentage for that year will be. This would indicate that banks do not grow by lowering the credit standard, as lowering the standard should increase the level of provisioning. When Laeven and Majnoni lag the provisioning level by two years, they find that loan growth has a positive effect. This would indicate that the higher the current growth, the higher the provisioning in the past. High provisions indicate low credit standards, thus this would indicate that low credit standards do grow the loan portfolio.

Bikker and Metzemakers (2005) find a positive relation between the loan growth and the level of provisioning during the same year. This is in contrast with Laeven and Majnoni (2003). Bikker and Metzemakers also note this difference and find that the effect of loan growth on provisioning is ambiguous. It is completely up to model specification and data choices. Foos, Norden, and Weber (2010) also have inconsistent results for the effect that preceding loan growth have on the current loan loss provisioning, which would also indicate that the loan loss provisioning (as proxy for credit standard) would not have an impact on the loan growth. Therefore I assume the null hypothesis, lowering credit standards does not drive loan growth, is correct.

This all leads to hypothesis 4: *The loan growth is mainly driven by lowering interest rates.*

This hypothesis follows from two sub hypotheses:

Sub-hypothesis 4.1: *Lowering interest rates significantly increases the growth rate of the loan portfolio.*

Sub-hypothesis 4.2: *Lowering the credit standard does not significantly drive the loan growth.*

2.6 Recession Crashes

In section 2.4 the hypothesis is that the loan growth of three years ago is the main driver for the current loan losses. But an interesting question is if this also holds during an recession. Given that there is a recession, which banks will crash the hardest?

Krishnamurthy, Muir, and Yale (2015) show that credit spreads are low before a crises. This indicates that banks and investors do not anticipate a crash, because otherwise they would have demanded a higher risk-premium, resulting in a higher spread. Cavallo and Majnoni (2002) show a similar conclusion, based on a theoretical model. Foos, Norden, and Weber (2010) find that the amount of lags has a different impact on the loan losses. Because loans do not immediately fail, they find that growth from three years ago has the biggest impact on the loan losses in the current year. But which loans will default the most during a banking downturn? There is only a finite amount of loans.

When a bank lowers its credit standards there are two possibilities, both of which have an adverse selection problem. The bank can either lower its standards so it can compete with other banks, or lower it so much that it gains access to an untapped pool of borrowers. The other banks will try to keep their high quality clients and only let go of their least profitable or least secure borrowers. With the untapped pool of borrowers the bank will have no benchmark for the interest rates. In both cases, the bank that is aimed at increasing its market share will get the lowest quality of borrowers. Shaffer (1998) shows that this adverse selection effect is especially strong for newly formed banks or branches. In this respect the banks that start growing the latest will have the worst loans, but also the lowest spreads. Combined this could implicate that banks that grow the fastest before a credit crunch will be hit the hardest.

Mian and Sufi (2009) explain via a theoretical model, and show empirically, how increasing the supply of credit can lead to overoptimistic lending and thus worse performing loans. In their case the supply was increased by the increasing market for mortgage backed securities (MBS), which allowed banks to grant loans to low quality of borrowers, but not bear the risk by immediately selling the MBS.

While normally the (excess) loans that were granted three years ago will have the biggest effect on the return, this might not be true during a recession. As explained in section 2.2, the worst loans are made during made when the credit standard is the lowest. In the same section is explained that the lowest standard is right before the credit crunch. This would also implicate that the worst loans are made right before a credit crunch.

In their robustness test, FPS remove the years which are marked as a recession by NBER, but find no difference. This section looks at the recessions the other way around. There are three hypothesis possible. The first hypothesis is in line with the research of FPS and assumes there is no difference between no recession and a recession.

Hypothesis 5: *Banks in the top loan growth quartile over the past three years will crash the hardest during a recession.*

Hypothesis 6 is in line with section 2.2: *Banks that are in the top loan growth quartile based on the growth three years ago will crash the hardest during a recession.*

The final hypothesis, which contradicts hypothesis 6, is based on the idea that the worst loans are made right before the crisis. This would mean that the banks in the top quartile before the recession granted the worst loans.

Hypothesis 7: *The banks in the top growth quartile, based on the loan growth in the year preceding a recession, will crash the hardest during a recession.*

2.7 Secured Loans

Another factor that affects the probability that loan losses need to be taken is the type of loans in the loan portfolio. Different kinds of loans have different kind of associated risks (e.g. student and car loans, commercial and industrial loans, and morgages). Banks can provision accordingly to the risks associated with these different kinds of loans, but loans with different risk levels can still have the same interest rate. This is because some loans are secured and have collateral.

Collateral works two ways. It is an easy way for high quality borrowers to lower the interest they have to pay as the lender feels more secure, but the borrower is sure they won't lose the asset. Low quality borrowers might want to signal they are high quality as well by providing a lot of collateral, but they know that they might lose their collateral, which are their houses or business assets. Optimists can do the same, with the distinct difference that they *think* that they are high quality, but when in fact they are not.

On the other hand, banks have a lower incentive to monitor borrowers which have provided high quality collateral, as the banks will takeover the collateral (Manove and Padilla, 1999; Berger and Udell, 1990). Berger and Udell find that most often collateral is associated, on average, with riskier borrowers, riskier loans, and riskier banks. Salas and Saurina (2002) do note that the research of Berger and Udell only covers loans to firms, which are more risky than mortgages. Salas and Saurina find in their own study that more collateral leads to lower problem loans for saving banks.

Foos, Norden, and Weber (2010) do not classify the different loans, but look at the different kind of banks, as described in their Bankscope dataset. They find that real estate and morgage banks, which provide highly secure (or via collateral secured) loans have lower losses than other banks.

Overall, the theory leaves us with two hypotheses that impact the story of FPS. First is the impact of secured loans on the provisioning level, while the second hypothesis is about the impact on the stock performance through loan losses.

Hypothesis 8: *Banks with a greater portion secured loans will have lower provisioning levels.*

Hypothesis 9: *Banks with a greater portion secured loans will have higher stock returns.*

If banks with more secured loans are indeed safer investments and have higher returns, growth in these secured loans should not lead to a decrease in the stock returns. This leads to the following.

Hypothesis 10: *Banks in the top growth quartile of secured loans do not experience worse stock performance.*

3 Data

This chapter explains how the data is obtained. It also describes how to construct the used variables.

3.1 Sample Construction

As this thesis is based on the paper of FPS, I try to construct the same database as FPS. This means that all depository credit institutions and bank holding companies are used for which there is data in the Financial Services format of Standard and Poor's Compustat and the monthly security file of the Center for Research in Security Prices (CRSP). The fundamental data mainly comes from Compustat. All the stock related data is obtained from CRSP. The recession indicators come from the National Bureau of Economic Research. As FPS find that most banks have been added to CRSP in 1972, they let their sample run from 1972. As they need at least one year of stock returns after the balance sheet data their sample ends in 2013.

The dataset used in this thesis will run from 1972 till 2016. For the main results the same time period as FPS will be used, but as the additional years are available I will include them in the overall database. In the robustness section I will control if these additional years provide any different results.

3.1.1 Standard Industry Classification

FPS start by filtering the CRSP database on Standard Industry Classification (SIC) codes for their database. Firms are included if their SIC code is between 6020 and 6079 (Commercial Banks, Savings Institutions, and Credit Unions), between 6710 and 6712 (Offices of Bank Holding Companies), or between 6120 and 6123 (Savings and Loan Associations prior to 1990) at a point in time. The reason for excluding non-depository credit institutions, brokerages, and investment banks is that the research is aimed at the traditional banking industry. For firms that first (or later) fall outside the used SIC range, only the observations for which the firms fall within the SIC range are used.[1]

It should be noted that both CRSP and Compustat sometimes report no historical SIC code (SICCD and SICH respectively) and only show the current SIC code (HSICCD and SIC). For these observations I assume that the historical SIC should be the same as the first non-missing SIC code.[2] If the database shows a missing SIC code for the entire history column I assume it is always had the current SIC code.[3]

As noted by FPS, the SIC codes sometimes oscillate between different classifications. Furthermore, updating the SIC codes might be delayed by CRSP. To improve precision FPS use EDGAR and Google searches to better classify what the correct SIC should be. This includes some subjectivity which is hard to mimic. Therefore I incorporate the SIC codes obtained from Compustat. As Guenther and Rosman (1994) show there *can* be a difference in the assigned SIC code to a company in the CRSP and Compustat databases.[4] I include observations when the firm falls within the SIC range according to CRSP SIC, and when the company oscillates I confirm with the Compustat SIC if it really should fall outside the dataset.

Note that while the SICs can be different this is not always the case, nor does the difference mean that firms would be excluded if use the other database's SIC codes. E.g. NASB Financial Inc., which is a Federally Chartered Savings Institutions (6035) according to Compustat, but a Bank Holding Company (6710) according to CRSP. In both cases NASB Financial Inc. would be included in the database. Also note that the Compustat database only contains the 6020-6079 SICs.[5]

3.1.2 Other CRSP filters

All American Depositary Receipts (ADRs) are excluded. Observations missing their share class are backfilled. This is justified as the share class does not change over time. If it is classified as a common share in the future, it must have been a common share in the past as well.[6]

[1] E.g. FPS mention that Morgan Stanley and Goldman Sachs used to be investment banks before September 2008, but became bank holding companies afterwards. Observations for these two firms are only included after September 2008.

[2] So a company that shows no SIC code from 1980 till 1985, but has a SIC code from 1986 onwards, I assume this SIC code should also apply from 1980.

[3] Sometimes the SICCD column is empty, but the HSICCD shows a SIC of 6712. In those cases I assume the company always was a Bank Holding Company.

[4] Guenther and Rosman do not give a preference over a database, but mention that researches should be cautious when they filter on SIC codes.

[5] In my database CRSP and Compustat agree in more than 85% of the observations.

[6] This means I include all observations which have a share code (SHRCD) of 10 or 11.

Furthermore, all firms incorporated outside of the U.S. are excluded. While it is interesting to see how the stock market in other countries reacts to the loan portfolio growth, it is important to stick to the database of FPS. Otherwise there might be a *joint-hypothesis problem*, in which the possible difference between my results and those of FPS are explained by either a different dataset or different model. This importance of the correctly replicating is well shown in the research of Guthrie, Sokolowsky, and Wan (2012), who show that even two outliers can significantly alter the outcome of research. Prior research in bank performance shows that there can be differences per region (e.g. Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005; Foos, Norden, and Weber, 2010).

All observations in which the stock price is less than one dollar are dropped. This is done to be in line with FPS, and this is a common practice in empirical research to the U.S. stock market. This does have the unfortunate additional effect that banks that fail are excluded from a certain point as their stock price will most likely be under one dollar before they collapse. Though this is acceptable, as the research point is not to see if banks that grew the fastest have a higher chance of collapsing.

FPS manually inspect the list and eliminate firms that are not depository banks or bank holding companies according to them. They list the following firms: American Express, Berkshire Hathaway, GEICO, Mellon Financial Corp and State Street. These firms are removed from the database. Unfortunately it is unclear which other firms FPS have eliminated.

After applying all these filters the database is compromised of 302,405 observations from 2,083 unique banks. This means an average of 145 bank-month observations, or 12 bank-year observations. This bank-year average is the same as the FPS report, but they report this after incorporating the Compustat fundamental data and filtering on size. I will do this below.

3.1.3 Fundamental Compustat filters

FPS also document that Compustat added a lot of small banks in 1993. They find that if they remove all banks that have less than $ 2 billion in total assets, the structural break in the data disappears. The $ 2 billion point is measured in 2013 US dollars, using the Bureau of Labor Statistics' Consumer Price Index (CPI) for all urban consumers. I also drop these 'small' banks, using the same CPI adjustment.

3.1.4 RSSD data

Data on bank mergers and more fundamental data is available through the U.S. Federal banking system. The Chicago FED has a M&A database, but the U.S. government keeps track of banks through their RSSD identifier. The New York Fed has a linking table for the RSSD to PERMCO's from CRSP.

Some PERMCO's appear twice in the dataset, so linking is not immediately available. I manually check all the doubles. Sometimes the RSSID changes after a certain date, but the PERMCO stays the same. Other times there are two different firms where a new firm reuses an old PERMCO, but the RSSD is different. For all the doubles I change the PERMCO to a unique number. I then manually check the main database and based on the name and date I adjust the PERMCO in the main database, so the RSSID is assigned to the correct company. In three cases there is also a duplicate RSSD, but as these banks do not appear in the other databases they are removed. The National Information Center (NIC) also has a database with all active and inactive banks with their RSSD and their CUSIP. By linking this database missing RSSD's can be found.

Additional fundamental loan data is obtained from call reports or FR-Y-9C reports. This data provides more detail on the loan portfolio (e.g. percentage of real estate back loans, commercial & industrial loans, ect.), but can also be used to determine the size of the assets and the loan portfolio of the target bank. First the call reports and FR-Y-9C reports are 'translated', because - while they provide the same information - they use different names for similar information.[7] This data is merged with the CRSP/Compustat database, based on the RSSD.

In the Chicago database the mergers that are actually a restructuring are removed.[8] The fundamentals of the target are obtained by merging the M&A database with the latest available call reports or FR-Y-9C reports before the merger. The Chicago database double counts a merger if both the ultimate owner and its subsidiary bank(s) are acquired, it will list both transactions as a merger. To prevent double counting of the acquired loans the subsidiary bank observations are dropped if fundamental data is available for the ultimate owner. If the fundamental data for the ultimate owner is missing the data of the subsidiary bank is used. If a bank is a acquired by multiple buyers it is assumed that each buyer will get $1/n$ of the loan.

[7] E.g. total assets is called RCFD2170 in call reports and BHCK2170 in FR-Y-9C reports.
[8] Mergers where the owner of the target is either the buyer or the owner of the buyer.

3.2 Variable Construction

For each bank a one-, two-, and three-year return statistic per fiscal year is calculated. This is done by first creating a total return index per bank. This return index incorporates stock splits and dividend payments.[9] As the subsequent return is of importance, the return is calculated by looking at the percentage increase from the level of the index on the month-end of the fiscal year end and its level one, two, or three years later. The two- and three-year returns are annualized. The formula is shown below, were i is the bank indicator, t is the current time, and k is the one-, two- or three-year period.

$$Annualized\ Stock\ Return_{i,t,k} = (\frac{Total\ Return\ Index_{i,t+k}}{Total\ Return\ Index_{i,t}})^{\frac{1}{k}} - 1 \tag{3.1}$$

For loan growth the total loans to customers is used (Compustat item LCUACU). This variable looks backward. So the one years loan growth is calculated by looking at the increase of the level of the total loans at the fiscal year end and the level at the previous year end. For two- and three-year growth the level of two and three years ago is taken. The two and three year loan growths are also annualized. The asset and loan growth of three years ago is calculated by dividing the level of the loan portfolio of two years ago by its level three years ago, minus one.

$$Annualized\ Loan\ Growth_{i,t,k} = (\frac{Loan\ Portfolio_{i,t}}{Loan\ Portfolio_{i,t-k}})^{\frac{1}{k}} - 1 \tag{3.2}$$

The loan loss provision percentage (LLP) is calculated by dividing the loan loss provision level (Compustat PCL) by the gross amount of the loans, multiplied by 100. Total gross loans are defined as total loans to customers plus reserves for credit losses (Compustat RCL). The loan loss reserve percentage (LLR) is calculated in a similar matter. The Equity ratio is calculated by dividing the tangible common equity (Compustat CEQT) by the total assets (Compustat AT), multiplied by 100. The reason I choose for the tangible common equity is that this metric is used in determining the capital ratio of a bank. The regulation around Tier 1 and Tier 2 has changed a lot during the sample period, but the tangible common equity remained the same (Ahmed, Takeda, and Thomas, 1999; Bouvatier and Lepetit, 2008). Cooper, Jackson III, and Patterson (2003) also note the importance of the equity-to-asset ratio on bank stock returns. Return on Assets (ROA) is expressed as a percentage and is calculated by dividing net income (Compustat NI) by total assets, multiplied by 100.

[9] This is the CRSP RET metric. If the RET is missing for a month I assume the return is zero, as is done by FPS.

$$Loan\ Loss\ Provision\ Percentage_{i,t} = \frac{Loan\ Loss\ Provision_{i,t}}{Loan\ Portfolio_{i,t} + Loan\ Loss\ Reserves_{i,t}} * 100 \tag{3.3}$$

The *Relative Interest Income* (RII) is constructed in a similar manner as done by Foos, Norden, and Weber (2010). It is the fraction of the total gross interest income (Compustat IDILC) over total gross customer loans.[10] In the income statement the interest income is prorated. This means that a loan granted in November will be on the balance sheet for the full amount, but the interest rate will only flow through the income statement for the months November and December. The full interest will only flow through the income statement the second year.

Foos, Norden and Weber control for this with the assumption that loans are granted uniformly throughout the year. Then, by taking the average of the customer loans from year $t-1$ and t, they minimize the effect of proration in the income statement.The variable is thus constructed as followed:

$$Relative\ Interest\ Income_{i,t} = \frac{Total\ Interest\ Income_{i,t}}{\frac{Gross\ Total\ Customer\ Loans_{i,t-1} + Gross\ Total\ Customer\ Loans_{i,t}}{2}} \tag{3.4}$$

Based on the federal banking data the percentage of special loans are calculated. This is done by dividing their value to the gross amount of loans, multiplied by 100.[11] This is done for Real Estate backed loans,[12] Agricultural loans,[13] Commercial and Industrial loans,[14] Personal loans (student loans, car loans, ect.)[15] and leases.[16] If the value is missing the value is set to zero as the missing value means the bank just has no loans of that kind.

3.2.1 Mergers & Acquisitions

To differentiate the organic and external growth the organic growth of year t is calculated as followed:

[10] Foos, Norden and Weber take the total gross interest income over total customer loans. The problem is that this is net of reserves for loan losses. The interest should be calculated over the gross loan amount.

[11] The gross loan amount is RCFD2122 on call reports and BHCK2122 for bank holding companies.

[12] This is variable RCFD1410 on call reports and BHCK1410 on FR-y-9C reports.

[13] RCFD1590 and BHCK1590.

[14] RCFD1600 and the sum of BHCK1763 and BHCK1764.

[15] RCFD1975 and the sum of BHCKB538, BHCKB539, BHCKK137 and BHCKK207.

[16] RCFD2165 and the sum of BHCKF162 and BHCKF163.

$$Organic\ Loan\ Growth_t = \frac{Total\ Loans_t - Loans\ Acquired_t}{Total\ Loans_{t-1}} - 1 \tag{3.5}$$

As mentioned before, when multiple banks acquire the same target, it is assumed each buyer gets $1/n$ of the target.

3.3 Summary Statistics

In the end the database is compromised of 8.173 observations for 679 unique banks, with an average of 12 bank-year observations. When the sample is restricted to the period from 1972 till 2013, the database shows 652 unique banks, with an average of 12 bank-year observations. This is a difference of 12 banks compared to the database of FPS, but the average of 12 year observations per bank remains.

In line with FPS loan growth, asset growth, ROA and loan loss provisions are windsorized. Furthermore, the loan loss reserve, equity ratio, the relative interest income and the percentages of the different loans are also windsorized. The winsorizing is done at the 1st and 99th percentile.

Table 3.1 shows the summary statistics for the database. The first interesting thing to see is the high average 1-year return of 15.4%. This average annual percentage drops if the window becomes wider, which means that banks cannot keep up the high returns. For the two- and three-year returns non-overlapping returns are used. This is done to prevent problems with the standard errors in the regressions. The asset growth hovers between the 12% and 13%, regardless of the chosen window. The loan portfolio growth is about 0.8% higher than its asset growth equivalent. This makes sense as the loan portfolio is a big part of the assets, but not 100%.

The loan loss provision shows that banks on average only provision for 0.69% of their loan portfolio, though one standard deviation already more than doubles this. The loan loss reserves are 1.59% of the gross loan portfolio, but is less volatile than the loan loss provision. This might be due to the fact that banks need to maintain a certain level of reserves by the regulators. The equity ratio shows that banks on average hold a 6.8% equity buffer, which is lower than Foos, Norden, and Weber (2010) found. This might be due to the fact that their dataset also includes European banks which have the tendency to hold higher buffers.

The ROA of 0.79% seems low, but is understandable given the fact that banks are very asset heavy, as the majority of the assets on the balance sheet of a bank will be loans. While the interest it receives on these loans are its main income, the main costs of a bank are the interest payments it must make on the deposits it uses

VARIABLES	N	mean	sd	min	max
1-year return	7,265	0.154	0.374	-0.985	4.297
2-year return	4,323	0.131	0.272	-0.873	1.400
3-year return	2,793	0.122	0.216	-0.825	1.151
1-year loan growth	7,297	0.135	0.200	-0.612	2.064
2-year loan growth	7,073	0.133	0.153	-0.364	1.539
3-year loan growth	6,702	0.132	0.133	-0.260	1.210
1-year asset growth	7,444	0.128	0.183	-0.274	2.168
2-year asset growth	7,274	0.126	0.133	-0.198	1.254
3-year asset growth	6,943	0.125	0.117	-0.152	1.148
Loan Loss Provision (%)	7,375	0.693	0.901	-0.857	11.466
ΔLoan Loss Provision	6,708	0.0361	0.807	-7.569	7.975
Loan Loss Reserves (%)	7,462	1.593	0.904	0.043	11.254
Equity Ratio (%)	7,569	6.754	2.660	-.259	25.316
ROA (%)	7,566	0.793	0.805	-8.937	4.109
Real Estate Loans (%)	4,320	59.768	20.054	2.239	100.000
Agricultural Loans (%)	4,320	0.834	1.577	0.000	13.234
C&I Loans (%)	4,320	20.480	11.977	0.000	72.587
Personal Loans (%)	4,320	0.728	3.497	0.000	49.424
Leases (%)	4,320	0.310	1.338	0.000	15.767
Relative Interest Income (%)	4,216	10.128	2.651	1.889	19.989
Δ Relative Interest Income (%)	3,963	-0.0921	1.272	-5.364	4.533

TABLE 3.1: **Summary statistics**
This table shows the summary statistics of multiple variables during the sample period of 1972 to 2013. The multiple year growth rates are annualized. The two- and three-year returns, only non-overlapping returns are used. Apart from the returns are all variables windsorized at the 1st and the 99th percentile. For the variable construction see section 3.2.

to grant loans. The interest spread, which is never extremely high, minus the other costs (e.g. salaries and rent) result in a relative low ROA.

The split of the loans show that real estate backed loans make up the majority in the average loan portfolio. This is followed by commercial & industrial loans. The agricultural, personal and lease loans are only a small portion of the loan portfolio.

The relative interest income shows that the average interest rate is 10.1%, this is in line with the research of Foos, Norden, and Weber (2010). They also note that this variable might be upward biased because of interest payments which are not related to the customer loans, hence the maximum of 20.0%.

Overall, table 3.1 shows similar values to table 2 of FPS for the same metrics. The only difference seems to be the outliers for the growth measures and the loan loss provisions. This despite the windsorizing.

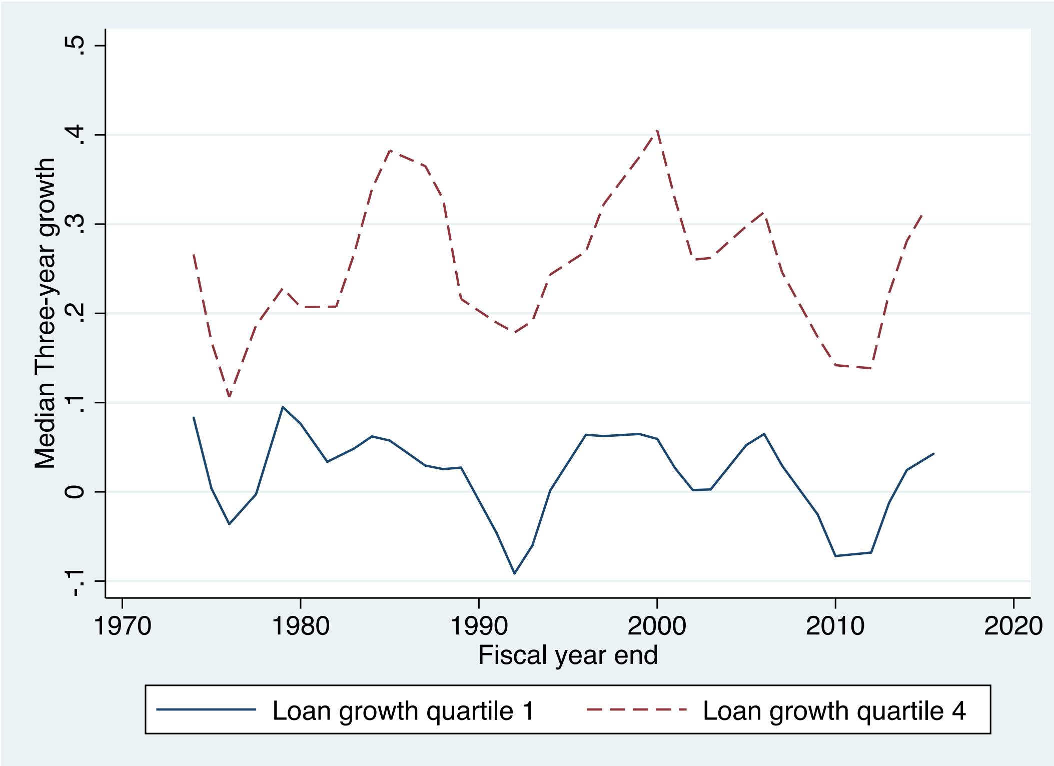

FIGURE 3.1: **Median three-year loan growth for high and low three-year loan growth quartiles**
The figure shows the time series of the median three-year loan portfolio growth for the banks in the top growth quartile and the bottom quartile. The quartiles are based on the loan growth of the preceding three years. The growth rates are annualized. The sample period is from 1972 to 2016.

Figure 3.1 shows the median three-year growth for the top and bottom quartile. These quartiles are made per year for the period 1972 to 2016. The graph shows that both groups follow a somewhat similar pattern. When banks grow, all banks grow and when there is a contraction, all banks contract. Though the range of the median growth of the bottom quartile banks is from -10% to 10%, whereas it is 10% to 40% for the top quartile. The graph looks similar to the one produced by FPS.[17]

Figure 3.2 shows that on average the banks in the highest growth quartile, based on the preceding three year loan portfolio growth, will have lower stock returns the preceding three years. This graph is in line with the research of FPS, stating that the banks that grew the fastest over the past three years, will have worse subsequent

[17] See their Figure 1.

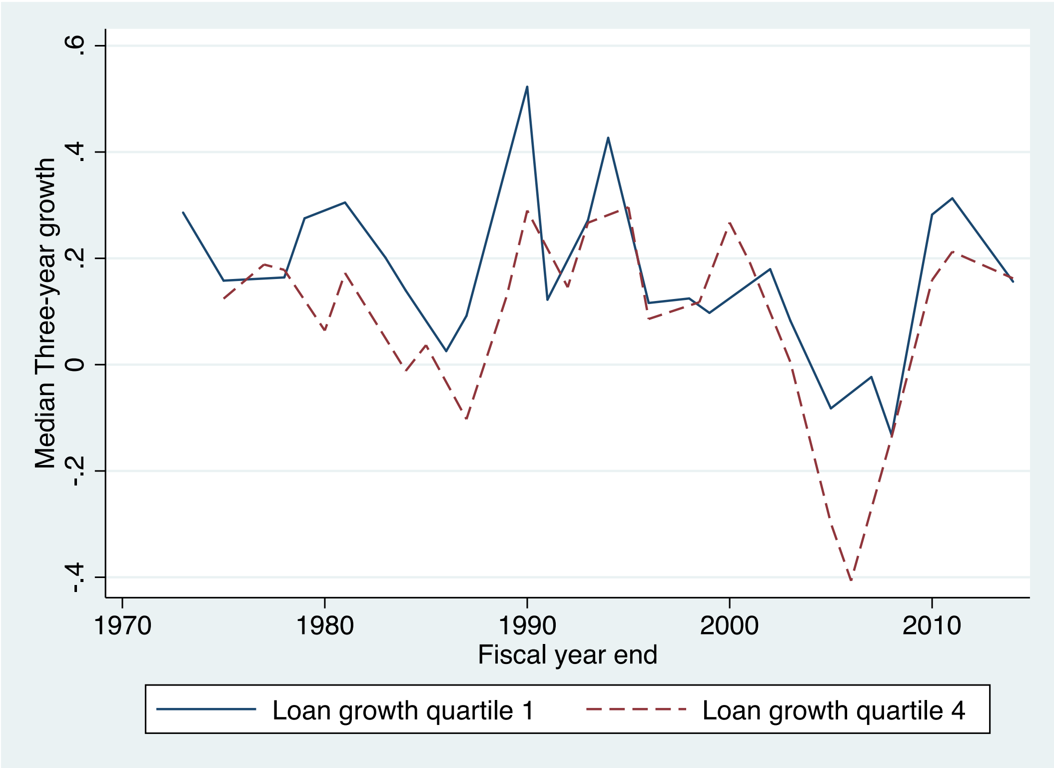

FIGURE 3.2: **Average three-year subsequent return for high and low three-year loan portfolio growth quartiles**
The figure shows the time series of the average three-year loan portfolio non-overlapping returns for the banks in the top growth quartile and the bottom quartile. The quartiles are based on the loan growth of the preceding three years. The returns rates are annualized. Non-overlapping values are used. The sample period is from 1972 to 2016.

performance. Figure 3.2 is slightly different from Figure 2 that FPS show. First, it is not extremely clear if they show the overlapping or non-overlapping returns. In their main body they state it is non-overlapping, in the caption under the figure they do not mention this. Given the smoothness of their graph it looks like they used the overlapping returns. Second, their figure can be best replicated by using the pre-collapsed data. See the Appendix for these figures. Despite the difference the main message of the graph remains.

4 Methodology

In this chapter the used methodology is presented and discussed. This will mainly involve the construction of the models used. The sections will follow the same pattern as the sections in Chapter 2.

4.1 Income Smoothing & Capital Management

In line with FPS and Baron and Xiong (2016) the regressions are estimated with the return index for multiple years as the dependent variable and the growth quartiles as the independent variables. The basic model is the one shown below. The expression $r_{i,t+k}$ stands for the stock return of bank i over period k at time t. The loan growth is measured in quartiles, FPS state this is for two reasons. First, it captures any nonlinearities in the relation between the loan growth and the stock performance. Secondly, it makes it easier to see the difference between high and low growing banks (top versus bottom quartile). The expression $I_{loan\ growth_{i,t} \in Qj}$ is a dummy variable which takes the value of 1 if bank i is in growth quartile j in year t. The value is zero otherwise. Furthermore, year fixed effect are also included to control for the general state of the economy. This is variable δ_t. This all leads to the formula below.

$$r_{i,t+k} = \beta_2 * I_{loan\ growth_{i,t} \in Q2} + \beta_3 * I_{loan\ growth_{i,t} \in Q3} + \beta_4 * I_{loan\ growth_{i,t} \in Q4} + \delta_t + \epsilon_{i,t} \tag{4.1}$$

This is a pooled time-series and corss-sectional regression. Like FPS, I use non-overlapping returns for the two- and three-year returns. For the three-year return model I thus use year one, four, seven, ect. Because new firms enter (and leave) every year I have data for all years. So bank A might enter the database in 1990 and thus will be included in 1990, 1993, 1996. Bank B might enter the database in 1991 and will thus be included in year 1991, 1994,1997. The reason for this method is to prevent autocorrelation in the error terms. Furthermore, standard errors are clustered at firm and time level.

FPS expand their model by including bank fixed effects (α_i) in their second model. I do the same, but also include the other variables; loan loss provision, loan loss reserves and equity ratio. First these additional variables are tested solely next to the standard model of FPS. Finally, a model is used which includes all the additional variables. Unlike the loan growth dummies, the loan loss provision, loan loss reserves and equity ratio are continuous variables. This is in line with previous research (e.g. Cooper, Jackson III, and Patterson, 2003; Ahmed, Takeda, and Thomas, 1999; Bikker and Metzemakers, 2005), but it is also because the main point of this test is to see if the significance of the loan growth quartiles holds when correcting with the additional variables. It therefore does not really matter how these variables are included.

For the multi-year loan growth the average loan loss provision percentage over the same period is used. This is because the loan loss provision is a yearly accounting post (in the income statement). It would not make sense to look at the loan portfolio growth over the past three year, but use the provisioning of only the last year. For the the loan loss reserves and the equity ratio the balance the balance sheet post at year t is used, as it shows how thick the 'cushion' is that the bank has against future losses. The most extensive model therefore becomes:

$$\begin{aligned} r_{i,t+k} = \alpha_i &+ \beta_2 * I_{loan\ growth_{i,t} \in Q2} + \beta_3 * I_{loan\ growth_{i,t} \in Q3} + \beta_4 * I_{loan\ growth_{i,t} \in Q4} \\ &+ \beta_5 * Average\ LLP_{i,t} + \beta_6 * LLR_{i,t} + \beta_7 * Equity\ Ratio_{i,t} + \delta_t + \epsilon_{i,t} \end{aligned} \tag{4.2}$$

4.2 Loan Seasoning

Hypothesis 2 looks at the effect of loan seasoning on the stock returns. To test subhypothesis 2.1 the approach of Foos, Norden, and Weber (2010) and Salas and Saurina (2002) is followed, who use a continuous growth variable and lag this variable. This should pose no problem for two reasons. First, FPS note that their results do not differ if they use the preceding loan growth variable in as a continuous variable, instead of based on quartiles. Second, sub-hypothesis 2.1 looks at which preceding year has the biggest effect on the subsequent returns, not what the effect is of the different quartiles on the subsequent return. This leads to the following extensive model.

$$r_{i,t+1} = \alpha_i + \beta_2 * Loan\ Growth_{i,t} + \beta_3 * Loan\ Growth_{i,t-1} + \beta_4 * Loan\ Growth_{i,t-2} + \delta_t + \epsilon_{i,t} \quad (4.3)$$

The expectation is that β_4 will be the most significant, because the dependent variable is the return over the next year. So the loan growth from $t-3$ to $t-2$ is three year ago for the return from t to $t+1$.

Hypothesis 2.2 can be tested with the following model, where $\Delta ROA_{i,t}$ represents the difference between the ROA on time t and $t-1$.

$$\Delta ROA_{i,t} = \alpha_i + \beta_2 * Loan\ Growth_{i,t} + \beta_3 * Loan\ Growth_{i,t-1} + \beta_4 * Loan\ Growth_{i,t-2} + \delta_t + \epsilon_{i,t} \quad (4.4)$$

The expectation is that β_4 will be the biggest negative coefficient. This coefficient shows the impact of the growth from the period $t-3$ to $t-2$. If the coefficient of β_4 is the most negative, it means that the ROA will have its biggest drop two years after the high growth. This will be one year before the stock market crashes, as posed by hypothesis 2.1.

4.3 How do banks grow fast

Foos, Norden and Weber note that one must take the first difference of the relative interest income, because $RRI_{i,t}$ is highly correlated with $RII_{i,t-1}$. This is because all the interest income from all active loans from before $t-1$ are included in the interest income of $RRI_{i,t}$ and $RII_{i,t-1}$. By taking the first difference we approximate the incremental change of the interest income.[1] This first difference approach is also taken for the loan loss provision, for the same reason.

As noted by Foos, Norden, and Weber, a lag of the growth rate like used in section 4.2 is not necessary. The hypothesis states that the fastest growing banks will have the biggest drop in the relative interest income. Thus the model will have the preceding (one year) loan growth as the independent variable. The quartile

[1] I say approximate, as this method shows the change in the average interest from the entire loan portfolio. Like Foos, Norden and Weber note it is impossible to determinate at what price/interest rate the new loans were granted.

approach of FPS is used again to measure the impact of the loan portfolio growth. This leads to the following model.

$$\Delta RII_{i,t} = (\alpha_i +)\beta_2 * I_{loan\ growth_{i,t} \in Q2} + \beta_3 * I_{loan\ growth_{i,t} \in Q3} + \beta_4 * I_{loan\ growth_{i,t} \in Q4} + \delta_t + \epsilon_{i,t} \quad (4.5)$$

For hypothesis 4, the sub-hypotheses need to be tested first. To test these sub-hypotheses the method of FPS is used once more. The quartiles are now based on the relevant metric (ΔRII or ΔLLP) with the difference between year t and $t-1$. For the model with ΔLLP quartiles, the LLR is included to control for any capital management.[2] The models therefore become as follows.

$$Loan\ Growth_{i,t} = \alpha_i + \beta_2 * \Delta RII_{i,t \in Q2} + \beta_3 * \Delta RII_{i,t \in Q3} + \beta_4 * \Delta RII_{i,t \in Q4} + \delta_t + \epsilon_{i,t} \quad (4.6)$$

and

$$Loan\ Growth_{i,t} = \alpha_i + \beta_2 * \Delta LLP_{i,t \in Q2} + \beta_3 * \Delta LLP_{i,t \in Q3} + \beta_4 * \Delta LLP_{i,t \in Q4} + \beta_5 * LLR + \delta_t + \epsilon_{i,t} \quad (4.7)$$

To test hypothesis 4, the two sub-hypotheses are combined in one model. By multiplying one standard deviation of the variable to the corresponding coefficient the effect per variable can be seen. The significant coefficient with the highest value when multiplied by one standard deviation of that variable is the main driver of the loan growth.

$$Loan\ Growth_{i,t} = \alpha_i + \beta_1 * \Delta RII + \beta_2 * \Delta LLP + \beta_3 * LLR + \delta_t + \epsilon_{i,t} \quad (4.8)$$

With the formula above the impact of the different variables on the loan growth as a percentage can be found. It is possible that the impact of the variables differs per growth quartile. Therefore the formula is used again, but now per growth quartile. Because e.g. the lower interest rate might be the main driver for the loan growth in

[2] See section 2.3 for the theoretical explanation of capital management.

general, for the fastest growing banks it might be the lowering of the credit standard. By looking at the drivers per growth quartile a differentiation can be made, and possibly the driver for the fast(est) loan growth can be found.

4.4 Recession Crashes

To test hypothesis 5, 6 and 7 some predefined formula's are used. Hypothesis 5 can be tested by using model 4.1 and hypotheses 6 and 7 can be done by using model 4.3. By including interaction variables between the loan growth and the observation preceding a crisis the effect can easily be seen. The interaction variable uses a dummy which takes the value of 1 in the year preceding a crisis. The NBER recession indicators show that most crises last multiple year. The years which are regarded as an actual crisis are dropped. If these year would not be excluded the regressions would include the effect of loan growth during a crisis. The main point of this section is to see if loans made before a crisis are worse than during a normal period. To clarify $r_{i,t+k}$ will lie in the crisis year(s) because $k > 0$.

The NBER recession indicators are used to determine when there is a crash. The following periods will be regarded as a crash: 1974 - 1975, 1980 - 1982, 1990 - 1991, 2001, 2008 - 2009. The observations for these years are dropped, while the interaction dummy will 'activate' the year before the crisis period.

4.5 Secured Loans

To test hypothesis 8 the percentage of the different kind of loans is regressed on the loan loss provision. The real estate backed loans have the highest level of collateral, so it is expected that this has a significant negative coefficient. The personal loans have the least amount of collateral, so it is expected that this has a significant positive coefficient. The loan loss reserves is included again to control for the capital management theory. The most extensive model therefore becomes.

$$\begin{aligned} &Loan\ Loss\ Provisions_{i,t} = \alpha_i + \beta_2 * Real\ Estate\ Loans_{i,t} + \beta_3 * Agricultural\ Loans_{i,t} \\ &+ \beta_4 * C\&I\ Loans_{i,t} + \beta_5 * Personal\ Loans_{i,t} + \beta_6 * Leases + \beta_7 * LLR_{i,t} + \delta_t + \epsilon_{i,t} \end{aligned} \tag{4.9}$$

To test hypothesis 9 the formula above is slightly altered to the following.

$$r_{i,t} = \alpha_i + \beta_2 * Real\ Estate\ Loans_{i,t} + \beta_3 * Agricultural\ Loans_{i,t} \\ + \beta_4 * C\&I\ Loans_{i,t} + \beta_5 * Personal\ Loans_{i,t} + \beta_6 * Leases + \delta_t + \epsilon_{i,t} \quad (4.10)$$

For hypothesis 10 model 4.1 from FPS is used, but instead of using the total loan growth, the loan growth per kind of loan is used. This lead to the following model. The basis is a bank that is in the lowest growth quartile for every kind of loan.

$$\begin{aligned} r_{i,t+k} = \alpha_i &+ \beta_2 * I_{Real\ Estate\ Loan\ Growth_{i,t} \in Q2} + \beta_3 * I_{Real\ Estate\ Loan\ Growth_{i,t} \in Q3} \\ &+ \beta_4 * I_{Real\ Estate\ Loan\ Growth_{i,t} \in Q4} + \beta_5 * I_{Agricultural\ Loan\ Growth_{i,t} \in Q2} \\ &+ \beta_6 * I_{Agricultural\ Loan\ Growth_{i,t} \in Q3} + \beta_7 * I_{Agricultural\ Loan\ Growth_{i,t} \in Q4} \\ &+ \beta_8 * I_{C\&I\ Loan\ Growth_{i,t} \in Q2} + \beta_9 * I_{C\&I\ Loan\ Growth_{i,t} \in Q3} \\ &+ \beta_{10} * I_{C\&I\ Loan\ Growth_{i,t} \in Q4} + \beta_{11} * I_{Personal\ Loan\ Growth_{i,t} \in Q2} \\ &+ \beta_{12} * I_{Personal\ Loan\ Growth_{i,t} \in Q3} + \beta_{13} * I_{Personal\ Loan\ Growth_{i,t} \in Q4} \\ &+ \beta_{14} * I_{Lease\ Loan\ Growth_{i,t} \in Q2} + \beta_{15} * I_{Lease\ Loan\ Growth_{i,t} \in Q3} \\ &+ \beta_{16} * I_{Lease\ Loan\ Growth_{i,t} \in Q4} + \delta_t + \epsilon_{i,t} \quad (4.11) \end{aligned}$$

5 Results

This chapter shows the results from the models of chapter 4 and interprets these results. The sections will follow the same pattern as the sections in chapter 2 & 4.

5.1 Income Smoothing & Capital Management

Tables 5.1 till 5.6 show the results for testing hypothesis 1. It shows the effect of one- and three-year preceding loan growth on the one-, two- and three-year subsequent returns. In the appendix are the results of the two-year loan growth.

Table 5.1 shows that the top growth banks, based on the preceding one year loan growth, do not perform significantly worse the next year. This result holds for both the between- and within-model. The between-model only has time fixed effects and looks at the difference between banks. For the growth quartiles it means how banks in the top quartile perform compared to banks in the bottom quartile. The within-model has both time and bank fixed effects. This model thus looks at the effect within a bank. Now the top quartile indicates how a bank performs compared to the situation it was in the bottom quartile. The result of table 5.1 is in line with FPS. Adding the loan loss provision variable does not change this result.

Model 5 and 6 also show no significance for the growth quartiles, though the within-model shows that the loan loss reserves have a positive effect, significant at the 5% level. This indicates that if a bank has higher reserves than usual, a one standard deviation results in a 3.7% higher stock return. Model 8 shows a significant (at 10%) negative effect for the equity ratio on the subsequent stock return. The negative effect of the equity ratio is surprising as Cantor and Johnson (1992) showed a positive stock return for banks that improved their capital ratio's. They do not that banks that are already well capitalized have less positive returns. This is because these banks could perhaps leverage their assets more to increase returns.

Model 9 and 10 show no significance for the loan growth quartiles, but the loan loss provisions and loan loss reserves are significant, while the equity ratio is also significant in the within-model. The effect of the loan loss reserves is positive, as in model 6, but the effect of the loan loss provision and the solvency ratio is negative.

TABLE 5.1: One year loan growth with one year returns

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quartile 2	0.0087	-0.0062	-0.0021	-0.0101	0.0138	0.0079	0.0090	-0.0057	0.0025	-0.0016
	(0.5533)	(0.6809)	(0.8707)	(0.4530)	(0.2703)	(0.5266)	(0.5316)	(0.7022)	(0.8341)	(0.8925)
Quartile 3	0.0006	-0.0201	-0.0125	-0.0245	0.0074	-0.0005	0.0010	-0.0199	-0.0066	-0.0135
	(0.9692)	(0.2604)	(0.3759)	(0.1135)	(0.5501)	(0.9691)	(0.9508)	(0.2626)	(0.6029)	(0.3098)
Quartile 4	-0.0002	-0.0216	-0.0143	-0.0255	0.0070	0.0008	-0.0002	-0.0228	-0.0088	-0.0155
	(0.9910)	(0.2574)	(0.3693)	(0.1126)	(0.6418)	(0.9571)	(0.9906)	(0.2372)	(0.5606)	(0.2667)
LLP			-0.0181	-0.0072					-0.0337**	-0.0387**
			(0.2360)	(0.6186)					(0.0280)	(0.0111)
LLR					0.0094	0.0403**			0.0247**	0.0589***
					(0.4489)	(0.0172)			(0.0424)	(0.0007)
EQ-ratio							-0.0009	-0.0080*	-0.0023	-0.0108**
							(0.7467)	(0.0733)	(0.4165)	(0.0118)
Observations	7,001	6,946	6,912	6,853	6,978	6,923	6,997	6,943	6,911	6,853
R^2	0.443	0.494	0.449	0.496	0.445	0.500	0.442	0.494	0.451	0.503
Adj. R^2	0.439	0.445	0.445	0.448	0.442	0.453	0.439	0.446	0.447	0.456
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-test									2.789	5.987
Prob > F									0.0525	0.00176

The table represents results from regressions of a bank's loan portfolio growth on its stock return. Banks are sorted into quartiles based on the loan portfolio growth during the previous year. 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 U.S. banks whose real assets in 2013 dollars are greater than $2 billion. *LLP* represents the loan loss provision as a percentage over total loans. *LLR* represents the loan loss reserves as a percentage over total loans. $EQ - ratio$ represents the percentage tangible common equity over total assets. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 5.2: One year loan growth with two year returns

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quantile 2	0.0047	-0.0190*	-0.0045	-0.0177*	0.0087	-0.0050	0.0044	-0.0183*	-0.0003	-0.0086
	(0.5832)	(0.0587)	(0.5785)	(0.0633)	(0.3064)	(0.6083)	(0.6025)	(0.0653)	(0.9666)	(0.3759)
Quantile 3	-0.0067	-0.0315***	-0.0166*	-0.0300***	-0.0018	-0.0138	-0.0069	-0.0311***	-0.0113	-0.0190*
	(0.5285)	(0.0072)	(0.0854)	(0.0040)	(0.8357)	(0.1615)	(0.5095)	(0.0073)	(0.2033)	(0.0538)
Quantile 4	-0.0081	-0.0375**	-0.0197	-0.0350**	-0.0025	-0.0170	-0.0079	-0.0382**	-0.0140	-0.0245
	(0.6101)	(0.0417)	(0.2266)	(0.0325)	(0.8606)	(0.2884)	(0.6210)	(0.0384)	(0.3618)	(0.1174)
LLP			-0.0128	0.0043					-0.0213*	-0.0156
			(0.2997)	(0.7367)					(0.0606)	(0.2222)
LLR					0.0086	0.0380***			0.0174***	0.0431***
					(0.3503)	(0.0011)			(0.0065)	(0.0001)
EQ-ratio							0.0010	-0.0047	0.0006	-0.0057*
							(0.6773)	(0.1652)	(0.8112)	(0.0754)
Observations	3,312	3,225	3,270	3,183	3,302	3,216	3,309	3,223	3,269	3,183
R^2	0.532	0.614	0.540	0.611	0.533	0.620	0.532	0.615	0.542	0.617
Adj. R^2	0.526	0.540	0.534	0.536	0.527	0.547	0.525	0.540	0.535	0.543
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-test									4.242	6.725
Prob > F									0.0106	0.000855

The table represents results from regressions of a bank's loan portfolio growth on its stock return. Banks are sorted into quartiles based on the loan portfolio growth during the previous year. 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 U.S. banks whose real assets in 2013 dollars are greater than $2 billion. LLP represents the loan loss provision as a percentage over total loans. LLR represents the loan loss reserves as a percentage over total loans. $EQ-ratio$ represents the percentage tangible common equity over total assets. Non-overlapping returns are used to avoid inflating the t-statistic due to serial correlation. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 5.3: One year loan growth with three year returns

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quantile 2	0.0040	-0.0182	-0.0012	-0.0140	0.0061	-0.0075	0.0031	-0.0170	0.0008	-0.0082
	(0.7551)	(0.1629)	(0.9136)	(0.2188)	(0.5958)	(0.5093)	(0.8025)	(0.1720)	(0.9420)	(0.4355)
Quantile 3	-0.0226	-0.0544***	-0.0286**	-0.0480***	-0.0198	-0.0378***	-0.0227	-0.0542***	-0.0250*	-0.0403***
	(0.1316)	(0.0007)	(0.0311)	(0.0007)	(0.1473)	(0.0048)	(0.1329)	(0.0006)	(0.0534)	(0.0017)
Quantile 4	-0.0342*	-0.0681***	-0.0399**	-0.0590***	-0.0305*	-0.0481***	-0.0340*	-0.0688***	-0.0354**	-0.0506***
	(0.0759)	(0.0008)	(0.0321)	(0.0009)	(0.0957)	(0.0063)	(0.0785)	(0.0006)	(0.0490)	(0.0027)
LLP			-0.0058	0.0150					-0.0106	-0.0021
			(0.6221)	(0.1830)					(0.3833)	(0.8649)
LLR					0.0057	0.0315***			0.0112*	0.0315***
					(0.4119)	(0.0024)			(0.0853)	(0.0065)
EQ-ratio							0.0024	-0.0065	0.0022	-0.0065
							(0.3686)	(0.1196)	(0.4298)	(0.1192)
Observations	2,121	2,006	2,097	1,989	2,113	2,001	2,119	2,006	2,096	1,989
R^2	0.503	0.614	0.508	0.617	0.504	0.623	0.504	0.615	0.510	0.623
Adj. R^2	0.493	0.503	0.498	0.506	0.494	0.514	0.493	0.505	0.499	0.513
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-test									1.295	3.493
Prob > F									0.289	0.0242

The table represents results from regressions of a bank's loan portfolio growth on its stock return. Banks are sorted into quartiles based on the loan portfolio growth during the previous year. 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 U.S. banks whose real assets in 2013 dollars are greater than $2 billion. *LLP* represents the loan loss provision as a percentage over total loans. *LLR* represents the loan loss reserves as a percentage over total loans. $EQ - ratio$ represents the percentage tangible common equity over total assets. Non-overlapping returns are used to avoid inflating the t-statistic due to serial correlation. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

The negative loan loss provision can be explained by the fact that earnings will be lower if provisions are higher. Based on findings of previous research, banks provision mostly during downturns. So when a bank has high provisions, it will mostly likely be in a downturn during which its earnings are already bad resulting in worse returns.

The F-test shows that adding the additional variables is significant at the 10% level for the between-model, but significant at the 1% level for the within-model. In line with previous research (e.g. Ahmed, Takeda, and Thomas, 1999; Cooper, Jackson III, and Patterson, 2003), this indicates that provisions, reserves and equity ratio (partly) explain the stock return of banks.

Table 5.2 shows similar results to FPS, though my results have stronger statistical significance. The main message still remains: the higher the preceding high growth, the worse the subsequent stock returns. Including the two-year average loan loss provisions does not really alter the basic results. The inclusion of the loan loss reserves makes all quartiles insignificant again. The loan loss reserves itself is only (though highly) significant in the within-model. Including the equity ratio shows the same results as model 1 and 2. The full model (9 and 10) makes the growth quartiles insignificant once more, except for quartile 3 in the within-model. The F-tests on the full model also show that the provisions, reserves and equity ratio should be included. In line with the expectation does the significance of the loan growth decrease if these variables are included. The loan loss reserves is the main driver of the two-year subsequent returns.

Model 1 and 2 of table 5.3 shows similar results as FPS, even hough the I show stronger significance and a bigger magnitude. This result also indicates support of the loan seasoning theory. If the loans indeed fail after three years, then the annualized return must be the lowest three years after the loans are granted, which is included in the annualized three year stock return. The top growth quartile is indeed the most significant and has the biggest magnitude in the 3-year return model.

All the additional variables react the same as in table 5.2. The growth indicators are slightly different. The between-models have now significant growth indicators, whereas the magnitude and significance of the within-models is stronger.

The biggest difference between table 5.3 and 5.2 is that in the full model, the growth indicators are significant again. This is thus a confirmation of FPS. However the magnitude and significance are lower. As indicated by the F-test, including the additional variables thus (partly) explain the subsequent returns. Though, when multiplying one standard deviation of the relevant metrics with it coefficients, model 9 and 10 show that the biggest driver of the three-year subsequent stock return is the one-year preceding loan growth quartile. This is a rejection of hypothesis 1 and confirms the findings of FPS.

The results from table 5.4 show that the basic model (1 & 2) is similar to the results of FPS. When a bank goes from bottom to top growth quartile based on the past three year growth, it will experience a 8.4% lower return. Adding the three-year average loan loss provision lowers the impact of the quartile dummy, yet the quartile 4 dummy remains highly significant. Adding the loan loss reserves has the same effect. Though the loan loss reserves variable is less significant, both in statistical as economical sense, than in the one-year growth models. Adding the equity ratio slightly increases the negative effect of the quartile dummies, though the difference is not big. The equity ratio itself is only significant at the 5% level for the within-model.

The F-test shows that adding the additional variables is significant at the 10% level for the within-model. The coefficient of the top growth quartile is lower than without the additional variables, but the past loan growth still has the biggest impact.

Table 5.5 shows similar results as FPS, though the impact of the top quartile growth dummy in model 2 is higher for FPS. Adding the three-year average loan loss provisioning has the same effect as in table 5.4, but the variable itself is now also significant at the 5% level for the within model. The more a bank provisioned over past three years, the higher the three-year annualized returns will be. This contradicts the finding of table 5.1. A possible reason is that banks that have provisioned a lot during the past three years, will most likely not have to provision a lot more during the upcoming three years. This means their earnings will be increasing, while having high reserves, explaining the positive effect.

Adding the loan loss reserves has the same effect as before. The equity ratio slightly increases the impact of the quartile dummies again, while the variable itself is significant at the 5% level. In the full model there is a drop in the magnitude of the top growth quartile dummy, but it remains significant. It also remains to have the strongest impact on the subsequent returns, rejection hypothesis 1.

The results of table 5.6 align with the results of FPS once more, despite a small difference in the coefficients. The results of models 3 till 8 have the same interpretation as these models have in table 5.5, as described above. In the full model the biggest change is now that the three-year average loan loss provision is significant in the within-model, while the loan loss reserves variable is not. Still the impact of the loan portfolio growth quartile remains the strongest.

TABLE 5.4: Three year loan growth with one year returns

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quartile 2	-0.0267	-0.0471**	-0.0218	-0.0294*	-0.0235*	-0.0343**	-0.0265	-0.0473**	-0.0209	-0.0280*
	(0.1379)	(0.0202)	(0.1743)	(0.0911)	(0.0936)	(0.0244)	(0.1298)	(0.0194)	(0.1618)	(0.0897)
Quartile 3	-0.0352*	-0.0635***	-0.0261	-0.0393**	-0.0316**	-0.0464***	-0.0354*	-0.0655***	-0.0257	-0.0399**
	(0.0808)	(0.0042)	(0.1494)	(0.0169)	(0.0498)	(0.0036)	(0.0781)	(0.0039)	(0.1414)	(0.0130)
Quartile 4	-0.0579**	-0.0842***	-0.0545**	-0.0634***	-0.0536***	-0.0639***	-0.0582**	-0.0871***	-0.0544***	-0.0656***
	(0.0123)	(0.0012)	(0.0128)	(0.0027)	(0.0053)	(0.0006)	(0.0121)	(0.0011)	(0.0092)	(0.0016)
LLP			0.0110	0.0432					0.0046	0.0126
			(0.6392)	(0.1102)					(0.8433)	(0.6794)
LLR					0.0059	0.0300*			0.0054	0.0283
					(0.6803)	(0.0785)			(0.6762)	(0.1111)
EQ-ratio							-0.0012	-0.0103**	-0.0019	-0.0121**
							(0.7189)	(0.0473)	(0.5498)	(0.0245)
Observations	6,419	6,362	5,709	5,670	6,404	6,349	6,417	6,362	5,709	5,670
R^2	0.439	0.491	0.425	0.482	0.442	0.496	0.439	0.492	0.425	0.485
Adj. R^2	0.435	0.441	0.420	0.431	0.438	0.446	0.435	0.442	0.420	0.433
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-test									0.152	2.300
Prob > F									0.928	0.0923

The table represents results from regressions of a bank's loan portfolio growth on its stock return. Banks are sorted into quartiles based on the loan portfolio 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 regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. LLP represents the three-year average loan loss provision as a percentage over total loans. LLR represents the loan loss reserves as a percentage over total loans. $EQ-ratio$ represents the percentage tangible common equity over total assets. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 5.5: Three year loan growth with two year returns

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quartile 2	-0.0206	-0.0430***	-0.0189	-0.0303**	-0.0179	-0.0315**	-0.0207	-0.0433***	-0.0177	-0.0289**
	(0.1134)	(0.0034)	(0.1219)	(0.0433)	(0.1133)	(0.0144)	(0.1116)	(0.0030)	(0.1285)	(0.0438)
Quartile 3	-0.0183	-0.0492***	-0.0124	-0.0313**	-0.0152	-0.0337***	-0.0184	-0.0506***	-0.0110	-0.0314**
	(0.1110)	(0.0004)	(0.2852)	(0.0299)	(0.1223)	(0.0044)	(0.1104)	(0.0003)	(0.3147)	(0.0244)
Quartile 4	-0.0529**	-0.0864***	-0.0501**	-0.0677***	-0.0494**	-0.0686***	-0.0528**	-0.0886***	-0.0482**	-0.0690***
	(0.0115)	(0.0002)	(0.0180)	(0.0025)	(0.0137)	(0.0004)	(0.0112)	(0.0001)	(0.0150)	(0.0014)
LLP			0.0090	0.0386**					0.0050	0.0151
			(0.5249)	(0.0286)					(0.7181)	(0.4383)
LLR					0.0056	0.0289***			0.0054	0.0234**
					(0.4776)	(0.0074)			(0.4318)	(0.0452)
EQ-ratio							0.0009	-0.0077**	0.0008	-0.0093**
							(0.7396)	(0.0349)	(0.7599)	(0.0177)
Observations	2,967	2,887	2,711	2,642	2,961	2,882	2,965	2,887	2,711	2,642
R^2	0.502	0.595	0.498	0.592	0.503	0.600	0.502	0.596	0.499	0.595
Adj. R^2	0.495	0.513	0.490	0.511	0.496	0.519	0.495	0.515	0.490	0.514
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-test									0.505	3.897
Prob > F									0.681	0.0158

The table represents results from regressions of a bank's loan portfolio growth on its stock return. Banks are sorted into quartiles based on the loan portfolio 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 regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. *LLP* represents the three-year average loan loss provision as a percentage over total loans. *LLR* represents the loan loss reserves as a percentage over total loans. $EQ - ratio$ represents the percentage tangible common equity over total assets. Non-overlapping returns are used to avoid inflating the t-statistic due to serial correlation. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 5.6: Three year loan growth with three year return

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quartile 2	-0.0180*	-0.0423***	-0.0151*	-0.0246**	-0.0164	-0.0297**	-0.0181*	-0.0431***	-0.0154*	-0.0270**
	(0.0951)	(0.0038)	(0.0930)	(0.0410)	(0.1054)	(0.0113)	(0.0936)	(0.0026)	(0.0814)	(0.0180)
Quartile 3	-0.0354**	-0.0724***	-0.0304**	-0.0458***	-0.0336**	-0.0554***	-0.0355**	-0.0753***	-0.0305**	-0.0494***
	(0.0279)	(0.0001)	(0.0452)	(0.0011)	(0.0333)	(0.0001)	(0.0282)	(0.0000)	(0.0445)	(0.0003)
Quartile 4	-0.0655***	-0.1000***	-0.0609***	-0.0721***	-0.0641***	-0.0811***	-0.0655***	-0.1042***	-0.0606***	-0.0785***
	(0.0009)	(0.0000)	(0.0027)	(0.0005)	(0.0015)	(0.0000)	(0.0008)	(0.0000)	(0.0016)	(0.0001)
LLP			0.0127	0.0537***					0.0165	0.0454**
			(0.3872)	(0.0006)					(0.2539)	(0.0155)
LLR					0.0024	0.0271***			-0.0031	0.0048
					(0.7443)	(0.0078)			(0.5973)	(0.6550)
EQ-ratio							0.0002	-0.0112**	0.0012	-0.0097**
							(0.9448)	(0.0141)	(0.6961)	(0.0195)
Observations	1,949	1,844	1,709	1,626	1,943	1,840	1,948	1,844	1,709	1,626
R^2	0.483	0.603	0.482	0.620	0.484	0.611	0.483	0.607	0.482	0.623
Adj. R^2	0.472	0.480	0.468	0.501	0.472	0.489	0.471	0.485	0.468	0.504
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-test									0.763	5.627
Prob > F									0.522	0.00272

The table represents results from regressions of a bank's loan portfolio growth on its stock return. Banks are sorted into quartiles based on the loan portfolio 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 regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. *LLP* represents the three-year average loan loss provision as a percentage over total loans. *LLR* represents the loan loss reserves as a percentage over total loans. $EQ - ratio$ represents the percentage tangible common equity over total assets. Non-overlapping returns are used to avoid inflating the *t*-statistic due to serial correlation. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Overall the result is that adding the additional variables is relevant for the within-model, as shown by the F-tests. But while these new variables explain a part of the subsequent returns, the main result from the tables is that hypothesis 1 should be rejected. The top quartile dummy (almost always) remains highly significant when these variables are added and it also keeps having the biggest impact on subsequent stock returns.

5.2 Loan Seasoning

Table 5.7 shows the results of the regressions for the loan seasoning theory. Panel A of table 5.7 shows mixed results for sub-hypothesis 2.1. The between-model has similar coefficients for the loan growth two and three years prior to the stock return. The within-model shows that the impact of the loan growth two years prior to the stock return has the biggest impact. This is a rejection of sub-hypothesis 2.1. But this result might be driver by loan growth prior to a bank's IPO. As mentioned by Houge and Loughran (1999) banks that aggressively grow prior to their IPO will experience worse returns. It is possible that banks grow their loan portfolio the year before their IPO, so they have a nice prospectus. Because of the bad post-IPO performance of the fast(est) growing banks, the loan growth prior to the IPO might have the most negative effect. In the appendix is an additional table which only looks at the loan growth post-IPO. Those results confirm sub-hypothesis 2.1, that it takes three years for the loans to go bad.

Panel B of table 5.7 shows support for sub-hypothesis 2.2. The biggest drop in the ROA will be two years after the loan growth. The higher the loan growth was two years ago, the bigger the drop in the ROA will be this year. Combined this table indicates that the market is aware of the worse performance, because the biggest drop in the stock return and the biggest drop in the ROA is both two years after the loans are granted. However, the additional result in the appendix shows that the market does not suspect the worse performance. Only after the bank reports the drop in ROA does the stock market drop.

Overall, this indicates there is some loan seasoning effect. Loans go bad after two to three years, which is in line with previous research. Model 3 and 4 in panel A and B do not show support for hypothesis 2 though. The annualized growth over the past three years is a much bigger indicator of worse subsequent performance. As the effect of prolonged fast loan growth is more negative than the effect of loan

TABLE 5.7: Loan Seasoning

A. One year return				
VARIABLES	(1)	(2)	(3)	(4)
$LoanGrowth_t$	-0.0167	-0.0546*		
	(0.5511)	(0.0897)		
$LoanGrowth_{t-1}$	-0.0593**	-0.0793**		
	(0.0365)	(0.0160)		
$LoanGrowth_{t-2}$	-0.0594**	-0.0668**		
	(0.0358)	(0.0321)		
$LoanGrowth_{t-3,t}$			-0.1489**	-0.2208***
			(0.0138)	(0.0041)
Observations	6,418	6,361	6,419	6,362
R-squared	0.4384	0.4892	0.4379	0.4894
Time FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes
R^2	0.438	0.489	0.438	0.489
Adj. R^2	0.435	0.439	0.434	0.440

B. Δ ROA				
VARIABLES	(1)	(2)	(3)	(4)
$LoanGrowth_t$	-0.0867	-0.1547		
	(0.5881)	(0.2714)		
$LoanGrowth_{t-1}$	0.0992	0.0634		
	(0.3071)	(0.5808)		
$LoanGrowth_{t-2}$	-0.3164**	-0.3613***		
	(0.0163)	(0.0079)		
$LoanGrowth_{t-3,t}$			-0.3180**	-0.4314**
			(0.0347)	(0.0484)
Observations	6,423	6,382	6,423	6,382
R^2	0.131	0.173	0.127	0.169
Adj. R^2	0.126	0.0915	0.121	0.0867
Time FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes

The table represents results from regressions of bank's loan portfolio growth on its one year stock return or ΔROA. $LoanGrowth_{t-3,t}$ represents the annualized loan growth over the past three years. The sample period is 1972 to 2013. The regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

seasoning (while present) it indicates that fast loan growth really is a shareholder value destroying policy.

TABLE 5.8: Lagged growth quartiles

	One year return			
VARIABLES	(1)	(2)	(3)	(4)
Quartile 2_{t-1}	-0.0179	-0.0315*		
	(0.2344)	(0.0579)		
Quartile 3_{t-1}	-0.0258	-0.0448**		
	(0.1477)	(0.0206)		
Quartile 4_{t-1}	-0.0363*	-0.0505**		
	(0.0758)	(0.0225)		
Quartile 2_{t-2}			-0.0189	-0.0283**
			(0.1279)	(0.0273)
Quartile 3_{t-2}			-0.0381***	-0.0502***
			(0.0037)	(0.0003)
Quartile 4_{t-2}			-0.0538***	-0.0601***
			(0.0005)	(0.0000)
Observations	6,779	6,727	6,419	6,362
R^2	0.442	0.496	0.439	0.489
Adj. R^2	0.438	0.448	0.435	0.439
Time FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes

The table represents results from regressions of a bank's loan portfolio growth on its stock return. Banks are sorted into quartiles based on the loan portfolio growth two and three years before the stock return. 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 U.S. banks whose real assets in 2013 dollars are greater than $2 billion. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Further analysis is provided in table 5.8, where the loan growth of two and three year prior to the stock returns are regressed on the stock returns. The results show that the loan seasoning effect has a non linear effect on the stock returns. Whereas table 5.7 showed the loan growth two year prior to the stock return will have the biggest impact, table 5.8 shows that for the top growth quartile the effect of three years prior to the returns have a more negative effect. But, for quartile 2 the effect is more negative for the two year prior to the returns.

Like the results from table 5.7 reject hypothesis 2, so does table 5.8. The annualized return for the top growing bank of two years prior to returns is -3.6% without firm fixed effects and -5.1% with firm fixed effects. For the quartiles base on the loan growth three years prior to the returns, the effect is -6.0% with firm fixed effects and -5.4% without firm fixed effects. Model 1 and 2 from table 5.4 show an annualized return of -8.4% with firm fixed effects and -5.8% without firm fixed effects. So while the moment the loan growth was realized has an effect on the subsequent returns, banks that grow the most during the previous three years have the worst subsequent returns.

Model 1 and 2 of table 5.6 show that the top growth quartile banks based on the past three years will have 10.0% lower returns with fixed effects and 6.6% without firm fixed effects. Because all returns are annualized we can see that the best returns can be obtained by looking at the past three year loan growth and invest for the next three years.

So both in a continuous model as in a model based on quartiles does the loan growth over the past three years have the biggest effect on the subsequent stock performance. While loan seasoning is present in the database, returns are not primarily driven by this effect. Banks that grow the most over the preceding three years will most likely have a harmful policy, as aggressive growth has more impact than loan seasoning. Both short-term as long-term investors should avoid the bank(s) that grew the most the past three years and not three years ago.

5.3 How do banks grow fast?

In table 5.9 are the results for hypothesis 3. Model 1 and 2 show that fast growing banks charge a much higher average interest rate, which contradicts the hypothesis. For completeness sake the model of Foos, Norden, and Weber (2010) is added to the table. Even when the model of Foos, Norden, and Weber is used I still get a different sign. A possible explanation for this is the used data. Whereas in this thesis only U.S. listed banks are used, Foos, Norden, and Weber use banks from OECD countries.

In models 1 and 2 of table 5.10 the highest quartile indicates the highest increase in the interest rate. Surprisingly it is positive for the top quartile, while it is negative for the bottom other quartiles (though only quartile 2 is significant in model 1). Banks that slightly increase their interest rates will see a drop in their loan growth, which is in line with the theory. But when banks increase their interest rate by a lot they will see a high increase in the loan growth. A possible explanation is that these banks started to accept more risky borrowers, but charge a high interest rate for these risky loans.

Sub-hypothesis 4.1 can thus be neither accepted nor rejected. The results show that slightly increasing the interest rate will lower the loan growth, a moderate

TABLE 5.9: One year loan growth on relative interest income

	Δ RII			
VARIABLES	(1)	(2)	(3)	(4)
Quartile 2	0.0468	0.0382		
	(0.3074)	(0.3188)		
Quartile 3	0.1073***	0.1090***		
	(0.0063)	(0.0037)		
Quartile 4	0.3287***	0.3560***		
	(0.0000)	(0.0000)		
Loan Growth$_t$			1.0539***	1.2019***
			(0.0000)	(0.0000)
Equity Ratio$_t$			-0.0009	0.0008
			(0.9254)	(0.9583)
Ln Customer Loans			-0.0295*	-0.1604***
			(0.0730)	(0.0086)
Observations	3,963	3,957	3,963	3,957
R^2	0.665	0.670	0.675	0.682
Adj. R^2	0.662	0.645	0.671	0.657
Time FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes

The table represents results from regressions of a bank's loan portfolio growth on ΔRII. In model 1 and 2 banks are sorted into quartiles based on the loan portfolio growth during the previous year. Indicator variables representing each quartile are included in the regression with the lowest growth quartile forming the base group. Model 3 and 4 use a continuous growth variable. *Equityratio* represents the percentage tangible common equity over total assets. Ln Customer loans is the natural logarithm of the total loans to customers. The sample period is 1972 to 2013. The regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

increase has no effect, and increasing the interest rate a lot will increase the loan growth.

Model 3 and 4 of table 5.10 show that when banks increase their provisioning a lot, indicating a lowering of the credit standard, the loan growth will decrease. This holds even when correcting for the capital management theory, as can be seen in model 5 and 6. A possible reason for this effect is that, in line with FPS and other research, banks start provisioning too late. The moment they start provisioning is when they are in trouble. This is also the moment when they cannot provide any more new loans, hence the high increase in loan loss provisions indicates a lower

TABLE 5.10: ΔRII and ΔLLP impact on Loan Growth

	One year loan growth					
Quartile driver	ΔRII		ΔLLP			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Quartile 2	-0.0173**	-0.0129	0.0266***	0.0198***	0.0095*	0.0065
	(0.0136)	(0.1019)	(0.0001)	(0.0007)	(0.0852)	(0.2229)
Quartile 3	-0.0043	-0.0054	0.0097	0.0049	-0.0072	-0.0093
	(0.5875)	(0.5283)	(0.2458)	(0.5316)	(0.2890)	(0.2034)
Quartile 4	0.0647***	0.0656***	-0.0152*	-0.0145*	-0.0166**	-0.0153**
	(0.0002)	(0.0002)	(0.0938)	(0.0816)	(0.0137)	(0.0314)
LLR					-0.0439***	-0.0588***
					(0.0000)	(0.0000)
Observations	3,963	3,957	6,708	6,669	6,708	6,669
R^2	0.179	0.257	0.139	0.260	0.176	0.298
Adj. R^2	0.170	0.201	0.134	0.188	0.171	0.230
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

The table represents results from regressions of a bank's first-difference in relative interest income (ΔRII) and Loan loss provisions (ΔLLP) on the bank's loan portfolio growth. Banks are sorted into quartiles per year based on either their ΔRII or ΔLLP. 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 U.S. banks whose real assets in 2013 dollars are greater than $2 billion. *LLR* represents the loan loss reserves as a percentage over total loans. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and **** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

loan growth.

Sub-hypothesis 4.2 seems to be rejected. The level of loan loss provisions has a significant effect on the loan growth. It is slightly ambiguous though if this is because of a lowering of the credit standard or insufficient provisioning in the past (as noted in previous research Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005; Foos, Norden, and Weber, 2010).

Table 5.11 shows multiple interesting results. First of all model 1 and 2 of panel A show that loan growth is mainly driven by an increase in the interest rate. The increase in loan loss provisioning is only significant at the 10% level in model 2. The sign of the coefficient for the relative interest rate is still opposite of expected. This conclusion for the full sample does not change when loan loss reserves are added. The loan loss reserve variable is highly significant and shows that banks with a higher level of reserves will grow less. Again, this could be because banks will build up their (or have the highest) reserve levels when they are in a crunch.

TABLE 5.11: ΔRII, ΔLLP and LLR combined impact on Loan Growth

A. One year loan growth						
	Full Sample		Growth Quartile 1		Growth Quartile 4	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ΔRII	0.0499***	0.0495***	0.0039	0.0065	0.0433**	0.0441**
	(0.0002)	(0.0002)	(0.5080)	(0.1566)	(0.0218)	(0.0108)
ΔLLP	-0.0126	-0.0127*	-0.0039	-0.0030	0.0015	-0.0089
	(0.1024)	(0.0715)	(0.2090)	(0.2443)	(0.8796)	(0.4626)
Observations	3,962	3,956	1,032	1,005	873	839
R^2	0.193	0.273	0.502	0.628	0.360	0.505
Adj. R^2	0.184	0.218	0.481	0.521	0.328	0.332
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

B. One year loan growth						
	Full Sample		Growth Quartile 1		Growth Quartile 4	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ΔRII	0.0492***	0.0493***	0.0041	0.0074	0.0428**	0.0441**
	(0.0003)	(0.0003)	(0.4165)	(0.1027)	(0.0221)	(0.0104)
ΔLLP	-0.0090*	-0.0081	-0.0011	-0.0003	0.0042	-0.0085
	(0.0537)	(0.1090)	(0.5574)	(0.8958)	(0.6509)	(0.4855)
LLR	-0.0426***	-0.0531***	-0.0208***	-0.0226***	0.0326**	0.0285*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0128)	(0.0919)
Observations	3,962	3,956	1,032	1,005	873	839
R^2	0.232	0.313	0.565	0.669	0.366	0.507
Adj. R^2	0.224	0.261	0.547	0.574	0.334	0.334
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

The table represents results from regressions of a bank's first difference in relative interest income (ΔRII) and Loan loss provisions (ΔLLP), and were indicated the level of LLR, on its one year stock return. The regressions are first run on the full sample, then they are rerun for the top and bottom growth quartile. Quartiles are based on the loan portfolio growth during the previous one year. The sample period is 1972 to 2013. The regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. *LLR* represents the loan loss reserves as a percentage over total loans. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

In both panel A and B, model 3 and 4 only use observations from the bottom one year growth quartile. Model 5 and 6 use the observations of the top one year growth quartile. Panel A shows that none of the used variables is able to explain the loan growth for the bottom quartile, despite the high R^2. Panel B shows that for the bottom quartile banks, only the level of loan loss reserves is able in explaining the loan growth. Within the banks that do not grow much, the ones that have the highest reserves will show the lowest growth. This could again be an indicator of banks that have grown fast in the past, build up a large reserve during the downturn and are now in a credit crunch, despite the fact that they have the biggest buffer.

For the top growth quartile the results show, like the full sample, that a higher interest rate will show higher loan growth. As mentioned earlier, this might be because these banks recognize that they are taking on more risky loans and thus charge a higher interest rate. The banks in this quartile that have higher reserves lend even more. This is a confirmation that these banks have willingly accepted high risky loans. They will (have to) hold higher reserves, but also charge more interest. Multiplying the coefficients with their standard deviations from the summary table show that the ΔRII has the biggest impacts.

Overall, hypothesis 4 is thus rejected. Loan growth does not seem to be driven by lowering interest rates, but by increasing them, which could be due to accepting new highly risky borrowers. Further research with a better proxy for the riskiness of the loans and the used credit standards by the banks is needed to check this theory.

5.4 Recession Crashes

Table 5.12 shows the result of including interaction variables to the basic FPS models. The time fixed effects controls for the fact that all banks will experience a drop in the subsequent stock returns during a recession. The interaction variables should thus be interpreted that, given a subsequent recession, does the level of loan growth preceding a recession result in different subsequent stock returns?

Model 1 in all panels is less significant than the results in tables 5.4 to 5.6. The results from model 2 are similar to the results in tables 5.4 to 5.6, confirming the research of FPS. The top growth quartile over the preceding three years is the biggest driver of the (worse) subsequent returns.

The magnitude of the coefficients is lower than those in their respective versions in tables 5.4 and 5.5. The difference is due to the exclusion of the recession years.

TABLE 5.12: Recession Crashes Quartiles

	A. One year return					
	3-year Growth		Loan Growth$_{t-2}$		Loan Growth$_t$	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Quartile 2	-0.0148	-0.0213*	-0.0361**	-0.0385***	0.0118	0.0045
	(0.2772)	(0.0818)	(0.0124)	(0.0040)	(0.4286)	(0.7601)
Quartile 3	-0.0156	-0.0308*	-0.0345**	-0.0414**	0.0096	-0.0044
	(0.3637)	(0.0607)	(0.0369)	(0.0110)	(0.5556)	(0.7770)
Quartile 4	-0.0257	-0.0434**	-0.0480**	-0.0516***	0.0147	0.0007
	(0.1478)	(0.0364)	(0.0115)	(0.0031)	(0.3785)	(0.9679)
Pre-crsis Quartile 2	0.0399	0.0329	0.0632**	0.0372	0.0124	-0.0070
	(0.3391)	(0.3852)	(0.0173)	(0.3041)	(0.6407)	(0.8248)
Pre-crsis Quartile 3	-0.0261	-0.0349	0.0061	-0.0072	0.0234	0.0046
	(0.5908)	(0.3619)	(0.8664)	(0.8784)	(0.3811)	(0.8606)
Pre-crsis Quartile 4	-0.0235	-0.0159	-0.0156	-0.0256	0.0163	0.0119
	(0.7704)	(0.8377)	(0.7071)	(0.6242)	(0.6995)	(0.7859)
Observations	4,921	4,858	4,921	4,858	5,407	5,350
R^2	0.479	0.544	0.481	0.545	0.482	0.543
Adj. R^2	0.475	0.486	0.477	0.487	0.478	0.486
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

	B. Two year return					
Quartile 2	-0.0147	-0.0274*	-0.0117	-0.0276*	0.0059	-0.0144
	(0.2766)	(0.0890)	(0.2501)	(0.0842)	(0.5284)	(0.1822)
Quartile 3	-0.0115	-0.0380***	-0.0264	-0.0401**	-0.0041	-0.0247**
	(0.3110)	(0.0042)	(0.1127)	(0.0434)	(0.6481)	(0.0230)
Quartile 4	-0.0362*	-0.0686***	-0.0338*	-0.0506**	-0.0009	-0.0257
	(0.0788)	(0.0056)	(0.0805)	(0.0126)	(0.9522)	(0.1209)
Pre-crsis Quartile 2	0.0645	0.0533	0.0041	-0.0190	0.0528***	0.0434
	(0.2044)	(0.2521)	(0.8754)	(0.6060)	(0.0081)	(0.1950)
Pre-crsis Quartile 3	0.0367	0.0194	-0.0000	-0.0010	0.0403	0.0091
	(0.1568)	(0.5501)	(0.9999)	(0.9886)	(0.3911)	(0.8670)
Pre-crsis Quartile 4	0.0237	0.0196	0.0427	0.0198	0.0519	0.0371
	(0.8394)	(0.8533)	(0.2821)	(0.7784)	(0.2852)	(0.3849)
Observations	2,214	2,126	2,214	2,126	2,500	2,392
R^2	0.487	0.602	0.487	0.600	0.537	0.633
Adj. R^2	0.479	0.493	0.478	0.490	0.530	0.540
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

Continues on next page...

C. Three year return						
	3-year Growth		Loan Growth$_{t-2}$		Loan Growth$_t$	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Quartile 2	-0.0192	-0.0415**	-0.0217**	-0.0482***	0.0040	-0.0154
	(0.1583)	(0.0165)	(0.0270)	(0.0012)	(0.7649)	(0.2107)
Quartile 3	-0.0444**	-0.0837***	-0.0328**	-0.0599***	-0.0199	-0.0444***
	(0.0144)	(0.0001)	(0.0158)	(0.0025)	(0.1652)	(0.0032)
Quartile 4	-0.0664***	-0.1107***	-0.0605***	-0.0938***	-0.0289	-0.0595***
	(0.0067)	(0.0001)	(0.0083)	(0.0001)	(0.1304)	(0.0005)
Pre-crisis Quartile 2	-0.0024	0.0441	-0.0775***	-0.0781**	-0.0036	-0.0132
	(0.9587)	(0.3403)	(0.0008)	(0.0460)	(0.9091)	(0.7436)
Pre-crisis Quartile 3	-0.0362	-0.0157	-0.0830	-0.1008	0.0184	-0.0041
	(0.3155)	(0.7330)	(0.1801)	(0.1068)	(0.6672)	(0.9353)
Pre-crisis Quartile 4	-0.0051	0.0758	0.0207	0.1019	-0.0219	-0.0433
	(0.9493)	(0.5122)	(0.6578)	(0.2839)	(0.7647)	(0.5822)
Observations	1,418	1,264	1,418	1,264	1,589	1,453
R^2	0.485	0.603	0.484	0.602	0.505	0.616
Adj. R^2	0.472	0.446	0.471	0.445	0.493	0.470
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

The table represents results from regressions of a bank's loan portfolio growth on its stock return. Model 1 and 2 use quartiles based on the loan portfolio growth during the previous three years. Model 3 and 4 use quartiles based on the loan portfolio growth two years before portfolio formation. Model 5 and 6 use quartiles based on the loan portfolio growth in the past year. Indicator variables representing each quartile are included in the regression with the lowest growth quartile forming the base group. The Pre-crisis variables are interaction variables, indicating if the quartile position in the year preceding a crisis differs for the subsequent returns. The sample period is 1972 to 2013, but crisis years are removed. The NBER recession indicators are used for crisis years. The regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. Non-overlapping returns are used in panel B and C to avoid inflating the *t*-statistic due to serial correlation. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

FPS also note the lower magnitude if the recession years are excluded. The message that the fastest banks crash the hardest still holds, supporting hypothesis 5.

None of the interaction variables is significant, indicating that it there is no difference in being the top growth bank during a normal period or just before a recession.

Model 3 and 4 also show that the top growth banks will experience the worst returns. In panel A model 3 shows a positive interaction variable for quartile 2. In a normal period banks in quartile 2 will experience 3.6% worse returns compared to quartile 1. But if this is two years before a crisis, banks in quartile 2 will have (-3.6+6.3=) 2.7% better returns than banks in the bottom quartile. It is thus better to have grown the loan portfolio a bit a few year before a crash. Note that this is corrected for any crash that all stocks will experience. So while perhaps all stocks will go down, stock in quartile 2 will experience higher returns than their counterparts during a crisis.

In panel B none of the interaction variables of model 3 or 4 are significant, but in panel C the quartile 2 interaction variable is significant again. Surprisingly it is now heavily negative. For the between-model it shows that a bank in quartile 2 will normally experience 2.2% three year annualized worse returns, but if the quartile 2 position was three years before a recession this will be (-2.2 - 7.8=) -9.9%. This extremely negative effect is also present in the within-model (4). This results indicates that over a three-year period banks in quartile 2 will have worse returns than banks in quartile 4. So while panel A and B show support for hypothesis 6, panel C rejects it.

Model 5 and 6 are in line with tables 5.1 to 5.3, except that the magnitude and significance is lower here. This can be explained by the removal of the recession years and the addition of new variables. The results are also a confirmation of the loan seasoning. As the worse returns are mostly present in the three year returns, it shows that it takes a few years before loans go bad.

The only significant interaction variable is in panel B model 5 quartile 2. Its positive sign should be interpreted in a similar matter as for panel A model 3 quartile 2. All the other interaction variables are not significant, thus indicating that it does not matter when the loan growth was realized.

To really answer hypothesis 5 to 7 one must look at the coefficient of quartile 4 per panel and compare it to its the other between- or within-model. Panel A shows that the loan growth of three years prior to the returns has the biggest effect. This is surprising as it contradicts the conclusion of table 5.4 and 5.8. Further research shows that this is driven by the removal of the recession years. Still panel A shows support for hypothesis 6 while rejecting hypothesis 5 and 7.

Panel B shows support for hypothesis 5, as the effect of the past three year loan growth has the biggest impact. Panel C has the most surprising result, rejecting all hypotheses. Over a three-year return period, the banks that were in quartile 2 two years prior to the portfolio formation will experience the worst returns. Yet between the top growing banks, the banks that grew the most over a tree year period will experience the worst returns.

Table 5.13 uses a continuous growth variable instead of quartiles. Model 1 and 2 confirm the loan seasoning theory once more and also show that the moment of growth does not impact the subsequent returns.

TABLE 5.13: Recession Crashes Continuous

	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Loan Growth$_t$	0.0033	-0.0320	-0.0159	-0.0708**	-0.0628***	-0.1349***
	(0.9083)	(0.2562)	(0.6251)	(0.0124)	(0.0097)	(0.0000)
Loan Growth$_{t-1}$	-0.0182	-0.0330	-0.0435	-0.0479	-0.0358	-0.0601
	(0.4816)	(0.2624)	(0.1452)	(0.1554)	(0.3465)	(0.1595)
Loan Growth$_{t-2}$	-0.0654*	-0.0564*	-0.0316	-0.0593	-0.0765*	-0.1267***
	(0.0738)	(0.0846)	(0.4017)	(0.1924)	(0.0712)	(0.0034)
Pre-crisis Loan Growth$_t$	0.0413	0.0958	0.0397	0.0268	-0.0045	0.0358
	(0.3298)	(0.1576)	(0.4684)	(0.6451)	(0.9621)	(0.7840)
Pre-crisis Loan Growth$_{t-1}$	-0.0926	-0.1226	-0.0281	-0.0610	-0.0381	0.0508
	(0.4244)	(0.2887)	(0.7265)	(0.6469)	(0.5040)	(0.6257)
Pre-crisis Loan Growth$_{t-2}$	0.0412	0.0434	0.0816**	0.1158*	0.1349**	0.2647***
	(0.5163)	(0.5744)	(0.0296)	(0.0520)	(0.0313)	(0.0057)
Observations	4,920	4,857	2,214	2,126	1,418	1,264
R-squared	0.4800	0.5444	0.4870	0.6021	0.4840	0.6053
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
R^2	0.480	0.544	0.487	0.602	0.484	0.605
Adj. R^2	0.476	0.486	0.478	0.493	0.471	0.449

The table represents results from regressions of a bank's loan portfolio growth on its stock return. The independent variables are the continuous growth variables for the past year, one year ago and two years ago. The Pre-crisis variables are interaction variables, indicating if the growth for per year for the three years preceding a crisis differs for the subsequent returns. The sample period is 1972 to 2013, but crisis years are removed. The NBER recession indicators are used for crisis years. The regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. Non-overlapping returns are used in model 3 till 6 to avoid inflating the *t*-statistic due to serial correlation. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Model 3 to 6 have a surprising result. All those models have a positive interaction variable for the loan growth two years prior to portfolio formation. This indicates that banks that grew a lot a few years before the recession will experience better returns than those that did not grow a lot during those years. This seems a strong rejection of hypothesis 6, though the hypothesis is focused on quartiles per loan growth period and this table looks at overall loan growth per period. In a similar fashion does hypothesis 7 seem to be accepted by model 4 and 6. The loan growth in the year prior to the recession has the most significant worst subsequent returns. This indicates that indeed in general the loans made before a crash are the worst loans, that start to affect the returns after two- to three-years as per the loan seasoning theory. But again, table 5.13 looks at years and not quartiles, which is what the hypotheses are based on.

The overall message of table 5.12 is thus as follows. In general the fastest growing banks will experience the worst returns (as per FPS). For almost all banks it does not differ if this loan growth was during a normal period or just before a crisis. Table 5.13 slightly alters this message stating that the loan growth of two years before the portfolio formation has less negative (or even a positive) effect on the subsequent multi-year returns. This (somewhat) confirms the non-linear relation between loan growth and subsequent returns. It also is evidence that in general the loans made before a crisis are worse than those granted a few years before a crisis.

Because investors (and regulators) cannot predict how long a recession will last the best advice I can give is to keep looking at banks that have the most aggressive growth policy and grow much more than they usually do. This is because the quartile 4 dummy based on the loan growth during the past three years is almost always the most negative in the within-models. The 'wrong' policy effect is stronger than the effect of loan seasoning, even during a recession.

5.5 Secured loans

Table 5.14 shows the effect of the different kind of loans on the loan loss provision and reserves. The difference between model 1 and 2, and 3 and 4 is the inclusion of the loan loss reserves to control for any capital management activity.

Model 1 shows a significant negative coefficient for agricultural loans and leases. This means that banks provision less if their loan portfolio mix has more agricultural or lease loans. The agricultural part can be explained as farms have stable incomes and are therefore less risky. Note however that these loans are not backed by any real estate as those are included in the real estate portion.[1] The lease loans have the collateral of the object being leases, so it also makes sense that these banks have to provision less.

Model 2 shows a surprising positive coefficient for the real estate segment. This means that when a bank increases it proportion of real estate loans it will provision more. The effect is statistically significant (at the 10%-level), but also high economical meaning. Multiplying one standard deviation by this coefficient is a change of 0.2%, which is a change of 30% of the mean.

[1] Loans secured by farmland, including farm residential and other improvements are coded 1420, which is included in the overall real estate backed loans of code 1410.

TABLE 5.14: Loan kind on loan loss provisioning and reserves

	Loan loss provision				Loss Reserves	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Real Estate (%)	-0.0049	0.0101*	-0.0003	0.0061	-0.0077*	0.0057
	(0.2804)	(0.0597)	(0.9422)	(0.1263)	(0.0664)	(0.1860)
Agri (%)	-0.0393**	-0.0250	-0.0202	-0.0293	-0.0320*	0.0077
	(0.0165)	(0.4333)	(0.1217)	(0.2633)	(0.0879)	(0.7584)
C&I (%)	0.0010	0.0073	-0.0053	0.0022	0.0107**	0.0072
	(0.8441)	(0.1979)	(0.2491)	(0.6425)	(0.0124)	(0.2375)
Personal (%)	0.0035	0.0006	0.0024	0.0013	0.0019	-0.0009
	(0.5941)	(0.9325)	(0.6859)	(0.8663)	(0.7423)	(0.8446)
Leases (%)	-0.0266*	-0.0169	-0.0086	-0.0251	-0.0303*	0.0119
	(0.0886)	(0.3871)	(0.5220)	(0.1285)	(0.0825)	(0.4521)
LLR			0.5930***	0.6971***		
			(0.0000)	(0.0000)		
Observations	4,314	4,270	4,314	4,270	4,315	4,271
R^2	0.309	0.480	0.545	0.653	0.227	0.590
Adj. R^2	0.304	0.419	0.542	0.612	0.221	0.541
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

The table represents results from regressions of a bank's loan portfolio mix on its loan loss provisions and reserves. The different kind of loans are calculated as a percentage of the total loan amount. The sample period is 1972 to 2013. The regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. *LLR* represents the loan loss reserves as a percentage over total loans. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

A possible reason why this coefficient is positive is the denominator when determining the size per loan segment. When in a downturn loans start to fail, it is likely the real estate loans fail last. As the other loans are written off, the total amount of loans outstanding decreases. This means that the percentage of real estate loans will increase. Therefore, during a moment when banks have to provision more, the percentage of real estate loans will increase. The support for this theory is that this effect only holds for the within-model and not the between-model.

Model 3 and 4 of table 5.14 show that the loan portfolio mix does not really have an effect on the loan loss provision. When the loan loss reserve is added, the significance of the other variables drops. This indicates that the loan loss provision is mostly dependent on the level of reserves and not the (possible) collateral the different loans provide. This is thus a rejection of hypothesis 8. The loan portfolio mix does not explain the provisioning level.

Model 5 and 6 provide further insight on the effect of collateral per loan segment on the loan loss reserves. Model 5 shows that banks that have more real estate, agricultural loans and leases will have lower reserves. This is in line with expectations. As the real estate loans have more collateral, they will need less reserves. The agricultural loans are safe as farmers have a relatively stable income. More commercial & industrial loans will increase the reserves. This is in line with Salas and Saurina (2002), who found loans to firms to be more risky than mortgages. Multiplying one standard deviation with the coefficients shows that the real estate segment is the most important driver of the loan loss reserves. The significance drops for the within-model. This implicates that once a bank sets it reserves percentage level, a change in the portfolio mix does not change the reserve percentage. This approach is justified for banks that keep a certain loan portfolio mix. Investors (and regulators) should be weary for banks that change their target audience and start adjusting their loan portfolio mix. They might start giving out loans to segments they are not familiar with and insufficiently provision, leading to wrong reserve levels. This is in line with the research of Shaffer (1998) who found that new branches make worse loans as they don't know their loan customers very well.

Overall this table shows that banks set their loan loss reserves level based on their idea of their (initial) portfolio mix. This level of reserves does not change if the portfolio mix changes. This set level of reserves is subsequently what drives the loan loss provisions.

Table 5.15 shows the results of the different kinds of loans on the subsequent one- and three-year stock returns. The only significant coefficient is that of the lease segment. It is positive, which suggest that when a bank increases its lease segment it will have higher returns the next year. The economical significance is not high though. Multiplying the coefficient with one standard deviation results in a difference of 0.9%, which is a 6.0% change of the mean of 15.4%. The effect disappears over the three-year window. So while increasing the proportion of leases has a positive effect in the short-term, it has no effect in the long term. This is a rejection of hypothesis 9. The mix of the loan portfolio does not drive the subsequent returns.

Table 5.16 and 5.17 are made by using growth quartiles based on the one- or three-year growth of the different kinds of loans.

Table 5.16 shows that the real estate loan segment is a driver of the subsequent one year return. Especially the top growth quartile shows statistically and economically significant worse returns. This contradicts hypothesis 10 as the real estate segment is the most secured loan segment. A possible explanation can be found by

TABLE 5.15: Loan kind on stock returns

	1-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)
Real Estate (%)	-0.0000	0.0001	-0.0004	0.0001
	(0.9843)	(0.9566)	(0.6147)	(0.9618)
Agricultural (%)	0.0007	-0.0013	0.0026	-0.0040
	(0.8205)	(0.8259)	(0.2393)	(0.4059)
C&I (%)	-0.0002	-0.0010	-0.0004	0.0004
	(0.8451)	(0.5537)	(0.5571)	(0.7321)
Personal (%)	-0.0003	-0.0004	0.0002	-0.0000
	(0.8528)	(0.8401)	(0.8623)	(0.9948)
Leases (%)	0.0015	0.0068**	-0.0042	0.0022
	(0.4391)	(0.0362)	(0.2545)	(0.6300)
Observations	4,132	4,091	1,272	1,170
R^2	0.452	0.514	0.519	0.617
Adj. R^2	0.448	0.456	0.506	0.483
Time FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes

The table represents results from regressions of a bank's loan portfolio mix on its stock return. The different kind of loans are calculated as a percentage of the total loan amount. The sample period is 1972 to 2013. The regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. Non-overlapping returns are used to avoid inflating the t-statistic due to serial correlation. Standard errors allow clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

the fact that the real estate segment is the biggest proportion of a banks loan portfolio. It is therefore the main driver of the loan growth of the total loan portfolio. If a bank is then in the top loan growth segment of the real estate segment is is also likely to be in the top growth quartile based on total loans to customers.

An other possible explanation is that real estate segment is truly the main driver of the subsequent worse returns. Deeper insight shows that in only 68% of the cases a bank in the top growth quartile is also in the top real estate growth quartile, based on the one year growth. For the three year loan growth this is only true in 55% of the cases. The reason for this could be that banks overstate the collateral that comes with the real estate loans. This is what happened in the financial crisis of 2007 - 2009. As shown in table 5.14 banks with more real estate loans have lower reserves. If banks grow their real estate portfolio, they will maintain a lower loan loss reserve percentage level, because they think the collateral will save them. If the collateral then seems to be less worth, they will have to increase their provisioning (as found

TABLE 5.16: One year different kinds of loan's growth

	One year loan growth					
	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Real Estate Quartile 2	-0.0254	-0.0335*	-0.0161	-0.0333**	-0.0036	-0.0044
	(0.1643)	(0.0529)	(0.1745)	(0.0375)	(0.8801)	(0.8258)
Real Estate Quartile 3	-0.0174	-0.0384*	-0.0270*	-0.0529***	-0.0106	-0.0392*
	(0.3660)	(0.0615)	(0.0530)	(0.0063)	(0.6041)	(0.0972)
Real Estate Quartile 4	-0.0357*	-0.0652***	-0.0411**	-0.0743***	-0.0468*	-0.0706**
	(0.0775)	(0.0044)	(0.0154)	(0.0006)	(0.0863)	(0.0116)
Agri Quartile 2	0.0047	-0.0086	0.0095	-0.0049	0.0040	-0.0138
	(0.7771)	(0.5939)	(0.3935)	(0.7374)	(0.7919)	(0.3784)
Agri Quartile 3	0.0027	0.0026	0.0148	0.0107	0.0039	0.0049
	(0.8909)	(0.8766)	(0.2568)	(0.4627)	(0.8018)	(0.7943)
Agri Quartile 4	-0.0101	-0.0070	0.0168*	0.0200	0.0276	0.0291
	(0.5299)	(0.5687)	(0.0776)	(0.1013)	(0.1568)	(0.1302)
C&I Quartile 2	0.0044	-0.0044	0.0360*	0.0271*	0.0028	0.0068
	(0.8369)	(0.8536)	(0.0513)	(0.0632)	(0.8769)	(0.7180)
C&I Quartile 3	-0.0102	-0.0186	0.0122	-0.0007	-0.0056	-0.0102
	(0.6113)	(0.3364)	(0.3813)	(0.9552)	(0.8139)	(0.6347)
C&I Quartile 4	0.0099	-0.0024	0.0180	-0.0040	-0.0028	-0.0256
	(0.6717)	(0.9118)	(0.3773)	(0.8486)	(0.8876)	(0.2111)
Personal Quartile 2	-0.0270	-0.0262	-0.0071	-0.0153	0.0307*	0.0826**
	(0.3392)	(0.4743)	(0.6298)	(0.5619)	(0.0862)	(0.0206)
Personal Quartile 3	-0.0565	-0.0694	-0.0351	-0.0238	0.0033	0.0416*
	(0.4627)	(0.2853)	(0.2748)	(0.4541)	(0.7909)	(0.0824)
Personal Quartile 4	-0.0565	-0.0579	-0.0348	-0.0268	0.0122	-0.0100
	(0.2235)	(0.2259)	(0.2799)	(0.3651)	(0.4975)	(0.7724)
Lease Quartile 2	-0.0356	-0.0187	-0.0257	-0.0143	-0.0167	0.0088
	(0.5585)	(0.7700)	(0.1449)	(0.5917)	(0.4000)	(0.7114)
Lease Quartile 3	-0.0495*	0.0070	-0.1056***	-0.0444	-0.0194	-0.0785***
	(0.0706)	(0.8262)	(0.0000)	(0.1699)	(0.4865)	(0.0068)
Lease Quartile 4	-0.0053	0.0034	0.0092	0.0280	-0.0202	-0.0336
	(0.8789)	(0.9225)	(0.6842)	(0.3306)	(0.2899)	(0.1562)
Observations	4,041	3,997	1,951	1,884	1,246	1,150
R^2	0.453	0.515	0.554	0.637	0.525	0.636
Adj. R^2	0.447	0.457	0.544	0.548	0.508	0.502
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

The table represents results from regressions of a bank's loan portfolio mix on its stock return. The different kind of loans are calculated as a percentage of the total loan amount. Banks are sorted into quartiles based on the loan segment growth during the previous year. 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 U.S. banks whose real assets in 2013 dollars are greater than $2 billion. Non-overlapping observations are used to avoid inflation the *t*-statistics due to serial correlation. The standard errors allow clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 5.17: Three year different kind of loan's growth

	Three year loan growth					
	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Real Estate Quartile 2	-0.0059	-0.0231	-0.0055	-0.0228**	-0.0003	-0.0163*
	(0.7701)	(0.1368)	(0.7737)	(0.0240)	(0.9845)	(0.0708)
Real Estate Quartile 3	-0.0292**	-0.0578***	-0.0226	-0.0505**	-0.0188	-0.0443**
	(0.0164)	(0.0012)	(0.1761)	(0.0115)	(0.2273)	(0.0157)
Real Estate Quartile 4	-0.0506***	-0.0936***	-0.0416***	-0.0815***	-0.0361**	-0.0732***
	(0.0000)	(0.0002)	(0.0090)	(0.0005)	(0.0327)	(0.0012)
Agri Quartile 2	-0.0251	-0.0445**	-0.0161	-0.0338**	-0.0171	-0.0379***
	(0.2075)	(0.0456)	(0.3600)	(0.0430)	(0.2108)	(0.0022)
Agri Quartile 3	0.0031	0.0135	0.0049	0.0057	-0.0032	-0.0064
	(0.8878)	(0.4211)	(0.6738)	(0.6472)	(0.7553)	(0.5653)
Agri Quartile 4	-0.0039	0.0131	-0.0029	0.0075	-0.0014	0.0042
	(0.8383)	(0.4053)	(0.8353)	(0.5242)	(0.9071)	(0.6620)
C&I Quartile 2	-0.0129	-0.0192	0.0002	-0.0023	-0.0039	-0.0044
	(0.6907)	(0.5047)	(0.9935)	(0.8955)	(0.8376)	(0.7218)
C&I Quartile 3	-0.0062	-0.0160	0.0140	0.0058	0.0090	0.0027
	(0.8692)	(0.6469)	(0.5396)	(0.7388)	(0.6716)	(0.8593)
C&I Quartile 4	-0.0075	-0.0261	0.0035	-0.0131	0.0023	-0.0081
	(0.8251)	(0.4192)	(0.8675)	(0.5077)	(0.9006)	(0.6028)
Personal Quartile 2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)
Personal Quartile 3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)
Personal Quartile 4	0.3044*	0.2956	0.1950***	0.1840*	0.1834***	0.1607**
	(0.0917)	(0.1272)	(0.0009)	(0.0541)	(0.0001)	(0.0358)
Lease Quartile 2	0.0250**	0.0530***	0.0211*	0.0379**	0.0264***	0.0433***
	(0.0165)	(0.0003)	(0.0886)	(0.0117)	(0.0085)	(0.0016)
Lease Quartile 3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)
Lease Quartile 4	0.0563**	0.0747***	0.0247**	0.0346**	0.0185**	0.0267*
	(0.0171)	(0.0027)	(0.0143)	(0.0337)	(0.0399)	(0.0895)
Observations	4,036	4,036	3,785	3,785	3,552	3,552
R^2	0.455	0.463	0.5161	0.534	0.5134	0.547
Number of groups	430	430	403	403	379	379
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

The table represents results from regressions of a bank's loan portfolio mix on its stock return. The different kind of loans are calculated as a percentage of the total loan amount. Banks are sorted into quartiles based on the loan segment 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 regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. The standard errors use the Discroll-Kraay estimator. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

in table 5.14), which will result in lower earnings and thus lower returns.

For the subsequent two- and three year returns this conclusion for the real estate segment remains. For the two year returns there is also a positive effect for the top agricultural growth quartile in the between-model (and is almost significant at the 10%-level for the within model). Further analysis shows that quartile 4 has an extremely positive mean of loan growth. This is well possibly due to merger activity, but also organic growth because the size of the agricultural segment is very small.[2] This makes it very volatile in its growth metric.[3] While agricultural loans are not secured, they are not that risky. As mentioned before, farms have a relatively stable income due to the in-elasticity of food. So banks that are able to grant a lot of agricultural loans will grant them to somebody who has access to stable income. Unfortunately this effect disappears in the three year return model. Meaning that actually growing the agricultural segment does not drive returns long-term.

For the commercial & industrial loans only quartile 2 is significant for the two year models. Deeper analysis shows that quartile 1 actually has a decreasing C&I segment. Quartile 2 has a slight growth, whereas quartile 3 and 4 have strong growth. It makes sense that a bank that slightly increases it loan portfolio will experience better returns than a bank that has a decreasing portfolio. But like the agricultural loans, the effect disappears in the long run.

The last (highly) significant indicator for the two year returns is quartile 3 for leases for the between-model. Further analysis shows that due to a lot of zero values in the lease segment, the quartiles based on growth are distorted. Quartile 3 has only six observations in model 3 and 4. In model 5 and 6 there are only 3 observations in quartile 3.[4] This could distorts the statistical model. Quartile 1 and 2 are slightly negative, while quartile 3 is a slightly positive and quartile 4 is a strong increase in the lease segment. The strong increase can be due to M&A growth, but also due to the small size of the lease segment, which results in a volatile growth variable. In the 3 year returns model the personal quartile 2 is significantly positive. Which has the same interpretation as for commercial & industrial loans.

For results based on the three year loan growth there are not enough observations to use non-overlapping observations. This problem is (partly) overcome in

[2] As show in the summary statistics, the agricultural segment is about 0.8% of the total loan portfolio.

[3] The one year agricultural loan growth variable has a mean of 21%, with a standard deviation of 182%. The three year agricultural loan growth has an average of 3% with a standard deviation of 35%. The real estate segment has an average of 12% with a standard deviation of 21% for the one year growth, and an average of 9% for the three year growth with a standard deviation of 12%.

[4] In all cases about 85% of the observations are in growth quartile 1.

table 5.17 by using the Discroll-Kraay standard error matrix (Driscoll and Kraay, 1998). This adjust for clustering and serial correlation.

The results of table 5.17 align with the findings of table 5.16. Real estate seem to be the main driver of the subsequent worse returns.

The personal segment only has a quartile 1 and quartile 4, and puts all non zero observations in the top quartile, hence the omitted values for quartile 2 and 3. This indicates that having any personal loan segment (growth) will be rewarded. This contradicts table 5.15, so it is most likely due to the model specification. The odd results for the lease segment are the most likely also due to the model specification.

Due to the distortion that is caused by the personal and lease loans[5] the regressions are redone, but now without these two segments. The results can be found in the appendix and show a confirmation that the real estate loan growth drives the subsequent negative returns. It is interesting to note that the one year loan growth of the real estate segment is also significant on the one year returns. This was not the case in table 5.1 or in the research of FPS. Indicating that there really might be something with the real estate segment.

Overall the results thus suggest that hypothesis 12 must be rejected. Top quartiles of more secured loans do not experience better stock stock performance compared to the less secure ones. There is more evidence to the contrary, the most secured loans (real estate backed loans) are the main driver for the worse subsequent returns.

It must be noted though that the effect of the real estate growth is not much different from the effect of the overall loan growth. This might be due to the fact that the real estate segment is the biggest portion of the loan portfolio. A big loan growth in the real estate segment therefore has a big impact on the overall performance of the firm.

This result is complimentary to the findings of FPS. The fastest growing banks do indeed see worse performance, but this might be driven by the loan growth of the real estate segment. However as the real estate segment is the biggest part of the loan portfolio (around 60% on average), it might also become a proxy of overall loan growth, as a chance in the real estate segment will have a significant impact on the overall loan portfolio. Still, seeing as this is not always the case, it indicates banks trust too much on their collateral, resulting in too low reserves. This exposes them

[5] This distortion is due to the fact that a lot of banks have no personal or lease loans, resulting in zero loan growth for the majority of the observations, which does not work with quartile-dummy based regressions.

to great risks when their loans fail as they will have the lowest buffers against these loan losses.

6 Robustness

This chapter looks at the robustness of the findings from chapter 5. All the tables are found in the appendix.

6.1 Gross Loan Growth

To be in line with the research of FPS, I also use the Compustat variable LCUACU (Total loans to Customers) to construct the loan growth variable. This variable is the total amount of loans outstanding to customers, net of loan loss reserves. This means that the growth might also be due to a drop in the level of reserves.

Let's take bank A and bank B for example. Both have a LCUACU of 100, but bank A has 110 in gross loans and 10 in reserves, while bank B had 120 gross loans and 20 in reserves. Now bank A gives out a new loan of 10, but does not increase their level of reserves. Their LCAUCU will become (110+10-10=) 110. Bank B does not give out new loans, but lower their reserve levels from 20 to 10. Their LCAUCU also becomes (120-10=) 110. Both banks have become more risky, because they both hold a lower reserves level than before, but only bank A actually gave out new loans.

By measuring the loan growth based on LCAUCU a change in the level of reserves is also incorporated. Though the impact might be small, because reserves are on average not even 2% of the gross loan portfolio. To have a 1% change in the growth of the loan portfolio, the average reserve level would have to change by 50%. Still it is worth controlling for this effect.

The results from the table A.7 are a replication of the main results of FPS, but now with the growth based on the gross loan growth. As can be seen from the table the message remains, though the effect is slightly different for a few models in panel B.

Model 5 of panel B shows a negative coefficient of 5.8% for the top quartile, while this same model shows a negative coefficient of 6.6% in table 5.6. The effect seems thus to be somewhat mitigated when the gross loan growth is used. But model 6 of panel B, indicating the result from the 'biggest' model of FPS, had a negative coefficient of 10.0% in table 5.6, but now shows a negative coefficient of 10.5%. The between-effect is thus mitigated, but the within effect is enhanced. Still the main message - banks that grow fast make worse returns - holds.

6.2 Mergers & Acquisitions

FPS also mention that banks can grow quickly due to M&A-activity. They list research that suggests - not unanimously - that the long-term effect of acquisitions are negative (eg. Rau and Vermaelen, 1998; Loughran and Vijh, 1997; Moeller, Schlingemann, and Stulz, 2005). Therefore, the banks that grow fast might have grown due to an acquisition and experience worse returns not due to the loan growth, but due to the negative effect of M&A-activity. To control for this, the loan growth is split in internal (organic) and external (M&A) loan growth.

Table A.8 shows the results form running the regression corrected for M&A activity. Panel A shows for all models similar results to tables 5.1, 5.2 and 5.3. Is also shows that banks that do big acquisitions have significantly worse returns.

Panel B shows slightly different results compared to the results in the main table. For the one year returns the top growth quartile is only significant at the 10%-level for the within-model. Model 3 has no significant quartiles. This differs from 5.5. This result differs from FPS, who do find a significant effect from the between-model on the two year stock returns. Model 4 does align with the result from 5.5. Model 5 and 6 are similar again to their respective models in table 5.6. Like in panel A (and in the research of FPS), the most acquisitive banks will experience a big drop in the subsequent return. Top merger-activity is always (negatively) significant, showing that big bank fusions do not create shareholder value.

Overall, this robustness test shows that big acquisitions partly explain the subsequent returns. This can be seen by the lower significance and magnitude of some of the coefficients. Despite this slight difference the conclusion of FPS - fast loan growth will lead to worse performance - seems to hold, even when corrected for M&A-activity. It should be noted that their conclusion mostly holds for the within-model, based on my results.

6.3 2016 data & different clustering

The regressions in chapter 5 are redone, but now including the years 2014 till 2016. Table A.9 shows the results are qualitative similar to the results in chapter 5 though the coefficients in table A.9 have a slightly lower magnitude. Still it shows the main results are robust to including the present years.

FPS also allow their standard errors to cluster at the bank and time level. This method is copied for the main results from chapter 5. In table A.10 the standard errors are clustered only at firm level. The results are qualitative and quantitative similar to the results in chapter 5.

Overall this robustness section shows that the results presented by FPS and in chapter 5 of this thesis are robust to different growth metrics, mergers & acquisitions, more years and different clustering.

7 Conclusion

This thesis set out to see if the research of Fahlenbrach, Prilmeier, and Stulz (2017) holds when corrected for different variables. Their research showed that the fastest growing banks had the worst subsequent performance due to granting worse loans than these banks think. Fahlenbrach, Prilmeier, and Stulz show that banks, investors and equity analysts all miss this relation between growth and quality.

The main point of this thesis is to see if the market really misses this relationship. If banks have more reserves to cushion for future loan losses, the effect of the loan growth should diminish (or even disappear). The loan loss provisions, loan loss reserves and equity ratio are added to the model. The results show that while the effect is diminished, the banks in the top loan growth will still experience significantly worse returns. So while the top growth banks might provision less (leading to lower reserves), this is not what drives the subsequent worse returns.

The results do show that these additional variables should be added for better returns as they are combined better able to predict subsequent returns.

Furthermore, the results show that loan seasoning is present in the database, meaning the moment of the loan growth has an effect on the subsequent returns. However, this effect is mitigated by using the loan growth over a three year period and the subsequent three year returns. As the effect of the loan growth over a three year period is stronger than the effect of the loan seasoning, it indicates that an aggressive loan growth policy is what really destroys shareholder value.

In an attempt to find out which banks grow the fastest, evidence is found that it might be the banks that grant loans to a new pool of risky customers. Banks can grow by lowering interest rates or lowering credit standards. The results show that banks that increase their interest rates the most are the ones that grow the fastest. This effect mostly holds for the top growth quartile. Banks will increase their interest rates if they know customers are more risky, to cover for the potential losses. As the biggest increase in the interest rate also means a significant increase in the loan growth, it would indicate that the fastest growing banks are the ones that accept new risky borrowers (and charge them a high risk premium). Future research could further investigate this matter by using a better proxy for the credit standard used by the loan officers.

My results also show that the results of Fahlenbrach, Prilmeier, and Stulz holds during recession times. Loan seasoning has an effect on the subsequent stock returns, mostly the loan growth two years prior to the portfolio formation has less negative (or even positive) effect on the multi-year returns. This would indicate that indeed the loans made before a recession are the worst. Still the effect of the loan growth over the past three years has a more severe effect on the subsequent stock returns. As nobody can truly predict how long a recession will last, investors are wise to look at at the loan growth over a longer period, than to invest based on loan seasoning.

The last results show different kinds of loans have no effect on the level of provisioning, but instead they have effect on the level of reserves banks hold. This reserve level then predicts the level of provisioning. In line with expectations, banks with more real estate, agricultural loans and leases have lower reserves, as these loans are safe or secured by collateral. The commercial & industrial loans increase the level of reserves. The loan loss reserve policy of banks seems sticky as they don't change when the loan portfolio mix changes, but they do differ between banks. Banks should check periodically if their loan loss reserve policy is still in line with their loan portfolio mix.

While the loan portfolio mix has an indirect effect on the income statement,[1] the mix has no real predictive power over the subsequent one- or three-year returns. For the loan growth per segment it seems that top loan growth in the real estate quartile is the main driver of subsequent worse returns. This could be due to two reasons. First, the real estate segment is the biggest, thus it will have the biggest impact. The top growth real estate bank, is likely to be the top growth bank overall as well. Further analysis shows this is not always the case. The second reasons is that it is really the real estate loan growth that impacts the subsequent returns. As banks with more real estate loans have lower reserves, they will experience the worst returns if the collateral turns out to be worse than expected. And in line with Fahlenbrach, Prilmeier, and Stulz, it seems that banks with the fastest growth make the worst loans, so it is highly likely they also overstate the collateral value. Indicating that the second theory might be the actual reason.

Multiple robustness checks are done to check the results by using different growth metrics, years, statistical methods and checking for the impact of merger-activity. Still the results hold. This thesis thus confirms the findings of Fahlenbrach, Prilmeier,

[1] The mix drives the reserves, the reserves drive the provisioning and the provisioning impacts the earnings.

and Stulz and answers the research question with: *"Yes the stock market really misses the risk associated with the fast loan portfolio growth"*.

Banks that have a policy of aggressive loan portfolio growth seem to destroy shareholder value. Because banks do not provision accordingly to their loan portfolio growth, the fast growing banks are at excessive risk. Investors and regulators should look at why banks are growing fast, as organic loan growth indicates that banks will have granted loans to worse borrowers, resulting in bad performance. In times of recessions regulators should really focus on which banks have grown the most during the past three-years as these banks are most likely to fail, though it should be noted that the loan growth of three years before the recession has a lower impact.

Overall, this thus confirms the research of Fahlenbrach, Prilmeier, and Stulz and I can only compliment the strong results their 'simple' metric shows. Investors should indeed be weary of investing in fast growing banks. Also, regulators should focus their limited resources on banks that have grown (or are growing) faster than their peers. As mentioned in previous papers, more attention must be given to how banks provision. This is already done for Basel III and IV, but the segmental research indicates the collateral should also be included in the determination of the reserves levels. As the recent financial crisis showed, (real estate) collateral is aimed at minimizing the loan loss damage, but is not always able to completely prevent it.

While this thesis has been constructed with great amount of effort and attention to detail, there are some limitations to this research. First of all the database of Fahlenbrach, Prilmeier, and Stulz could not be perfectly replicated, most likely due to the subjective manual check of bank activity descriptions. Still the results come close. The second limitation is that only banks with at least $2 billion in assets, based on 2013 inflation numbers, are used. The third limitation is the lack of federal banking data available for all observations. There is a drop of about 50% when the RSSD data is used, compared to the fundamental Compustat data. Within the RSSD database, there are a lot of zero values for the personal and lease loans. This resulted in some distortions within the segmental regressions, though the results remained the same when these segments were removed. Furthermore, the use of the loan loss provisions seems to be inadequate to be used as a proxy for the credit standard maintained by banks. A final limitation of this research is that it only looks at banks in the U.S. As mentioned in chapter 2 (Literature) there seems to be differences in banking systems between countries/regions.

Further interesting research would thus be to see if the findings of FPS also holds in other regions (e.g. Europe, Asia, OECD). Furthermore, it would be interesting to see what the results are for the drivers of fast loan growth by using a different variable for the credit standard used by banks. An other interesting research question is to look into the relationship between real estate loan growth and the value of its collateral. This would be to check if the fastest growing real estate banks experience a big drop in the subsequent collateral value, which results in high provisioning posts, thus lower earnings and stock returns. Finally, I would encourage somebody to research if credit rating agencies do see the risk associated with fast loan growth, given their expertise in credit and their feel for the current credit market.

A Appendix

A.1 Pre-collapsing graphs

As mentioned in section 3.3, it is unsure how FPS got their figure 2. First it is not clear if they used overlapping or non-overlapping returns. Second it seems that they did not collapse their database after merging the merger database and the 'main' database. If a bank acquires multiple banks in one year, the observation of the buyer will show multiple times in the database. In section 3.3, the post-collapse non-overlapping returns are shown. Below the other possible graphs are shown. Figure A.2 looks the most like figure 2 of FPS.

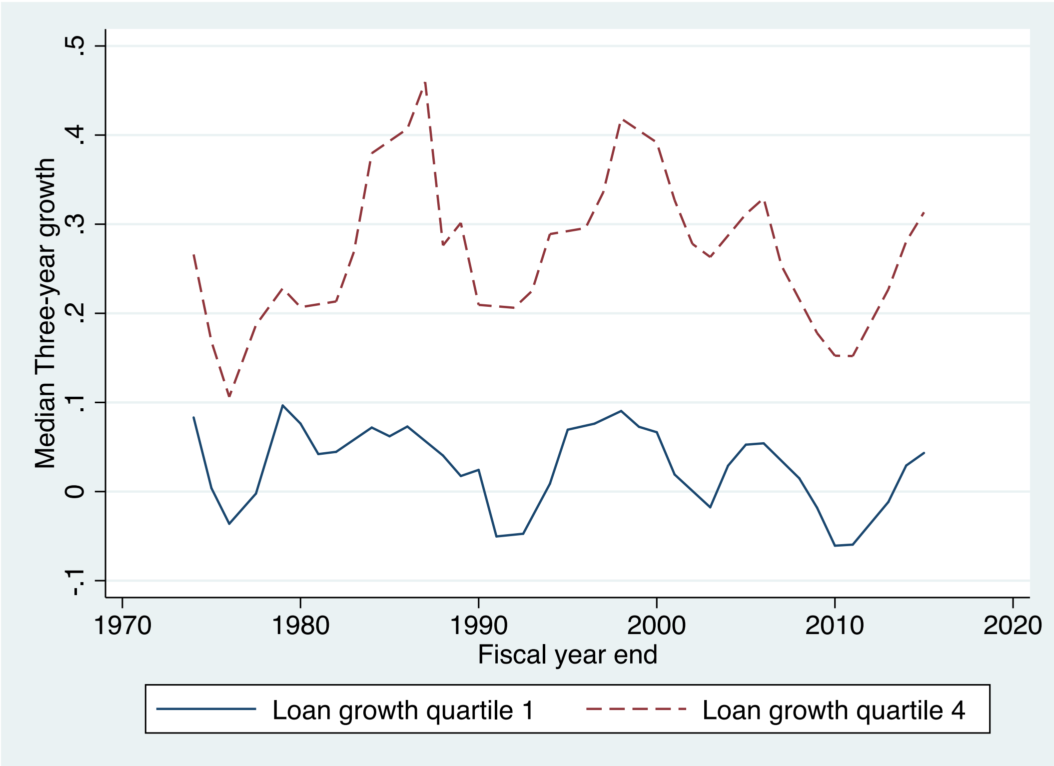

FIGURE A.1: **Median three-year loan growth for high and low three-year loan growth quartiles**
The figure shows the time series of the median three-year loan portfolio growth for the banks in the top growth quartile and the bottom quartile. The quartiles are based on the loan growth of the preceding three years. The growth rates are annualized. The sample period is from 1972 to 2016. This is done before the collapsing of the data. When linking the acquisitions to the CRSP/Compustat database, duplicates of the CRSP/Compustat will arise if banks acquired multiple banks in one year.

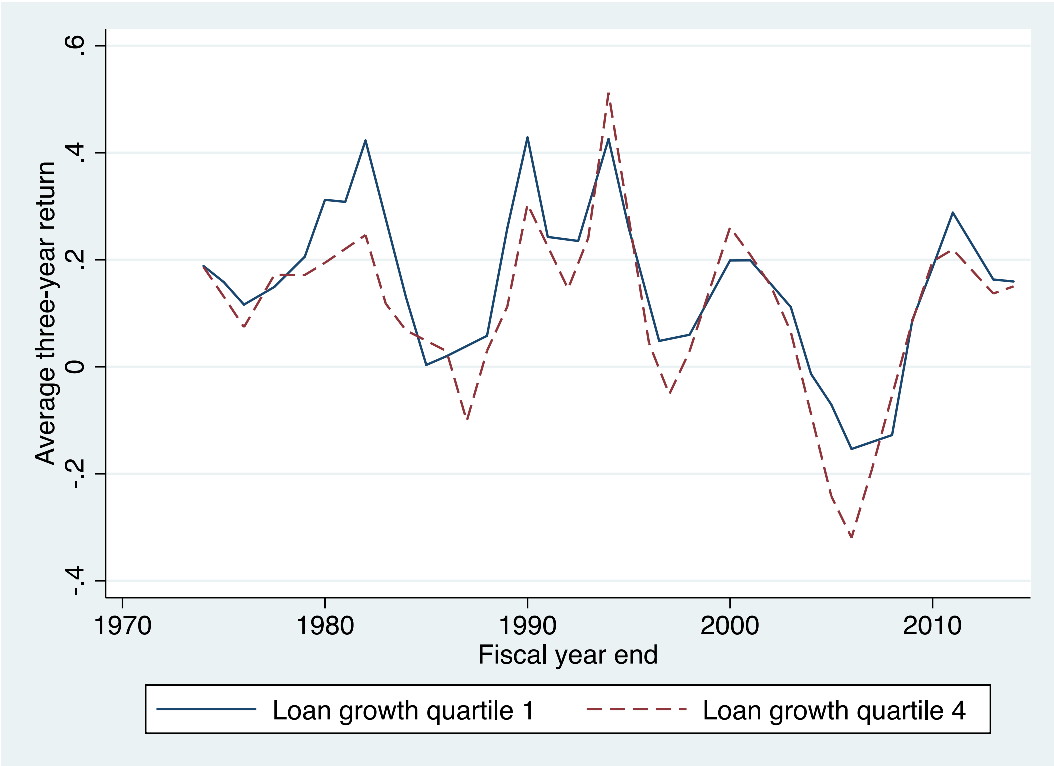

FIGURE A.2: **Average three-year subsequent overlapping return for high and low three-year loan portfolio growth quartiles**

The figure shows the time series of the average three-year loan portfolio overlapping returns for the banks in the top growth quartile and the bottom quartile. The quartiles are based on the loan growth of the preceding three years. The returns rates are annualized. The sample period is from 1972 to 2016. This is done before the collapsing of the data. When linking the acquisitions to the CRSP/Compustat database, duplicates of the CRSP/Compustat will arise if banks acquired multiple banks in one year.

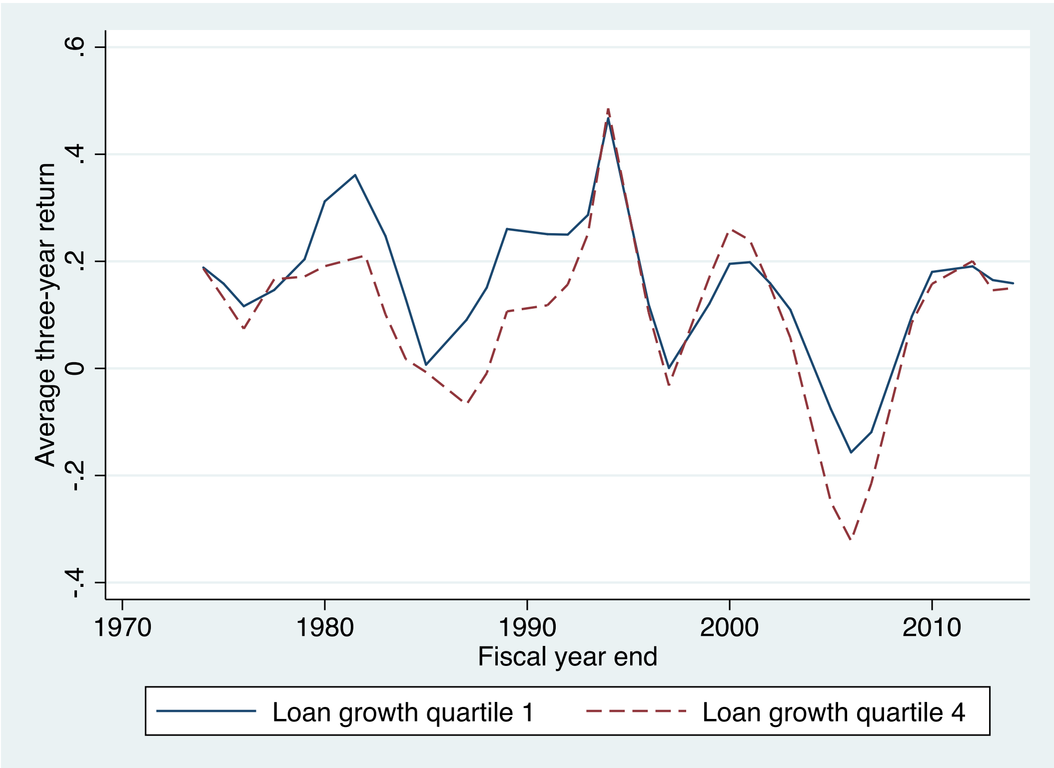

FIGURE A.3: **Average three-year subsequent overlapping return for high and low three-year loan portfolio growth quartiles**
The figure shows the time series of the average three-year loan portfolio overlapping returns for the banks in the top growth quartile and the bottom quartile. The quartiles are based on the loan growth of the preceding three years. The returns rates are annualized. The sample period is from 1972 to 2016. This is done after the collapsing of the data.

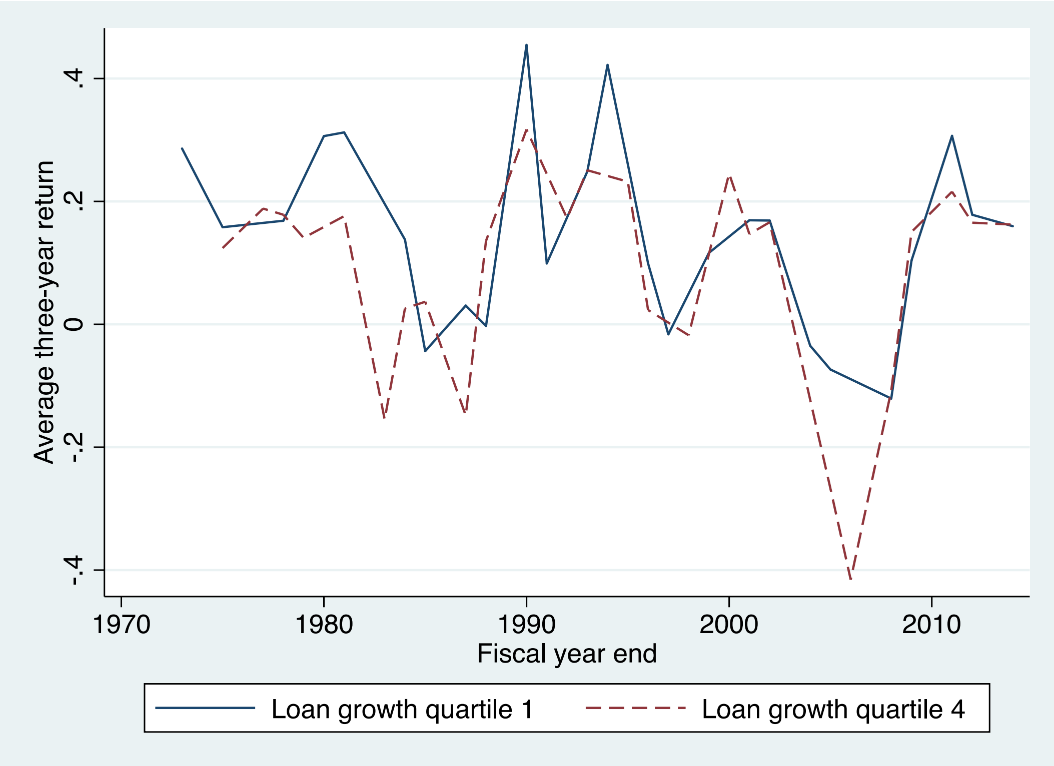

FIGURE A.4: **Average three-year subsequent non-overlapping return for high and low three-year loan portfolio growth quartiles**
The figure shows the time series of the average three-year loan portfolio non-overlapping returns for the banks in the top growth quartile and the bottom quartile. The quartiles are based on the loan growth of the preceding three years. The returns rates are annualized. The sample period is from 1972 to 2016. This is done before the collapsing of the data. When linking the acquisitions to the CRSP/Compustat database, duplicates of the CRSP/Compustat will arise if banks acquired multiple banks in one year.

A.2 Two year loan growth

TABLE A.1: Two year loan growth with one year returns

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quartile 2	-0.0213	-0.0411**	-0.0282**	-0.0364***	-0.0188	-0.0277**	-0.0208	-0.0409**	-0.0259**	-0.0329**
	(0.2113)	(0.0288)	(0.0235)	(0.0089)	(0.1362)	(0.0481)	(0.2081)	(0.0285)	(0.0348)	(0.0171)
Quartile 3	-0.0191	-0.0438**	-0.0248*	-0.0344**	-0.0159	-0.0252	-0.0189	-0.0449**	-0.0224	-0.0304*
	(0.3289)	(0.0459)	(0.0966)	(0.0327)	(0.2778)	(0.1108)	(0.3277)	(0.0435)	(0.1257)	(0.0512)
Quartile 4	-0.0373*	-0.0640***	-0.0392**	-0.0504***	-0.0330*	-0.0418**	-0.0374*	-0.0661***	-0.0369**	-0.0477**
	(0.0731)	(0.0096)	(0.0291)	(0.0091)	(0.0531)	(0.0234)	(0.0748)	(0.0090)	(0.0363)	(0.0113)
LLP			-0.0003	0.0223					-0.0128	-0.0119
			(0.9882)	(0.3755)					(0.5768)	(0.6444)
LLR					0.0050	0.0340**			0.0145	0.0420***
					(0.6880)	(0.0372)			(0.1480)	(0.0037)
EQ-ratio							-0.0011	-0.0089*	-0.0018	-0.0110**
							(0.7406)	(0.0722)	(0.5632)	(0.0218)
Observations	6,780	6,728	6,274	6,234	6,761	6,709	6,777	6,726	6,274	6,234
R^2	0.442	0.497	0.444	0.503	0.444	0.502	0.442	0.498	0.445	0.506
Adj. R^2	0.438	0.449	0.440	0.454	0.441	0.454	0.438	0.449	0.441	0.458
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-test									0.789	3.925
Prob > F									0.507	0.0151

The table represents results from regressions of a bank's loan portfolio growth on its stock return. Banks are sorted into quartiles based on the loan portfolio growth during the previous two 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 regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. LLP represents the two-year average loan loss provision as a percentage over total loans. LLR represents the loan loss reserves as a percentage over total loans. $EQ-ratio$ represents the percentage tangible common equity over total assets. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE A.2: Two year loan growth with two year returns

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quartile 2	-0.0148	-0.0361***	-0.0215**	-0.0305***	-0.0125	-0.0246**	-0.0148	-0.0362***	-0.0200*	-0.0277**
	(0.1374)	(0.0004)	(0.0402)	(0.0072)	(0.2910)	(0.0205)	(0.1383)	(0.0004)	(0.0694)	(0.0168)
Quartile 3	-0.0170*	-0.0406***	-0.0157*	-0.0274**	-0.0145	-0.0244**	-0.0170*	-0.0415***	-0.0142	-0.0237**
	(0.0993)	(0.0009)	(0.0875)	(0.0133)	(0.1355)	(0.0271)	(0.0999)	(0.0008)	(0.1190)	(0.0302)
Quartile 4	-0.0420***	-0.0742***	-0.0440***	-0.0638***	-0.0389***	-0.0565***	-0.0420***	-0.0759***	-0.0426***	-0.0621***
	(0.0041)	(0.0000)	(0.0039)	(0.0000)	(0.0065)	(0.0001)	(0.0037)	(0.0000)	(0.0028)	(0.0000)
LLP			-0.0032	0.0206					-0.0115	-0.0076
			(0.8048)	(0.1283)					(0.3019)	(0.5754)
LLR					0.0044	0.0311***			0.0097	0.0363***
					(0.6496)	(0.0091)			(0.2215)	(0.0058)
EQ-ratio							0.0002	-0.0059*	-0.0015	-0.0099**
							(0.9287)	(0.0959)	(0.5865)	(0.0132)
Observations	3,276	3,193	2,864	2,795	3,267	3,186	3,274	3,193	2,864	2,795
R^2	0.535	0.619	0.505	0.585	0.536	0.624	0.535	0.620	0.506	0.590
Adj. R^2	0.529	0.546	0.497	0.504	0.530	0.551	0.529	0.546	0.498	0.509
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-test									1.209	4.380
Prob > F									0.319	0.00946

The table represents results from regressions of a bank's loan portfolio growth on its stock return. Banks are sorted into quartiles based on the loan portfolio growth during the previous two 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 regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. *LLP* represents the two-year average loan loss provision as a percentage over total loans. *LLR* represents the loan loss reserves as a percentage over total loans. $EQ - ratio$ represents the percentage tangible common equity over total assets. Non-overlapping returns are used to avoid inflating the *t*-statistic due to serial correlation. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE A.3: Two year loan growth with three year returns

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quartile 2	-0.0179	-0.0386***	-0.0202	-0.0256**	-0.0163	-0.0277**	-0.0179	-0.0385***	-0.0190	-0.0254**
	(0.1856)	(0.0063)	(0.1053)	(0.0370)	(0.2161)	(0.0186)	(0.1855)	(0.0053)	(0.1229)	(0.0309)
Quartile 3	-0.0365**	-0.0617***	-0.0315**	-0.0365**	-0.0345**	-0.0459***	-0.0365**	-0.0636***	-0.0302**	-0.0370***
	(0.0314)	(0.0001)	(0.0342)	(0.0105)	(0.0353)	(0.0007)	(0.0315)	(0.0001)	(0.0379)	(0.0068)
Quartile 4	-0.0557***	-0.0873***	-0.0513***	-0.0622***	-0.0531***	-0.0681***	-0.0552***	-0.0905***	-0.0497***	-0.0652***
	(0.0016)	(0.0000)	(0.0043)	(0.0025)	(0.0024)	(0.0002)	(0.0017)	(0.0000)	(0.0035)	(0.0010)
LLP			0.0039	0.0376***					-0.0022	0.0131
			(0.8049)	(0.0059)					(0.8909)	(0.3133)
LLR					0.0036	0.0281***			0.0075	0.0258**
					(0.6054)	(0.0065)			(0.2588)	(0.0206)
EQ-ratio							0.0013	-0.0090**	-0.0001	-0.0123**
							(0.6436)	(0.0367)	(0.9789)	(0.0142)
Observations	2,088	1,973	1,723	1,641	2,081	1,968	2,087	1,973	1,723	1,641
R^2	0.507	0.619	0.473	0.599	0.507	0.626	0.507	0.622	0.473	0.606
Adj. R^2	0.496	0.509	0.460	0.474	0.497	0.518	0.496	0.512	0.459	0.482
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-test									0.492	4.470
Prob > F									0.690	0.00876

The table represents results from regressions of a bank's loan portfolio growth on its stock return. Banks are sorted into quartiles based on the loan portfolio growth during the previous two 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 regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. *LLP* represents the two-year average loan loss provision as a percentage over total loans. *LLR* represents the loan loss reserves as a percentage over total loans. $EQ - ratio$ represents the percentage tangible common equity over total assets. Non-overlapping returns are used to avoid inflating the *t*-statistic due to serial correlation. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

A.3 Loan Seasoning

TABLE A.4: Loan Seasoning

	A. One year return			
VARIABLES	(1)	(2)	(3)	(4)
$LoanGrowth_t$	-0.0178	-0.0627*		
	(0.6153)	(0.0673)		
$LoanGrowth_{t-1}$	-0.0604*	-0.0872**		
	(0.0816)	(0.0147)		
$LoanGrowth_{t-2}$	-0.0704**	-0.0933***		
	(0.0186)	(0.0034)		
$LoanGrowth_{t-3,t}$			-0.1489**	-0.2208***
			(0.0138)	(0.0041)
Observations	5,780	5,739	6,419	6,362
R^2	0.420	0.475	0.438	0.489
Adj. R^2	0.416	0.423	0.434	0.440
Time FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes

	B. Δ ROA			
VARIABLES	(1)	(2)	(3)	(4)
$LoanGrowth_t$	-0.0744	-0.1504		
	(0.6517)	(0.2885)		
$LoanGrowth_{t-1}$	0.0973	0.0698		
	(0.3420)	(0.5116)		
$LoanGrowth_{t-2}$	-0.3518**	-0.3569***		
	(0.0158)	(0.0091)		
$LoanGrowth_{t-3,t}$			-0.3180**	-0.4314**
			(0.0347)	(0.0484)
Observations	6,037	5,983	6,423	6,382
R-squared	0.1336	0.1585	0.1270	0.1689
Time FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes
R^2	0.134	0.158	0.127	0.169
Adj. R^2	0.128	0.0757	0.121	0.0867

The table represents results from regressions of bank's loan portfolio growth on its one year stock return or ΔROA. $LoanGrowth_{t-3,t}$ represents the annualized loan growth over the past three years. The sample period is 1972 to 2013. Loan growth is measured from the IPO onward. The regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

A.4 Segment loan growth

TABLE A.5: One year different kind of loan's growth

	One year loan growth					
	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Real Estate Quartile 2	-0.0259	-0.0344**	-0.0172	-0.0337**	-0.0034	-0.0031
	(0.1508)	(0.0425)	(0.1431)	(0.0276)	(0.8834)	(0.8737)
Real Estate Quartile 3	-0.0197	-0.0416*	-0.0289**	-0.0539***	-0.0106	-0.0382
	(0.3200)	(0.0504)	(0.0349)	(0.0042)	(0.5912)	(0.1018)
Real Estate Quartile 4	-0.0389*	-0.0679***	-0.0430***	-0.0749***	-0.0470*	-0.0701***
	(0.0523)	(0.0026)	(0.0097)	(0.0004)	(0.0743)	(0.0096)
Agri Quartile 2	0.0034	-0.0098	0.0080	-0.0065	0.0035	-0.0125
	(0.8264)	(0.5311)	(0.4532)	(0.6590)	(0.8157)	(0.4166)
Agri Quartile 3	0.0022	0.0025	0.0137	0.0090	0.0045	0.0078
	(0.9145)	(0.8841)	(0.2952)	(0.5315)	(0.7715)	(0.6772)
Agri Quartile 4	-0.0103	-0.0070	0.0170*	0.0196	0.0273	0.0289
	(0.5227)	(0.5789)	(0.0614)	(0.1025)	(0.1536)	(0.1256)
C&I Quartile 2	0.0041	-0.0046	0.0358*	0.0272*	0.0016	0.0055
	(0.8437)	(0.8451)	(0.0504)	(0.0609)	(0.9292)	(0.7669)
C&I Quartile 3	-0.0102	-0.0195	0.0126	-0.0008	-0.0070	-0.0113
	(0.5925)	(0.2934)	(0.3608)	(0.9468)	(0.7643)	(0.5840)
C&I Quartile 4	0.0121	-0.0009	0.0206	-0.0030	-0.0040	-0.0271
	(0.5895)	(0.9667)	(0.3060)	(0.8815)	(0.8381)	(0.1767)
Observations	4,065	4,022	1,958	1,890	1,254	1,158
R^2	0.454	0.516	0.554	0.637	0.525	0.634
Adj. R^2	0.449	0.459	0.546	0.551	0.511	0.504
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

The table represents results from regressions of a bank's loan portfolio mix on its stock return. The different kind of loans are calculated as a percentage of the total loan amount. Banks are sorted into quartiles based on the loan segment growth during the previous year. 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 U.S. banks whose real assets in 2013 dollars are greater than $2 billion. Non-overlapping observations are used to avoid inflation the *t*-statistics due to serial correlation. The standard errors allow clustering at the bank and time levels. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE A.6: Three year different kind of loan's growth

	Three year loan growth					
	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Real Estate Quartile 2	-0.0044	-0.0227	-0.0034	-0.0216**	0.0013	-0.0153*
	(0.8258)	(0.1363)	(0.8545)	(0.0282)	(0.9314)	(0.0887)
Real Estate Quartile 3	-0.0260**	-0.0549***	-0.0196	-0.0478**	-0.0163	-0.0419**
	(0.0346)	(0.0021)	(0.2313)	(0.0153)	(0.2927)	(0.0199)
Real Estate Quartile 4	-0.0464***	-0.0893***	-0.0381**	-0.0782***	-0.0334*	-0.0707***
	(0.0001)	(0.0002)	(0.0143)	(0.0006)	(0.0506)	(0.0014)
Agri Quartile 2	-0.0230	-0.0434**	-0.0140	-0.0330**	-0.0149	-0.0375***
	(0.2325)	(0.0469)	(0.4096)	(0.0433)	(0.2733)	(0.0024)
Agri Quartile 3	0.0011	0.0127	0.0032	0.0046	-0.0042	-0.0067
	(0.9607)	(0.4563)	(0.7782)	(0.6997)	(0.6823)	(0.5310)
Agri Quartile 4	-0.0047	0.0131	-0.0031	0.0076	-0.0018	0.0044
	(0.8073)	(0.4026)	(0.8219)	(0.5090)	(0.8776)	(0.6468)
C&I Quartile 2	-0.0132	-0.0195	-0.0003	-0.0029	-0.0035	-0.0043
	(0.6856)	(0.5095)	(0.9903)	(0.8742)	(0.8515)	(0.7390)
C&I Quartile 3	-0.0074	-0.0164	0.0123	0.0049	0.0076	0.0025
	(0.8445)	(0.6410)	(0.5953)	(0.7843)	(0.7200)	(0.8739)
C&I Quartile 4	-0.0108	-0.0284	0.0009	-0.0145	0.0005	-0.0085
	(0.7555)	(0.3951)	(0.9678)	(0.4759)	(0.9767)	(0.5852)
Observations	4,059	4,059	3,808	3,808	3,575	3,575
R^2	0.4545		0.5152		0.5123	
Number of groups	430	430	403	403	379	379
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

The table represents results from regressions of a bank's loan portfolio mix on its stock return. The different kind of loans are calculated as a percentage of the total loan amount. Banks are sorted into quartiles based on the loan segment 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 regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. The standard errors use the Discroll-Kraay estimator. Number in parentheses are the robust p-values. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

A.5 Robustness

TABLE A.7: Gross loan growth

A. One year loan growth						
	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Quartile 2	-0.0021	-0.0152	0.0020	-0.0199*	-0.0009	-0.0210
	(0.8918)	(0.3523)	(0.8112)	(0.0551)	(0.9474)	(0.1370)
Quartile 3	-0.0009	-0.0227	-0.0031	-0.0276**	-0.0195	-0.0527***
	(0.9588)	(0.2465)	(0.7793)	(0.0308)	(0.2225)	(0.0023)
Quartile 4	-0.0067	-0.0272	-0.0085	-0.0365**	-0.0375*	-0.0666***
	(0.7267)	(0.1806)	(0.5760)	(0.0490)	(0.0748)	(0.0019)
Observations	6,514	6,471	2,893	2,826	1,738	1,652
R-squared	0.441	0.500	0.494	0.584	0.464	0.590
Adj. R-squared	0.437	0.452	0.487	0.502	0.451	0.463
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

B. Three year loan growth						
	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Quartile 2	-0.0300	-0.0487**	-0.0232**	-0.0399***	-0.0136	-0.0454***
	(0.1051)	(0.0170)	(0.0499)	(0.0024)	(0.2365)	(0.0034)
Quartile 3	-0.0292	-0.0477**	-0.0257**	-0.0442***	-0.0316**	-0.0683***
	(0.1402)	(0.0213)	(0.0139)	(0.0001)	(0.0364)	(0.0001)
Quartile 4	-0.0584**	-0.0852***	-0.0527***	-0.0812***	-0.0584***	-0.1049***
	(0.0105)	(0.0013)	(0.0003)	(0.0000)	(0.0029)	(0.0000)
Observations	5,970	5,933	2,902	2,834	1,742	1,656
R-squared	0.418	0.481	0.499	0.591	0.466	0.602
Adj. R-squared	0.414	0.429	0.492	0.511	0.453	0.478
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

The table represents results from regressions of bank stock returns on a bank's gross loan portfolio growth. Banks are sorted into quartiles based on the gross loan portfolio growth during the previous one- or 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 regressions include time fixed effects and, where indicated, bank fixed effects. For the two- and three-year returns non-overlapping observations are used to avoid serial correlation. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TABLE A.8: Organic Loan Growth

A. One year loan growth						
	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Quartile 2	-0.0034	-0.0174	-0.0053	-0.0302**	-0.0087	-0.0364**
	(0.8306)	(0.2960)	(0.5418)	(0.0116)	(0.5010)	(0.0121)
Quartile 3	-0.0003	-0.0217	-0.0167	-0.0420***	-0.0244	-0.0642***
	(0.9881)	(0.3041)	(0.1286)	(0.0028)	(0.1770)	(0.0011)
Quartile 4	0.0020	-0.0200	-0.0102	-0.0444*	-0.0383*	-0.0657***
	(0.9156)	(0.3402)	(0.5708)	(0.0507)	(0.0829)	(0.0034)
Low M&A	-0.0070	-0.0122	0.0174	0.0041	0.0031	-0.0104
	(0.6550)	(0.3871)	(0.2056)	(0.7597)	(0.8444)	(0.4580)
Medium M&A	0.0090	0.0001	0.0238	0.0078	-0.0026	-0.0043
	(0.5046)	(0.9968)	(0.1167)	(0.6900)	(0.8895)	(0.8458)
High M&A	-0.0592***	-0.0754***	-0.0254**	-0.0488***	-0.0324	-0.0478*
	(0.0018)	(0.0003)	(0.0275)	(0.0036)	(0.1420)	(0.0948)
Observations	5,511	5,473	2,482	2,411	1,505	1,399
R-squared	0.418	0.483	0.484	0.583	0.456	0.594
Adj. R-squared	0.414	0.424	0.476	0.485	0.441	0.448
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
B. Three year loan growth						
	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Quartile 2	-0.0201	-0.0369*	0.0034	-0.0212	-0.0161	-0.0392***
	(0.3494)	(0.0984)	(0.8268)	(0.1309)	(0.1842)	(0.0074)
Quartile 3	-0.0231	-0.0421*	-0.0187	-0.0454***	-0.0290*	-0.0527***
	(0.3136)	(0.0882)	(0.1587)	(0.0033)	(0.0735)	(0.0047)
Quartile 4	-0.0242	-0.0511*	-0.0219	-0.0671***	-0.0470**	-0.0818***
	(0.2997)	(0.0587)	(0.2026)	(0.0021)	(0.0261)	(0.0005)
Low M&A	0.0061	-0.0051	0.0213	0.0044	0.0221**	0.0094
	(0.6585)	(0.7644)	(0.1638)	(0.7621)	(0.0417)	(0.4917)
Medium M&A	-0.0032	-0.0172	0.0150	-0.0055	0.0056	-0.0022
	(0.8308)	(0.3123)	(0.1765)	(0.7005)	(0.5523)	(0.8792)
High M&A	-0.0408***	-0.0630***	-0.0381***	-0.0714***	-0.0300**	-0.0592**
	(0.0053)	(0.0027)	(0.0016)	(0.0000)	(0.0449)	(0.0103)
Observations	5,073	5,033	2,479	2,408	1,496	1,389
R-squared	0.413	0.479	0.488	0.589	0.466	0.612
Adj. R-squared	0.408	0.418	0.479	0.492	0.451	0.472
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

The table represents results from regressions of a bank's loan portfolio growth on its stock return. Banks are sorted into quartiles based on the organic loan portfolio growth during the previous one or three years. Indicator variables representing each quartile are included in the regression with the lowest growth quartile forming the base group. The M%A indicators group banks that did any M&A into tertiles based on the percentage of acquired loans. The sample period is 1978 to 2013. The regressions include time fixed effects and, where indicated, bank fixed effects. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. The standard errors allow for clustering at the bank level. Number in parentheses are the robust p-values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TABLE A.9: 1972 - 2016 sample data

	A. One year loan growth					
	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Quartile 2	0.0106	-0.0031	0.0067	-0.0157*	0.0062	-0.0147
	(0.4406)	(0.8254)	(0.4197)	(0.0911)	(0.6172)	(0.2693)
Quartile 3	0.0026	-0.0171	-0.0030	-0.0278**	-0.0195	-0.0503***
	(0.8648)	(0.3053)	(0.7753)	(0.0131)	(0.1864)	(0.0014)
Quartile 4	0.0005	-0.0192	-0.0062	-0.0344*	-0.0305	-0.0641***
	(0.9765)	(0.2811)	(0.6841)	(0.0530)	(0.1071)	(0.0015)
Observations	7,575	7,520	3,487	3,388	2,206	2,083
R^2	0.444	0.492	0.531	0.611	0.501	0.610
Adj. R^2	0.441	0.445	0.525	0.538	0.491	0.501
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

	B. Three year loan growth					
	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Quartile 2	-0.0224	-0.0424**	-0.0186	-0.0402***	-0.0174*	-0.0410***
	(0.1792)	(0.0228)	(0.1337)	(0.0036)	(0.0916)	(0.0027)
Quartile 3	-0.0307	-0.0576***	-0.0164	-0.0474***	-0.0331**	-0.0682***
	(0.1011)	(0.0048)	(0.1359)	(0.0004)	(0.0332)	(0.0001)
Quartile 4	-0.0528**	-0.0806***	-0.0485**	-0.0822***	-0.0625***	-0.0992***
	(0.0134)	(0.0008)	(0.0156)	(0.0002)	(0.0011)	(0.0000)
Observations	6,985	6,928	3,135	3,048	2,029	1,919
R^2	0.441	0.490	0.502	0.591	0.480	0.599
Adj. R^2	0.437	0.442	0.494	0.512	0.469	0.479
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

The table represents results from regressions of bank stock returns on a bank's loan portfolio growth. Banks are sorted into quartiles based on the loan portfolio growth during the previous year. 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 2016. The regressions include time fixed effects and, where indicated, bank fixed effects. For the two- and three-year returns non-overlapping observations are used to avoid serial correlation. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. The standard errors allow for clustering at the bank and time levels. Number in parentheses are the robust p-values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TABLE A.10: Main results with firm clustering

A. One year loan growth						
	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Quartile 2	0.0087	-0.0062	0.0047	-0.0190*	0.0040	-0.0182*
	(0.4166)	(0.5691)	(0.6257)	(0.0544)	(0.6667)	(0.0702)
Quartile 3	0.0006	-0.0201*	-0.0067	-0.0315***	-0.0226**	-0.0544***
	(0.9504)	(0.0621)	(0.5011)	(0.0021)	(0.0162)	(0.0000)
Quartile 4	-0.0002	-0.0216*	-0.0081	-0.0375***	-0.0342***	-0.0681***
	(0.9846)	(0.0593)	(0.4289)	(0.0005)	(0.0010)	(0.0000)
Observations	7,001	6,946	3,312	3,225	2,121	2,006
R^2	0.443	0.494	0.532	0.614	0.503	0.614
Adj. R^2	0.439	0.445	0.526	0.540	0.493	0.503
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

B. Three year loan growth						
	1-year return		2-year return		3-year return	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Quartile 2	-0.0267**	-0.0471***	-0.0206**	-0.0430***	-0.0180*	-0.0423***
	(0.0132)	(0.0001)	(0.0442)	(0.0002)	(0.0612)	(0.0001)
Quartile 3	-0.0352***	-0.0635***	-0.0183**	-0.0492***	-0.0354***	-0.0724***
	(0.0004)	(0.0000)	(0.0458)	(0.0000)	(0.0003)	(0.0000)
Quartile 4	-0.0579***	-0.0842***	-0.0529***	-0.0864***	-0.0655***	-0.1000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	6,419	6,362	2,967	2,887	1,949	1,844
R^2	0.439	0.491	0.502	0.595	0.483	0.603
Adj. R^2	0.435	0.441	0.495	0.513	0.472	0.480
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes

The table represents results from regressions of bank stock returns on a bank's loan portfolio growth. Banks are sorted into quartiles based on the loan portfolio growth during the previous year. 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. For the two- and three-year returns non-overlapping observations are used to avoid serial correlation. The sample includes all U.S. banks whose real assets in 2013 dollars are greater than $2 billion. The standard errors allow for clustering at the bank level. Number in parentheses are the robust p-values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

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