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Abstract

This article examines the relationship between capital ratios and returns on US bank stocks between 1973 and 2019. Banks with low capital ratios do not have higher, but rather lower returns than banks with intermediate levels of capital. This is not explained by standard risk factors. As a result, risk-adjusted returns (alphas) of low-capital banks are negative. Moreover, the stock returns exhibit a delayed reaction to changes in capital ratios. Low-capital banks that further increase their debt have high abnormal returns on the day of announcement, but tend to have low risk-adjusted returns in the 9 months that follow. The paper uncovers several explanations for this leverage anomaly: under-priced default risk, under-priced systematic risk and sensitivity to idiosyncratic volatility.

Keywords: Asset pricing anomaly; Bank regulation; Capital requirements; Leverage JEL Classification codes: G12, G14, G21, G32

1 Introduction

Standard theories in corporate finance suggest that banks with high leverage, that is, a low ratio of capital (common equity) over assets, will have a higher expected return. This is because high leverage will concentrate the assets' risk into a relatively small amount of capital (Modigliani and Miller, 1958). Taking financial distress risk into account should lead to an even stronger positive relationship between leverage and expected returns (Baxter, 1967; DeAngelo and Masulis, 1980). Debt overhang theory, which considers the dynamics of leverage, also predicts higher capital risk for low-capital banks, even though long-term debtors and governments take up part of the extra risk after a decrease in capital ratios (Myers, 1977; Admati et al., 2012).¹

By contrast, this study shows that the relationship between capital ratios and expected returns on US bank stocks is hump-shaped. Low-capital banks do not have higher returns. Nevertheless, they do have a higher exposure

¹Risks related to agency conflicts between shareholders and managers could be alleviated with higher levels of debt, but this is unlikely to be of importance in the case of banks, because all banks have a relatively high level of leverage (Admati et al., 2013). Agency conflicts between debt holders and equity holders are likely to be more relevant for banks. They increase with leverage.

to systematic risk factors. This contrast between higher risk and low returns yields an abnormal return (alpha) of -5% per year for a portfolio containing the 10% of banks with the lowest capital ratios. The Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965) also shows a much lower alpha for low-capital banks compared to median-capital banks. Moreover, there is a delayed effect of a change in capital on stock prices, which makes the leverage anomaly even more puzzling. On the day that quarterly returns are announced, banks which increase their debt have higher abnormal returns than banks which decrease their debt, especially when capital is already low. However, the debt-increasing banks have lower returns in the following quarters. This indicates that the market insufficiently penalizes banks when an increase in debt is announced.

I find that low capital is a good predictor of low future asset growth, and that, conditional on correctly anticipating future asset growth, the leverage anomaly disappears. Furthermore, the data shows three other pricing anomalies, contributing to a flat leverage-return relationship and a delayed reaction to leverage. First, default risk is not rewarded in the stock returns. The portfolio constituted of the quintile of banks with the best credit ratings has a 3% larger yearly return compared to the portfolio containing the quintile with the lowest credit ratings. As a result, low-rated stocks have negative alphas. Second, there is an almost flat relationship between CAPM betas and future returns in my data. In other words, risk in the form of covariance with the market return is not rewarded in stock returns. As a result, my portfolio constituting the highest beta decile, underperforms the market by 5% per year, as measured by the alpha on a 5-factor risk model. Similarly, the portfolio constituted of the highest idiosyncratic volatility (thereafter ivol) also has a negative alpha of 3.8% per year. These anomalies are also observed in the literature for non-financial stocks (Campbell et al., 2008; Avramov et al., 2009; Frazzini and Pedersen, 2014; Baker et al., 2016; Liu et al., 2018).

In theory, it is possible that low-capital banks have safer equity, because they have safer assets or long debt maturities compensating for their more risky finance structure. However, this seems unlikely for three reasons. Firstly, low-capital banks are more risky on many dimensions of measurable risk. These banks have a higher beta; a higher expected return based on a 5-factor risk model; a lower credit rating; and a higher book-to-price ratio. The banks that went bankrupt in the database all had very low capital ratios. Second, leverage is mean-reverting, and low-capital banks have lower asset growth during the next four years. This is in line with a dynamic theory of leverage where unexpected shocks lead to sub-optimal levels of leverage, and where banks only return to their optimal leverage gradually, because changing leverage is costly (Flannery and Rangan, 2006). Finally, the magnitude of the capital ratios matters. The quintile of banks with the lowest capital ratios have a capital ratio below 4%. It is unlikely that capital ratios below this level would be associated with lower risk.

Although there is a consensus in the literature that bank capital ratios were too low at the start of the financial crisis in 2008, there is no consensus on optimal leverage for banks (Admati et al., 2013; Thakor, 2014). Low capital ratios add systemic risk to the economy, while very high capital ratios may impede liquidity formation and

increase lending costs to firms. In order to determine optimal leverage empirically, understanding the relationship between expected returns and leverage in the banking sector is of particular importance, because the expected return corresponds to the cost of capital. Imposing stricter capital requirements may have two very different effects. Firstly, banks may increase their lending rate to the economy (an effect on the numerator of the cost of capital). This is the assumption in most of the empirical literature (Kashyap et al., 2010; Miles et al., 2013; Baker and Wurgler, 2015; Clark et al., 2014). Alternatively, the value of banks' stocks may decrease, ending a period of under-valued leverage risk (an effect on the denominator of the cost of capital). My dynamic analysis shows evidence for this second mechanism. As explained above, a decrease in debt leads on average to a negative announcement return, but is followed by subsequent higher returns, indicating a misperception of increased capital ratios by investors. This mechanism contributes to higher alphas for high-capital banks. When leverage risk is under-priced, it is optimal for banks from an individual perspective to increase leverage (Baker and Wurgler, 2015; Baker et al., 2016). From a social point of view, however, the private incentive created by the mispricing of leverage risk is a market distortion leading to lower-than-optimal capital ratios. This incentive is all the more detrimental because it amplifies other incentives for lower-than-optimal capital created by government bail-outs and deposit guarantees.

There is a very recent strand of the literature focusing on the low risk-adjusted returns (alphas) for low-capital banks (Baker and Wurgler, 2015; Bouwman et al., 2018; Huang et al., 2020). This paper adds three major elements to the literature. First, the paper is the first to uncover a delayed reaction to a change in leverage on future returns. As explained above, this is very relevant for modeling the effect of an increase in capital requirements on banks' lending rate to the economy. Second, I show that it is unlikely that the negative alphas are the result of an omitted risk factor, because I test nine risk models, one of which I especially design for leverage.² Third, following Baker and Wurgler (2015) who connect the leverage puzzle to the beta anomaly in banks, I show that not only the beta anomaly, but also the credit rating anomaly and idiosyncratic volatility anomaly are observed in bank stocks. Each of these mechanisms contributes to the leverage anomaly, but none of them, taken separately, is sufficient to explain the leverage puzzle exclusively.

The remainder of the paper is organized as follows. I start with a literature review and a data section. Next, section four describes the relationship between the levels of leverage and returns, whereas section five describes the dynamic effect of a change in leverage. Section six investigates announcement returns and section seven looks at the relationship with other pricing anomalies. Finally, section eight concludes and discusses policy implications.

 $^{^{2}}$ Following the method in Gandhi and Lustig (2015), the factor is loosely speaking a high minus medium leverage factor, based on the second principal component of the errors of leverage decile portfolios.

2 Literature

This paper has been written simultaneously with two other papers, Bouwman et al. (2018) and Huang et al. (2020) who also look at the relationship between bank capital and stock performance.³ The three papers start with the observation that the relationship between bank capital ratios and return is hump shaped and focus on the puzzle that low-capital banks do not give an extra return for the leverage risk. Both Bouwman et al. (2018) and Huang et al. (2020) show that the puzzle mainly stems from low-capital banks performing badly during recessions, arguing that the puzzle can be explained by a 'surprised investor channel' at the start of recessions.⁴ The fact that low-capital stocks perform badly in recessions is not a puzzle in itself given that leverage mechanically increases returns on equity in good times and magnifies negative returns on equity in bad times (Modigliani and Miller, 1958). However, it is puzzling that these negative returns are not captured by common risk factors, which capture the effect of flightto-safety in risky periods (Adrian et al., 2019). Investors do not seem to fully anticipate the particular difficulties of low-capital banks in recessions. This paper investigates the surprised investor channel further, by showing that an increase in debt is on average positively perceived by the market, including for banks that have already low capital ratios. However, in subsequent months, low-capital banks which increased their debt, have lower returns.⁵ By looking at the dynamics of the puzzle more in detail, I also avoid the endogeneity of the announcement effect of losses, which both reduce capital and lead to low returns.⁶ Belkhir et al. (2021) investigates the effect of capital ratios on future return expectations by financial experts, showing that lower capital increases the expected returns on equity, in line with standard theory. Yet Bouwman et al. (2018) and Huang et al. (2020) report lower returns for low-capital banks. I show that investors indeed tend to underestimate the detrimental effect of low capital ratios, by contrasting announcement returns and subsequent returns. Using a large set of banks across different countries Pelster et al. (2018) test a linear effect of capital ratios on returns and find almost no effect, in line with the leverage puzzle. An increase in capital by one standard deviations increases returns by a mere 0.2% per year.

Several recent papers have looked at risk factors explaining banks stock returns. Gandhi and Lustig (2015) develop a small-minus-large bank-specific factor which is negative in recessions, when investors anticipate that too big-too-fail banks are more likely to be bailed out than small banks. Similarly, Carmichael and Coën (2018) show that banks' stock returns are affected by risk in the real estate market, and develop a risk factor based on the leverage of real estate investment trusts (REIT). Adrian et al. (2015) develop two bank-risk factors: a factor representing

 $^{^{3}}$ Bouwman et al. (2018) was posted in July 2017, this paper was posted in June 2018 and Huang et al. (2020) was posted in October 2018 on SSRN.

 $^{^{4}}$ Bouwman et al. (2018) give 2 arguments for a "surprised investor channel". First, alphas in crisis periods are much lower during the start of the crisis period. Second, low-capital banks have lower abnormal returns at the announcement of their quarterly results, especially in crisis periods.

⁵Adrian et al. (2015) find, as I do, that in the cross section, financial firms which recently decreased capital ratios show lower returns.

⁶Many studies explain returns by capital ratios of the preceding month(Cai and Zhang, 2011; Pelster et al., 2018; Huang et al., 2020). Since the capital ratio is not yet publicly available at the start of the return period, they cannot demonstrate arbitrage opportunities or mispricing. The low returns of low-capital banks can be the result of losses, which become publicly available when the bank is already in the low-capital portfolio.

risk appetite from financial institutions with low return on equity ⁷ and the spread between the financial sector return and the total market return. Finally, Adrian et al. (2014) and He et al. (2017) argue that large financial brokers' are often the marginal investors in markets. Therefore, returns at times when their leverage is high, has larger marginal 'utility' or value than returns when their leverage is low. Hence, they show that the leverage of primary broker dealers affects the pricing kernel and is priced in many asset classes, not only banks.⁸ I show that the low alphas for low-capital banks are robust to the inclusion of these risk factors.

An older strand of literature discusses the leverage puzzle in non-financial firms.⁹ Penman et al. (2007) show that firms with high leverage tend to have lower returns, and that this is still the case for companies with a similar book-to-price ratio. Cai and Zhang (2011) also look at the dynamics of the leverage anomaly. They find that the announcement of an increase in leverage is associated with a lower return (especially for low-capital companies), and that the announcement effect is not subject to subsequent abnormal returns during the next twelve-month period. I observe the opposite for financial firms: an announced increase in debt is positively perceived, but followed by lower returns. Caskey et al. (2012) find that companies with excess leverage have low returns. High leveraged companies have on average lower future asset growth, and a correct anticipation of future asset growth would solve the leverage puzzle. Indeed, investors may find it hard to distinguish between an increase in leverage as a signal of safer assets or a signal of increased financial distress. I find that this also holds true for banks.

Several papers relate the leverage anomaly to other pricing anomalies. Since the majority of these papers investigates non-financial stocks, I show that their findings also apply to bank stocks. For example, non-financial stocks with low credit ratings have lower returns on average (Campbell et al., 2008; Avramov et al., 2009; Caskey et al., 2012; Avramov et al., 2013). The puzzle may be related to dynamic feedback effects of downgraded firms (Manso, 2013) and the ability of shareholders to bargain with debt holders under financial stress (Garlappi et al., 2008). Kisgen (2006; 2019) shows that credit ratings are a major motivation for firms to choose their capital structure. Second, risk in the form of covariance with the market return is not rewarded in stock returns. This is known as the beta anomaly. As a result, risky high-beta stocks under-perform the market (negative alpha),

⁷The factor is the difference between returns of high and low ROE of financial firms. They argue that financial institutions try to meet ROE targets by taking on more debt and buying riskier assets in periods of low earnings. This causal channel is less likely for banks since losses reduce bank capital and make Basel regulation more constraining. Inversely, retained earnings allow for asset expansion. I indeed find a positive correlation coefficient of 0.10 between the relative change in debt $\frac{D_t - D_{t-1}}{D_{t-1}}$ and ROE, for data winsorized at 1 and 99%.

⁸Both studies find a different pattern for broker-dealers' leverage however. In Adrian et al. (2014), broker-dealer's leverage is procyclical, driven by asset expansion in economic booms, and an increase in leverage over time is associated with higher returns. By contrast, leverage is countercyclical in He et al. (2017) driven by an increase of market value of equity (as well as book equity) in economic booms, and an increase in leverage is associated with lower returns. He et al. (2017) attribute this difference to the fact that they use leverage at the consolidated level, whereas Adrian et al. measure leverage at the broker-subsidiary level. In my data, the correlation coefficient between the excess market return and the average monthly change in leverage ($\bar{L}_t - \bar{L}_{t-1}$) is -0.70 for market leverage and -0.13 for book leverage, in line with He et al.'s results.

⁹Some studies argue that low returns on low-capital firms can be explained by lower risk. Companies with low financial distress costs, and a low exposure to systematic (procyclical) risk, may choose a high level of leverage, leading to a negative correlation between leverage and risk premiums in the cross section, as suggested by George and Hwang (2010). Leverage and risk could also be negatively correlated over time(Gomes and Schmid, 2010; Obreja, 2013). However, these theories are difficult to extend to banks.

whereas low-beta stocks over-perform the market (Baker et al., 2016). The beta anomaly is also observed in bank stocks Baker and Wurgler (2015), in markets on other continents, and within bond markets (Frazzini and Pedersen, 2014), but not between stocks and bonds.¹⁰ Third, stocks with high idiosyncratic volatility show low returns (Liu et al., 2018). Leverage mechanically increases both the covariance with the market return and volatility (Modigliani and Miller, 1958; Hamada, 1971), both the beta anomaly and the ivol anomaly contribute to (or are driven by) the leverage puzzle. Indeed, Doshi et al. (2019) show that both the beta and ivol anomalies are much lower for unlevered returns, i.e. the returns on assets rather than on equity.

3 Data

The study is based on the Compustat-CRSP database containing all listed US banks during the period January 1973 to December 2019. I select the sample in a similar way to Gandhi and Lustig (2015). For each bank, only the mother holding is included. I keep securities with sharecode 10 and 11, excluding banks which are also listed on a foreign stock market. I keep all banks with SIC code 60—depository institutions.¹¹ Investment banks are therefore not included in the sample. The Standard Industry Classification codes of the sample are listed in Appendix A. The resulting database constitutes of 135 banks in 1973, 760 in 2000 and 382 in 2019. The list of all included and excluded banks is available in the online appendix, and the thirty largest banks in 2015 are listed in Appendix B.

The market return, size, price-to-book, and momentum factors were downloaded from Kenneth French's data website, the return on the 30-year bond index is from CRSP, the spread between AAA and BAA bonds is from the Federal Reserve, S&P ratings are from Capital IQ, and the Dow Jones bond return index is from Global Financial Data. The intermediary capital risk factor form He et al. (2017) was downloaded from Github.

I use quarterly accounting data and monthly returns. Table 1 gives an overview of variable definitions. Monthly returns (*Return*) are holding period returns from month-end to month-end, including ordinary dividends and delisting returns as reported by CRSP.¹² I use geometric means $\left(1 + \bar{R}_i = \sqrt[T]{\Pi(1 + r_{it})}\right)$ when I report mean returns over time or convert to yearly returns. Excess returns (*ReturnE*) are defined as the difference between stock returns and the 1-month T-bill return. Size adjusted returns (*ReturnS*) are defined as the return minus the return on the size-decile portfolio, where size deciles are determined by the market value the preceding month. When I use beta as a time-variant explanatory variable, it is the sum of β_1 and β_2 in the following regression on a

 $^{^{10}}$ The beta anomaly can be the result of leverage-restrained investors who prefer a portfolio with an expected return that exceeds the market return, regardless of the risk that comes with this return. Fund managers may have an incentive to do so if their performance is benchmarked against a market index (Frazzini and Pedersen, 2014; Buffa et al., 2019). Barberis and Huang (2008) and Bali et al. (2011) explain the beta anomaly by preferences for lotteries, i.e. highly positively skewed returns. Finally Liu et al. (2018) argue that idiosyncratic volatility is the driver behind the beta anomaly.

¹¹Manual verification showed that Compustat SIC codes are more reliable than CRSP SIC codes, as reported in Adrian et al. (2015). My sample includes 9171 observations with CRSP historial SIC code 6712—Offices of Bank Holding Companies. Therefore, with the exception of 120 observation-months, the sample encompasses all observations in Gandhi and Lustig (2015), who use CRSP header SIC code 60 and historical SIC code 6712. I did not use the 'Compustat banks' database, because it only has a subset of banks.

 $^{^{12}}$ Virtually all stocks are traded. Only 2.6% of the monthly returns and 0.01% of the quarterly returns are zero.

rolling window of 5 years, with a minimum of 2 years $Return E_{i,t} = \alpha + \beta_1 (Rm_{it} - Rf_t) + \beta_2 (Rm_{i,t-1} - Rf_{t-1})$, with Rm the market return and Rf the return on 1-month treasury bonds.

I use the market capital ratio in the main analysis because most corporate finance theories predict a relationship between market leverage and return (Modigliani and Miller, 1958; Baxter, 1967; Myers, 1977; DeAngelo and Masulis, 1980). The market capital ratio is defined as $MCR = \frac{MV}{MV+D}$, where MV is the market value of common equity at the end of the quarter¹³ and D is the book value of total liabilities.¹⁴ In the sensitivity analysis, I also use 3 other capital ratios. In the Merton-adjusted capital ratio I replace the book value of debt by its risk-adjusted value using the Merton (1974) model.¹⁵ Next, for a subset of banks from 1993 onward, the database also contains Basel-adjusted capital ratios defined as $BaselCR = \frac{Tier1+Tier2}{TA_{riskadj}}$ according to the Basel agreement. Finally, when I want to avoid momentum effects from market prices, I also use the book capital ratio ($BCR = \frac{CE}{CE+D}$), where CE denotes the common equity.

Book-to-price $(BtP = \frac{CE}{MV})$ is the book value of common equity over its market value at the end of the quarter. Since book-to-price is mechanically affected by leverage, I also define asset-book-to-price as the book value of total assets over the market value of all equity and liabilities, where the market value of debt and preferred stock is proxied by its book value, i.e. $AssetBtP = \frac{TA}{TA-CE+MV}$ (Penman et al., 2007). Observations with missing total assets, common equity or market value are excluded. Summary statistics are reported in Table 2, illustrating that the market value is highly skewed. Therefore, value weighted portfolios are almost entirely determined by the returns of the largest 1% of banks. For this reason, I report equally weighted portfolios in the main text and value weighted portfolios in Appendix C. The relationship between risk and return can be highly non-linear (Adrian et al. 2019). Therefore, I use deciles or quintiles of leverage in my regressions. This also avoids a disproportionate weight of outliers.

4 The relationship between capital ratios and returns

4.1 Portfolios sorted on capital ratios

Figure 1a and Table 3 report the return on portfolios sorted on capital ratios and show that there is a humpshaped relationship between future returns and capital ratios.¹⁶ Returns are substantially lower for the 1st decile of low-capital banks and merely decrease between the 2nd and 7th decile of capital ratios. The pattern is similar

 $^{^{13}}$ Market value is computed as the numbers of shares outstanding * price per share. For a few banks (0.4% of observations), Compustat's market value at the end of the quarter differs from CRSP's market value. In that case I give priority to Compustat's value because sometimes non-voting common stocks or convertible stocks are not reported in CRSP (e.g. First Interstate Banksys, Limestone...).

 $^{^{14}}$ Preferred stock is zero for 90% of all observations, the 99th percentile of preferred stock over total assets is only 2.6%. I do not include it in total liabilities.

 $^{^{15}\}mathrm{I}$ thank the anonymous reviewer for this suggestion.

 $^{^{16}}$ The sorting of portfolios happens 4 months after quarter-end (as in Caskey et al. 2012), such that leverage is publicly known (for 99.7% of the observations quarterly results are announced within 4 months).

for portfolios sorted on market, book and risk-adjusted capital ratios (Figure 1a and Appendix D)¹⁷, for value weighted portfolios (Appendix C) during good and bad times (Appendix E), for different size groups of banks and different regulatory periods (Appendix F), and is robust to resampling (Appendix G). Bootstrapping shows that the differences in returns are statistically significant (Appendix G).

If the flat relationship between capital ratios and future returns seems puzzling already, the substantial increase of returns (7% on a yearly basis) on portfolios between the first and fourth decile of leverage seems to defy standard theory on capital, because higher leveraged banks are riskier in many ways: they have a higher beta, a higher expected return according to a 5-factor model, much higher idiosyncratic volatility, a higher BtP, and lower S&P rating. The first decile portfolio has a mean capital ratio of 4% (Table 3). The financial crisis during the last decade showed that a leverage beyond this level is likely to increase financial distress risk. Returns on leverage-sorted portfolios of non-financials (all US stocks excluding SIC 6) show a very different pattern; they are monotonically increasing in leverage (Table 3). Table 4 shows that low-capital is a good predictor of low asset growth over the four following years. The table also shows that capital ratios are mean-reverting, in line with a model where banks gradually return to an optimal intermediate level of leverage.

In order to quantify the discrepancy between risk and return for these low-capital banks, Figure 1b reports risk-adjusted returns also known as alphas for 9 different factor models. The CAPM (Sharpe, 1964; Lintner, 1965) is the simplest model having the correlation with the market return (a handicap for the diversification of a portfolio) as a single risk factor. Alphas of the 5-factor model, which is used in most of the rest of the paper, are calculated using the following regression

$$R_{it} - Rf_t = \alpha_i + \beta_i^{mkt} (Rm_t - Rf_t) + \beta_i^{smb} smb_t + \beta_i^{hml} hml_t + \beta_i^{umd} mom_t + \beta_i^{10y} R10y_t + \epsilon_{it},$$
(1)

where R_{it} is the monthly return on portfolio i at time t and Rf_t the return on 1-month treasury bonds. Rmis the market return, the value-weighted return of all CRSP firms with code 10 or 11. The size factor (smb) is the return on a portfolio long in the tercile of smallest companies and short in the tercile of largest companies by market value. Similarly, the value factor (hml) is the return on a long-short portfolios based on book-to-price (Fama and French, 1993; Schuermann and Stiroh, 2006; Baek and Bilson, 2014) and the momentum factor (mom)is a long-short portfolio based on past returns (Carhart, 1997). Including a momentum factor is meaningful because the portfolio with high leverage is more likely to contain stocks whose price recently decreased. Finally, R10y is the return on an index of 10-year treasury bonds. A change in the long-term interest rate is a relevant risk factor for banks because it shifts the spread between the return on their assets and liabilities (Viale et al., 2009; Baek and

¹⁷Huang et al. (2020) find different results for market and book capital ratios. This may be due to their short lag between leverage and return. Leverage information on, say, the 31st of December, explains returns in January. Therefore, a bank with a quarterly loss, is already in a low-book-ratio portfolios when losses are discovered by the market. By constrast, this bank will only enter the low-market-capital ratio at the end of January when the loss has already lowered its price.

Bilson, 2014; Gandhi and Lustig, 2015).

If the risk model is well specified, a market without arbitrage opportunities implies zero alphas.¹⁸ Figure 1b shows that the lowest-capital portfolios (first and second decile) yield a much lower alpha compared to the middle deciles. For example, the 4th decile portfolio outperforms the first by 5% per year according to the CAPM, the 5-factor model in equation 1 and the 5-factor model of Fama and French (2015). As a result, for each of the 3 risk models, the Gibbons-Ross-Shanken test rejects the null hypothesis of zero alphas for the decile portfolios (last line Table 3). This result contrasts again with leverage portfolios composed of non-financial stocks showing small and insignificant alphas (last column Table 3). Appendix G shows that the results are robust to resampling. The 90% bootstrapping uncertainty intervals indicate that differences in alphas are significant.

Models 3 to 5 reported in Figure 1b give similar results using other factor models. Gandhi and Lustig (2015) include the return on the Dow Jones Corporate Bond index capturing default risk.¹⁹ Fama and French (2015) develop a 5-factor model, adding a profitability factor and an investment factor. The 5th model shows that a model with 8 factors, i.e. the 5-factors in equation 1, a credit factor and the 2 extra factors from Fama and French gives very similar alphas. This indicates that the 5-factor model captures different risks in a parsimonious model.

Factor models are based on arbitrage pricing theory, predicting that alphas should be zero after correcting for a limited number of risk factors which represent risk for specific groups of investors or specific sources of risk. In model 6, I added a factor based on the 2nd principal component of the error in equation 1, following the method in Gandhi and Lustig (2015). This factor is the return on a portfolio that goes long in high leverage portfolios and short in high-capital portfolios (see Appendix H). Adding this factor, which is tailored to decrease the leverage puzzle, does a poor job of solving the puzzle. This means that the returns on different low-capital portfolios (say, in decile portfolio 1 and 2) have low cross-sectional correlation, which cannot be explained by a single risk factor containing common shocks.

Models 7 to 9 in Figure 1b include factors that are specifically linked to the banking sector. Gandhi and Lustig (2015) add a factor which is the return of large banks minus the returns on small banks, capturing a too-big-to-fail effect. He et al. (2017) argue that the change in leverage of primary dealers is a relevant risk factor, because these large financial intermediaries are likely to be the marginal investors in financial markets.²⁰ Adrian et al. (2015) develop two specific pricing factors for bank stocks. On top of the three Fama and French (1993) factors, their

 $^{^{18}}$ In fact, the negative alphas for low-capital portfolios can have 2 different interpretations. First, returns are too low, given their riskyness. When stocks enter the portfolio, after an increase in leverage, stock prices are overvalued, based on overly optimistic expectations of high mean and low (co)variance of future cash flows. Similarly, just before stocks leave the portfolio, when deleveraging is announced, stock prices are undervalued, based on overly pessimistic expectations for banks with higher capital ratios. This pattern is confirmed in the dynamic analysis of this paper.

Second, the estimated risk-adjusted returns are too high, the risk model is over-estimates risk. This may be due to a missing risk factor (unlikely because I test many risk models) or to misperceptions leading to over-estimated betas in the factor model (again unlikely because I find evidence of under-estimated CAPM betas).

 $^{^{19}}$ Viale et al. (2009) do not find a significant effect for default risk on bank stock returns.

 $^{^{20}}$ Adrian et al. (2014) use a similar approach using the quarterly change in leverage of American broker-dealers reported in the Federal Reserve's Flow of Funds (Table L.129).

model has a fourth factor containing the difference between the returns on bank stocks with high and low ROE and a fifth factor composed of the difference between the returns on bank stocks and non-financial stocks. In general, these specific bank sector models (7-9) also show the same hump-shaped pattern for alphas.²¹ Moreover, they tend to have larger alphas than the 5-factor model of equation 1. Appendix E shows returns and alphas for NBER recessions and non-recessionary periods and for periods with high and low volatility. In good as well as in bad times the hump-shaped relationship between capital ratios and returns/alphas is observed, and the Gibbons-Ross-Shanken test rejects the hypothesis of zero alphas, also in good times. Further research is needed in order to understand why this is different from the results in Bouwman et al. (2018) and Huang et al. (2020), who do not find a leverage anomaly in good times.

Doshi et al. (2019) calculate unlevered returns, that is the excess market returns on assets using the following formula²²

$$R^{A} - Rf = \left(R^{E} - Rf\right) \frac{MV}{MV + D_{Merton}},\tag{3}$$

with R^A the return on assets and R^E the return on equity. Unlevered returns are the empirical counterpart of the weighted average cost of capital (WACC) and are reported in Table 3. The returns on assets for the 10% of banks with the lowest capital ratios are 0.5% per year lower compared to banks with median leverage. Although the empirical literature suggests that a low cost of capital implies that low-capital banks provide cheaper loans to the economy, there may be three other explanations for a low return on assets: 1) low-capital banks manage their assets in a less efficient way, 2) low-capital banks have less risky assets, and 3) low capital banks are overvalued by the market. Section 5 argues that the latter is the case.

Doshi et al. (2019) show that unlevered returns tend to show smaller anomalies in non-financial stocks. Alphas for unlevered returns are also reported in Table 3. Although in absolute terms the alphas are relatively small, they are large in relative terms. The alphas are roughly 60% of the observed excess returns; in other words, the risk model explains only 40% of the returns.²³

$$R^{A} = R^{E} \frac{MV}{MV + D_{Merton}} + R^{D} \frac{D_{Merton}}{MV + D_{Merton}}$$
(2)

 $^{^{21}}$ Note that the model of Gandhi and Lustig (2015) shows a relatively smaller drop in alphas of low-capital banks. This is counterintuitive, since the low-capital banks are a bit smaller, the too-big-to-fail effect should give the opposite effect: higher risk and lower alphas for low-capital banks. It suggests that the leverage puzzle is not driven by bank size.

 $^{^{22}}$ Acknowledging that the return on assets, as for any portfolio, corresponds to the weighted return of its constituents we have

where R^U, R^E, R^D are the returns on assets, equity and debt respectively. D_{Merton} is an estimation of the market value of debt, using the Merton (1974) model. Approximating the interest rate on debt by the return on bonds gives equation 3. The formula is close to Hamada (1971).

 $^{^{23}}$ I thank the anonymous reviewer for his suggestion to include delevered returns in the analysis.

4.2 Regressions

Fama-MacBeth (1973) regressions are another popular method for investigating the predictability of returns based on cross-sectional characteristics. Whereas portfolio analysis has the advantage of being non-parametric, Fama-MacBeth regressions allow us to control for more dependent variables, at the cost of assuming a linear structure. To allow for a non-linear effect of leverage, I use quintiles as regressors. I use the following regression equation

$$R_{it} = \alpha + \sum_{j=2}^{5} \beta_j C R_{quintilej_{t-5}} + \beta_6 \Delta C R_{quintile_{t-5}} + \beta_7 \Delta C R_{quintile_{5t-5}} + \beta_8 B t P_{Asset_{t-5}} + \beta_9 ln M V_{t-1} + \beta_{10} B eta_{CAPM_{t-1}} + e_{it}$$

$$\tag{4}$$

where R_{it} is the quarterly return for a given bank i, $CR_{quintile}$ and $\Delta CR_{quintile}$ are dummy variables indicating a capital ratio quintiles and $Beta_{CAPM}$ is the beta on a rolling window for the preceding 5 years. Table 5 shows the results. The specification in the first column shows the explanatory power of quintiles of capital ratios on future returns without any other explanatory variables and confirms the concave relationship between leverage and future returns. Compared to returns for the fifth quintile (high capital), returns are higher for banks with median capital ratios, in line with the expected standard relationship between leverage and risk. However, being in the first leverage quintile leads to a lower return than the second quintile, only marginally higher than the fifth quintile, contradicting the expected risk-return relationship. The second regression in Table 5 adds CAPM betas, book-to-price and size as explanatory variables. If leverage risk were fully reflected in these standard risk factors, the coefficients on leverage should be insignificant. By contrast, the regression shows that the effect of leverage remains significant and of the same magnitude. Moreover, the effects of beta, book-to-price and size are insignificant.²⁴ The third column shows that, even though a low-capital ratio has an insignificant effect on future returns, the decrease in the capital ratio compared to the preceding quarter decreases future returns by 1% per quarter.²⁵ The effect of the change in capital conditional on the level of capital hints at a delayed market reaction, which will be investigated in more detail in

the next two sections.

²⁴This is in line with Viale et al. (2009) who also find low explanatory power for these factors in bank stock returns.

 $^{^{25}}$ I use the change in book leverage instead of the change in market leverage, to avoid momentum effects. Moreover, the change in book leverage, unlike the change in market leverage, also captures relevant information on retained earnings/losses, equity issues, shares buy backs and dividends. For example, if the fiscal year ends on the 31st of December, retained earnings for quarter 4 are announced in January, February or March. They affect the change of book equity between September and December, but not the change of market equity, because earnings are not yet determined in December.

5 The effect of a change in the capital ratio

5.1 Debt overhang theory versus over-optimism

In an informationally efficient market, a change in the capital ratio creates an instantaneous shock to the market price on the day the change is discovered and a positive risk-return relationship afterwards. Since risk is related to the level of leverage, rather than the change of leverage, most theories predict that, conditional on the level of leverage, the change of leverage during the preceding quarter is irrelevant for future returns.

However, according to debt overhang theory (Myers 1977), both the level of leverage and the change of leverage may affect returns.²⁶ Debt overhang theory predicts that for low-capital banks, an increase in leverage shifts risk from equity holders to debt holders, for which the existing debtors are not compensated. The associated transfer in value is depicted in grey in Figure 2.²⁷ This can be a motivation for equity holders to increase leverage. However, debt overhang theory also predicts that an increase in leverage decreases the total value of the bank, that is the value of debt plus the value of equity, for the following reason: New projects typically require retained earnings or new capital. If the associated deleveraging creates a transfer from shareholders to debt holders exceeding the net present value of the project, the project will not be carried out, even if it has a positive net present value. Therefore, under high leverage, debt overhang destroys growth options (ΔV in Figure 2) and may ultimately result in bankruptcy. Higher bankruptcy risk increases the risk for debtors but also for equity holders. Therefore, an increase in leverage must lead to an increase in returns on equity, because debtors will take up only part of the leverage risk.

By contrast, if investors are on average over-optimistic about an increase in leverage, the price will converge downwards to its real value as new information arrives, which will lead to low future returns. Since these low returns are not driven by risk, but by a misperception in the past, an increase in leverage can lead to a decrease in returns (dotted line in Figure 2). In the following sections, I show that this is the case.

5.2 Double-sort portfolios

Table 6 reports monthly returns and alphas for double-sort portfolios, first on the capital ratio, then on the quarterly change in the capital ratio. Portfolios are formed 1, 4 and 7 months after a change in the capital ratio, and banks

²⁶Adrian et al. (2015) develop another argument to connect changes in leverage to returns. They argue that financial firms have internal targets for ROE. Therefore, when financial companies expect a period with low profits, they expand their assets aggressively and increase the riskiness of their assets, in an attempt to increase their ROE. It seems likely that banks (in contrast to other financial firms) are not able to do this due to their capital requirements. Indeed, the correlation coefficient between the relative change in debt $\frac{D_t - D_{t-1}}{D_{t-1}}$ and the excess market return is 0.003 in my data. As shown in figure 1b the inclusion of their financial ROE factor still yields

a hump-shaped relationship between leverage and alphas.

²⁷The value of debt can be considered as the discounted value of the future payments to debtors (at the riskless rate) minus a call option on the value of the company with strike price the debt. The value of this call option corresponds to the fact that equity holders are not liable in the case of bankruptcy and is included in the value of equity. Increasing leverage boils down to an increase of the strike price of the option. The value of the call option decreases as debt matures.

whose information on the capital ratio is not yet available are excluded.

Results reported in column 'mean' correspond to aggregated portfolios, composed of the banks in the respective row. These results show that the returns of the 20% of banks which decreased their capital ratio most are significantly lower than returns of the banks which increased their capital ratios (-0.33% per month if sorted after 1 month, -0.21% if sorted after 4 months and -0.22% if sorted after 7 months). The effect for alphas is comparable (0.45%, 0.15% and 0.13% respectively). The Gibbons-Ross-Shanken test statistic rejects the hypothesis of all alphas of these portfolios being zero with a p-value below 0.0%, 2% and 1% respectively. In other words, if a given level of capital in, say, December, is the result of a decrease rather than an increase in capital ratio, this leads to low returns from February to October.

Within the quintile with lowest capital ratios, I find the same pattern of lower returns after a large decrease in capital ratios. Moreover, the magnitude of the effect is larger. The difference between the fifth and first quintile of leverage change at different time lags is -0.90%, -0.98% and -0.92% per month for returns and -1.41%, -0.85%, -0.86% for alphas. In other words, the delayed detrimental effect of an increase in leverage is particularly severe for low-capital banks which recently decreased their capital ratio. The return on the portfolio of low-capital banks with the largest decrease in capital (-0.04% after 4 months) is much lower than the mean return for the portfolio with high-capital (0.85% after 4 months). This contradicts debt overhang theory, but is in line with an under-reaction in the market, where investors gradually update their perception about the effect of high leverage.

5.3 Regressions

Table 7 shows Fama MacBeth (1973) regressions assessing the different effects of a change in leverage on quarterly returns at different time lags. Since the effect of a change in leverage is likely to be non-linear, the explanatory variables are dummy variables, indicating that the change in leverage is in the first or fifth quintile. The specification reported in the first column shows that a large decrease in capital ratio (Δ BCR_quintile1) has a negative effect on future returns, long after the information on leverage has become available. For example, an increase in leverage between the 30th September and 31st December of year t decreases the expected quarterly return between May and July of year t+1 by 0.69% (Δ BCR_quintile1_lag4). Moreover, the same change in leverage will also decrease the expected return between August and October of year t+1 by 0.44% (Δ BCR_quintile5_lag7). Adrian et al. (2015) also find a large effect for a change of leverage on returns of financial firms.

Column 2 shows that the effect of a change in leverage is still significant after conditioning on the level of leverage, whereas column 3 shows that the effects are robust to adding the standard risk factors book-to-price, size and CAPM betas. Finally, column 4 shows that the negative effect of a large increase of leverage on future returns is most important among the banks that have a large leverage already – the expected returns decrease by 1.61% during the quarter following the announcement and 1.05% the quarter thereafter (Δ BCRquint1_MCRquint1). Debt overhang may contribute to this result, but it cannot explain that the coefficient on the change of leverage (-1.61%) more than compensates for the effect of absolute high leverage (L_quint5=0.59%). The magnitude of the effect therefore indicates over-optimism regarding low capital ratios.

6 Investors' perception of leverage

In order to understand how leverage is perceived by investors, this section looks at announcement returns, unlike the preceding section, which investigated returns after information on leverage was available. I will show that, despite low returns after an increase in debt, equity prices of banks tend to increase when this increase in debt is announced, especially when the capital ratio is already low. This is the expected pattern in the case of leverage over-optimism.

Table 8 shows cumulative returns and cumulative abnormal returns over a 6-day period around the earnings announcement (J-2 until J+3), when new information on leverage is incorporated into stock prices. Earning announcements are relevant for leverage, because they also contain the composition of the balance sheet. On average, banks that announce an increase in their debt²⁸ have a higher announcement return (0.63%), than banks that announce a decrease in debt (+0.36%). This difference of 0.23% is significant. This might be explained by the fact that debt is considered to increase future income because it allows more loans. However, this appreciation by the market for an increase in debt is much higher for low-capital banks (+0.54%) compared to high-capital banks (+0.19%), a contrast that is similar for abnormal returns (+0.45% and +0.15% respectively). The contrast between a positive announcement return and lower subsequent returns that are insufficient to reward risk is in line with an initial misperception which is gradually corrected by the market (Figure 2). Investors may underestimate financial distress costs, they may overestimate the leverage risk taken up by debtors and regulators (grey zone in Figure 2), they may think that bank regulators are monitoring leverage risk and that they would bail out banks anyway. Alternatively, they may perceive a decrease in the capital ratio as a signal that assets are safe, justifying such a high leverage. Lastly, investors may underestimate the extent to which low capital ratios decrease future asset growth potential (ΔV in figure 2). Indeed, the positive reaction to an increase in debt for low-capital banks contrasts with the results in Table 4, which show that low capital is a good predictor for low future asset growth. The data do not allow me to distinguish between the different potential misperceptions; only the last hypothesis will be tested more in detail below.

²⁸Note that announced earnings affect stock prices in two distinct ways. Retained earnings are included in the book value of equity, and therefore affect stock prices through leverage risk. However, they also affect stock prices through updated expectations on future earnings, which is not the scope of this paper. Therefore, stocks are sorted by the relative increase of debt as a second sort within each quintile of capital ratios. As a result, both portfolio selection criteria are driven by new information on debt, not on earnings. Market capital ratio is defined as $\frac{MV}{MV+D}$, but the market value of equity (MV) is already known at the time of earning announcements and thus not affected by announced profits or losses.

Table 9 shows regression results where the return is explained by capital ratios as well as by future asset growth, following the approach of Caskey et al. (2012). The odd columns correspond to the first regressions in Table 5. Next, regression 2 and 4 show that when future asset growth is added to the model, there is a strong positive relationship between leverage and return. This means that, conditional on a correct assessment of future asset growth, leverage is priced as expected in standard finance models. In other words, the flat relationship between capital ratios and future returns could be due, in part, to the market's failure to understand the information in excess leverage about future asset growth. Regression 4 shows that the strong relationship between capital ratios and future return is not absorbed by standard risk factors. Regression 6 shows that the effect of an increase in leverage has become much smaller (-0.6% instead of -1,0%) when future asset growth is added to the model, which further suggests that future asset growth is key to understanding the leverage puzzle.

7 The role of price-to-book, distress risk, the beta anomaly, ivol and government bail-outs

This section describes how the leverage anomaly is related to five other pricing puzzles described in the literature, namely the price-to-book effect, the distress risk anomaly, the beta anomaly, the idiosyncratic volatility (ivol) effect and the bank size anomaly. On the one hand, I show that these anomalies are also present in my banking data and argue that they all should contribute to the leverage puzzle (except for bank size). On the other hand, I show that the low return for low-capital banks remains a puzzle within each subcategory of price-to-book, S&P rating, beta, ivol or size.²⁹ This means that none of the above-mentioned puzzles, taken separately, is sufficient to understand the leverage anomaly.³⁰

A portfolio containing shares with a large book-to-price ratio has larger expected returns, even after correcting for covariance with the market return (CAPM beta) (Fama and French, 1993). Since I measure capital ratios at market prices, a bank with a high book-to-price ratio will have a lower capital ratio, all else being equal. Therefore, the book-to-price effect may explain the observed relationship between leverage and returns, as suggested by Fama and French (1996). In order to disentangle the two effects, Table 10 reports returns for double-sort portfolios, first on book-to-price, then on leverage. Results on line 'mean' correspond to one-dimensional sorts on book-to-price and reveal that low book-to-price stocks tend to have much lower returns, as expected. Next, the table shows that the leverage effect can be distinguished from the book-to-price effect. Within each category of book-to-price, the relationship between capital ratios and returns is hump-shaped, as in a one-dimensional sort, with an insignificant

 $^{^{29}}$ For the all the conditional subcategories I consider, low-capital banks never show a significantly higher return, a contrario, their returns are lower in 19 out of 23 subgroups.

 $^{^{30}}$ The leverage puzzle even remains after taking several contributing factors together. I showed already the effect of leverage on returns, conditional on price-to-book, beta and market size in the regressions in Table 5 and Table 7. The relationship between leverage and the alphas of the five factor model also takes into account price-to-book, size and beta risk.

difference between the return on high- and low-capital banks. Within each category of book-to-price, the first quintile of low-capital banks has a lower return and a lower alpha compared to the second and third quintile. Appendix I shows the same patterns for size-adjusted returns.

In non-financial firms, default risk does not lead to higher returns like any risk-return model would predict (Campbell et al., 2008; Avramov et al., 2009). This is also observed in my bank data. The returns reported on line 'mean' in Table 11 correspond to 1-dimensional sorts on terciles of S&P rating in the preceding month. They show that the portfolio containing the tercile of lowest S&P ratings (high default risk) has an average monthly return of 0.77%, whereas the portfolio of the safest banks with the best S&P ratings has an average return of 0.85%.³¹ Financial distress risk plays a major role in the trade-off theory in corporate finance and, therefore, if it is under-priced, this should contribute to the leverage puzzle. However, Table 11 shows that distress mispricing alone does not explain the leverage puzzle because, within each category of S&P rating, the return on the portfolio containing the lowest capital ratios is lower than the return on the portfolio containing the median capital ratios. The same pattern applies to the alphas.

The beta anomaly, i.e. under-pricing of covariance risk with the market return, measured by the CAPM betas, also contributes to the low return on low-capital banks. The line 'mean' in Table 12 shows that low beta portfolios have more or less the same return as high beta portfolios, as reported by Baker and Wurgler (2015).³² As a consequence, high-beta portfolios have lower alphas, including when alphas are measured with a 5-factor model (row 'mean' in Table 12). Everything else being equal, a lower capital ratio leads to a higher covariance with the market return. Since the beta anomaly insufficiently rewards this market risk, the beta anomaly contributes to the leverage puzzle (Baker et al., 2016). However, Table 12 also shows that the hump-shaped leverage-return relationship is observed within each beta-class. This indicates again that the beta anomaly is not the only driver behind the hump-shaped relationship.³³

Liu et al. (2018) argue that the driver behind the beta anomaly is, in fact, an anomaly related to idiosyncratic volatility (ivol). They measure idiosyncratic volatility as the monthly variance of the error term of a 3-factor model (Fama and French, 1993), run on daily returns. The line 'mean' in Table 13 shows that one dimensional portfolios selected on a high ivol of the preceding month have much lower returns and much lower alphas. Appendix J reports 1-dimensional portfolio sorts and shows that bank stocks with high idiosyncratic volatility indeed have much lower returns and tend to have very low capital ratios. Regarding beta, all else being equal, a low-capital ratio will mechanically increase idiosyncratic volatility. The gradient of the alphas is larger than in the case of beta portfolios, in line with Liu et al. (2018). Next, conditional on ivol, the leverage puzzle is much smaller. The decrease in return between the middle and highest quintile of leverage within each group of ivol is modest on average (-0.11%).

³¹Appendix J shows more details on one-dimensional sorts on S&P ratings.

³²Appendix J gives more information for a one-dimensional sort on betas.

³³Appendix I shows that this also holds for size-adjusted returns.

for returns and -0.14% for alphas).

A last anomaly I consider is the too-big-to-fail effect. Gandhi and Lustig (2015) show that large banks with high market value³⁴ have lower alphas. They attribute this to a reduction in risk for private investors due to a too-big-to-fail assumption. Table 14 shows monthly returns and alphas for portfolios sorted first on total assets, then on leverage. Returns are slightly lower for large banks (0.85%) than for small banks (1.05%). This contrast is much stronger for alphas, in line with the findings of Gandhi and Lustig (2015). Large banks have an alpha of -0.42%, whereas small banks have an alpha of 0.18%. This implies that large banks have higher loadings on standard risk factors, but this is attenuated by a too-big-to fail protection.

The size anomaly cannot drive the leverage puzzle however, because the highest and lowest leverage deciles both have low returns and are smaller (Table 3). Figure 1b shows that the hump-shaped relationship indeed holds after adding Gandhi and Lustig's (2015) size risk factor. Table 14 also shows that the leverage puzzle is present within each size group of banks. Within each size group, the relationship between leverage and return and between leverage and alphas, is similarly hump-shaped. Note that low capital in large banks leads to particularly large exposure to risk factors, resulting in an alpha of -0.62% per month (-7.7% per year).

8 Discussion and conclusion

This paper shows that risk-adjusted returns (alphas) on US bank stocks are lower for low-capital banks. Similarly, leverage has predictive power in the cross section of returns of US bank equity, conditional on well-known drivers of cross-sectional differences in return, such as betas, size and book-to-price. This can lead to three non-mutually exclusive conclusions: a) measurement error of leverage, b) an omitted risk factor in the risk model that is negatively correlated with leverage, and c) mispricing of leverage by the market. Disentangling them is not easy. Nevertheless, four elements in the analysis point towards mispricing. First, for low-capital banks, even below very low ratios such as 3 or 4%, leverage is associated with lower returns. It seems unlikely that this is related to any decrease in riskiness. On the contrary, these banks score higher on standard risk factors, resulting in lower alphas. This relationship is also observed for non-financial firms by Penman et al. (2007), but the effect is larger for banks. Second, not only the capital ratio, but also the change of the capital ratio affects expected returns. Although debt overhang theory is in line with dynamic effects of leverage, it cannot explain the fact that low-capital banks that further decrease their capital ratio have lower returns than banks with median capital ratios for several months. The dynamic profile of the effect of a change in leverage for low-capital banks typically corresponds to a case of over-optimism about the detrimental effect of leverage – the announcement effect of an increase in the level of debt for low-capital banks is positive, but these banks under-perform during the subsequent quarters. Third, the absence

 $^{^{34}}$ I will consider total assets as a proxy for size, because market value is mechanically related to leverage.

of a risk premium contrasts with the low future asset growth of low-capital banks. Indeed, conditional on the correct anticipation of future asset growth, the leverage puzzle disappears in the data, suggesting that the difficulty for investors to correctly anticipate the effect of leverage on future asset growth contributes to the leverage puzzle. Fourth, the financial distress anomaly, the beta anomaly, and ivol anomaly, all observed in the data, partially explain the leverage puzzle.

Measurement error and an omitted risk factor in the risk model cannot be excluded but are less convincing as main drivers. Other proxies of leverage, such as risk-adjusted leverage according to the Basel rules, show similar results. To mitigate the probability of an omitted risk factor, I have mainly worked with a 5-factor risk model, including a term structure factor as a bank-specific risk factor. Seven other risk models, and a model adding a factor based on low minus high capital, also show a steep decline in alphas for low-capital banks.

The effect of leverage on expected returns is of particular importance for banks because it underlies the assessment of the effect of the Basel regulation on banks' cost of capital. Other authors have investigated the effect of leverage on the cost of capital using different rational pricing models (Kashyap et al., 2010; Miles et al., 2013; Clark et al., 2014), finding a modest but increasing effect of higher capital ratios on banks' cost of capital. The results in this paper suggest, however, in line with Baker and Wurgler (2015), that the effect of reduced leverage among low-capital banks is higher than estimated with a typical risk model, because leverage risk is not fully priced by the market. My results suggest that for the quintile of banks with the highest levels of leverage, which are among the first to be regulated, a reduction in leverage barely affects the 'cost of equity' and, therefore, it increases the weighted average cost of capital.

What policy implications can be learned from the above insights? When leverage risk is under-priced by the market, banks with high leverage have a lower cost of capital, and owners of these banks earn a lower return (Baker and Wurgler, 2015). This is merely a transfer from under-rewarded equity holders to under-charged borrowers (and/or over-rewarded lenders). It depends, among other things, on the created incentives and interactions with other market failures whether this is a desirable outcome or not.

During the financial crisis of 2008, several banks were bailed out and government guarantees on deposits increased. These government guarantees and government bail-outs of banks, despite being necessary, create incentives for banks to take on too much risk, since part of the risk is paid for by tax-payers (Admati et al., 2013). On top of this, the residual private risk is under-priced, creating an even greater incentive for banks to increase leverage risk. In this sense, under-priced leverage risk is an additional reason to impose strict capital requirements on banks, especially in periods of high credit growth, as imposed by the Basel III agreement.

In contrast, if the economy has a sub-optimal level of bank lending, under-priced leverage risk may partly compensate other market failures that cause sub-optimal bank lending. Sub-optimal bank lending can be an issue in a deleveraging crisis during economic downturns. For bank managers, this study suggests that the general mild reaction of the market to a decrease in the capital ratio does not have, on average, a neutral effect on the value of the bank because it tends to be followed by lower returns during the following quarters. For regulators, the study suggests that the insufficient penalization of an increase in leverage by the market, which is at the root of the lower subsequent returns, constitutes an extra justification for counter-cyclical capital regulation, on top of other well-known motives.

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Figure 1: Returns and alphas on portfolios sorted on capital ratios. Yearly returns and risk-adjusted returns (alphas) on equally weighted portfolios sorted on deciles of capital ratios (1a, 1b, 2a and 2b are halfdeciles). Returns are yearly buy-and-hold returns in %, including dividend payouts and delisting returns. Portfolios are sorted monthly and formed on quarterly data four months earlier. Eg. accounting data from the 31st December is used to reallocate portfolios on the 1st May. Alphas are calculated according to equation 1 on monthly data, but using different sets of factors, as in Fama and French (2015); Gandhi and Lustig (2015); He et al. (2017); Adrian et al. (2014). PC2 is a factor long in high-leverage portfolios and short in low-leverage portfolios, with loadings according to the second principal component of the error in equation 1. Figure 1a distinguishes between sorts on market capital ratio $\left(MCR = \frac{MV}{MV + Debt}\right)$, book capital ratio $\left(BCR = \frac{CE}{CE + Debt}\right)$, Basel-adjusted capital ratio $\left(BaselCR = \frac{Tier1 + Tier2}{TA_{riskadjusted}}\right)$ and Merton-adjusted capital ratio $\left(MertonCR = \frac{MV}{MV + Debt_{Merton}}\right)$. Period 1973-2019.



9 Mkt Size Value FROE BankSpread (Adrian Friedman Muir)

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Market Capital Ratio Decile

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Figure 2: Stylized representation of the effect of a decrease of the capital ratio at time t^{*}. The black (upper) lines represent the price of the stock (lnP), whereas the orange (lower) lines show the corresponding return $(Return = \frac{d}{dt}lnP)$. ΔV is the decrease in value due to unrealized growth options under higher leverage, followed by a higher return which compensates leverage risk. The long-dashed lines represent a situation with debt overhang. The grey zone represents the transfer from debtors to shareholders who have limited liability in the case of bankruptcy. By time T, all debt contracted during the high-capital period has matured. Debt overhang theory predicts that the price can either increase or decrease but the return (risk) must increase. The short-dashed lines represent an over-optimistic perception of a decrease in the capital ratio. By time T, new information has corrected any misperceptions. Unlike debt overhang, misperceptions can explain a temporary decrease in return.

(a) Without transfer of leverage risk to governments



(b) With permanent transfer of leverage risk to governments (deposit guarantees and potential bail-outs).



Variable	Description
TA	Total Assets
CE	Common equity
D	Total liabilities (Debt)
D_{Merton}	Value of debt using the Merton (1974) model, following Doshi et al. (2019)
MV	Market value of equity=shares outstanding x price per share
MCR	Market Capital Ratio = $\frac{MV}{MV+D}$
BCR	Book Capital Ratio= $\frac{CE}{CE+D}$
BaselCR	Risk-adjusted Basel-adjusted Capital Ratio= $\frac{Tier1+Tier2}{TArishadi}$
MertonCR	Merton (1974)-adjusted Capital Ratio= $\frac{MV}{MV+D_{M-1}}$
BtP	Book-to-Price $\frac{CE}{MV}$
Asset BtP	Asset Book-to-Price $= \frac{TA}{TA - CE + MV}$
Return	Buy-and-hold return, including dividends and delisting returns
Rf	Risk free $rate = 1$ -month T-bill return
ReturnE	Excess return=Return- R_f
ReturnS	Size-adjusted return=Return - return on the portfolio
	containing the stocks in the same size decile 4 months earlier.

Table 1: Definition of variables

Table 2: Summary statistics. Mean, percentiles, standard deviation and number of observation for total assets (TA, million \$), market value of common equity (MV, million \$), market capital ratio $\left(MCR = \frac{MV}{MV+Debt}\right)$ with debt book value of total liabilities, book capital ratio $\left(BCR = \frac{CE}{CE+Debt}\right)$ with CE common equity, risk-adjusted capital ratio $\left(RCR = \frac{Tier1+Tier2}{TA_{riskadj}}\right)$, book-to-price $(BtP = \frac{CE}{MV})$, and monthly buy-and-hold return (%). Monthly data from January 1973 to December 2019. The sample contains on average 482 banks.

	Mean	p10	p50	p90	StDev	Ν
TA	12686.	247	1364	14577	99399	229735
MV	1673	23	134	1777	12037	229735
MCR	0.155	0.040	0.116	0.220	1.955	229735
BCR	0.096	0.054	0.086	0.139	0.134	229735
RCR	0.162	0.111	0.139	0.210	1.127	161505
BtP	0.919	0.439	0.804	1.515	1.883	229735
Return	0.012	-0.083	0.007	0.109	0.100	228816

Table 3: Returns and alphas on portfolios sorted on capital ratios. Yearly returns (%) on equally weighted portfolios sorted on deciles of market capital ratio $\left(MCR = \frac{MV}{MV+D}\right)$ (1a, 1b, 2a and 2b are half-deciles). Returns are yearly buy-and-hold returns in %, including dividend payouts and delisting returns. Portfolios are sorted monthly and formed on data four months earlier to ensure that the data is publicly available. Eg. accounting data from the 31st December is used to reallocate portfolios on the 1st May. Alpha5F, and the expected return (ExpReturn5F), are calculated using a monthly 5-factor risk model, according to equation 1. Alpha 5F&F is based on the Fama and French (2015) 5-factor model. Alphas and expected returns are expressed in yearly %. Ivol is idiosyncratic volatility as in Liu et al. (2018). Book to Price (BtP) is book value of common equity over its market value. Mean S&P ratings are calculated assuming equal differences between each category. Unlevered returns (UnlevReturn) are the excess returns of the bank's assets using equation 3 as in Doshi et al. (2019). UnlevAlpha is calculated using equation 1 on unlevered returns. ReturnS is the return minus the return on the size decile portfolio of each bank. p(GRS) reports the p-value of the Gibbons-Ross-Shanken test, testing the null hypothesis that the alphas on the 10 decile portfolios is zero. Data includes all banks (SIC 60) or all non-financials (excluding SIC 60-67) in the CRSP-Compustat database between January 1973 and December 2019 (N=216 456).

${\rm MCR_decile}$	Return	AlphaCAPM	$\operatorname{BetaCAPM}$	Alpha5F	ExpReturn 5F	Alpha5F&F	ivol	MCR	BtP	SPrating	MV	TA	$\operatorname{ReturnS}$	UnlevReturn	AlphaUnlev	Return	Alpha5F&F
	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Non financials	Non-financials
1a	5.4	-0.3	1.05	-5.5	16.3	-5.7	0.48	0.03	1.8	BB-	295	8779	-7.5	1.1	0.6	18.2	2.1
1b	8.6	1.2	0.88	-5.2	17.0	-3.5	0.22	0.05	1.7	BB+	631	13341	-3.8	1.1	0.6	16.8	0.6
2a	14.4	5.7	0.84	0.8	15.0	1.4	0.15	0.06	1.5	BBB	993	17051	0.2	1.4	0.9	17.6	2.3
2b	16.1	7.0	0.83	1.0	16.1	2.1	0.12	0.06	1.3	BBB	1769	24073	1.5	1.5	0.9	14.9	0.2
3	15.4	6.1	0.79	0.7	15.3	2.0	0.10	0.07	1.2	BBB	1626	18500	1.4	1.4	0.8	15.0	0.8
4	14.3	5.1	0.77	0.0	14.9	0.7	0.09	0.08	1.1	BBB+	1472	15355	0.7	1.6	0.9	14.8	0.7
5	13.9	4.7	0.75	-0.3	14.7	0.4	0.07	0.09	1.0	BBB+	1261	12772	0.3	1.6	0.8	14.0	0.6
6	14.4	5.2	0.74	0.4	14.5	0.8	0.06	0.10	0.9	BBB+	1202	11010	1.1	1.7	0.9	13.3	1.0
7	14.3	5.1	0.74	0.6	14.1	0.7	0.06	0.11	0.9	A-	1458	11355	1.1	1.8	0.9	12.6	1.8
8	11.8	2.8	0.72	-1.6	14.1	-1.4	0.05	0.13	0.8	A-	1521	10621	-1.4	1.7	0.8	11.4	2.3
9	10.7	1.8	0.72	-2.4	13.9	-2.2	0.05	0.15	0.7	A-	1445	8494	-2.1	1.6	0.6	8.1	0.9
10	10.4	1.1	0.78	-1.4	12.4	-1.6	0.06	0.44	0.6	BBB+	2583	5445	-2.2	3.8	2.2	5.9	0.5
p(GRS)		0.001		0.040		0.015											0.749

Table 4: Mean-reverting capital ratios and low assets growth for low-capital banks. Mean future market capital ratio $\left(MCR = \frac{MV}{MV+D}\right)$ deciles and future asset growth (% per year) for equally weighted MCR portfolios. Portfolios are sorted monthly and formed on data four months earlier to ensure that the data is publicly available. Period 1973-2019.

MCR decile		Future M	CR deciles			TA gro	wth (%)	
	+1 year	+2 years	+3 years	+4 years	+1 year	+2 years	+3 years	+4 years
1a	10	9.6	9.2	8.9	5.4	6.7	7.5	8.3
$1\mathrm{b}$	9.5	9.1	8.6	8.4	7.7	8.3	7.7	9
2a	8.9	8.6	8.2	8	8	8	8.1	8.4
2b	8.5	8.1	7.9	7.7	8.6	9	9	8.8
3	7.8	7.6	7.4	7.3	9.9	9.4	9.1	9.3
4	6.9	6.8	6.7	6.7	10.6	10.2	10	9.6
5	6	6.1	6.1	6	12.4	11.7	10.7	10.3
6	5.2	5.4	5.4	5.5	12.8	12.6	11.1	10.8
7	4.4	4.6	4.8	4.9	13.4	12.4	11.6	11
8	3.6	4	4.2	4.4	14.5	12.9	12.1	11.1
9	2.7	3.2	3.5	3.8	14.9	13.5	11.6	11.1
10	1.6	2	2.5	2.8	21.9	19.7	16.6	15.5

Table 5: The effect of capital ratios on returns. Fama-MacBeth (1973) regressions explaining quarterly buyand-hold returns in %. Asset BtP is defined as $\frac{TA}{TA-CE+MV}$ with TA being the total assets, CE the book value of common equity, and MV the market value of equity. MCR_quint1 is a dummy variable indicating that a bank belongs to the quintile with lowest market capital ratio $\left(MCR = \frac{MV}{MV+D}\right)$ in a given month. Δ BCR_quint1 is a dummy variable indicating that a bank belongs to the quintile with the largest quarterly decrease in book capital ratio $\left(BCR = \frac{CE}{CE+D}\right)$ in a given month. Δ BCR is a second sort, after a first sort on BCR. Betas are calculated using the CAPM over a rolling window over the preceding 5 years, with a minimum of 2 years. Capital ratios and asset BtP explain returns starting 4 months later. For example, in the case of a fiscal year-end in December, the return from the 1st May until the 31st July is explained by leverage on the 31st December 2013. MV and beta are lagged by 1 month. Standard errors are corrected for correlation within periods and within firms (Newey and West, 1987) and for the first stage estimation of betas (Shanken, 1992). Period 1973-2019.

	(1)	(2)	(3)
MCR_quint1_lag4	0.41	0.52	0.77
	(0.60)	(0.68)	(0.66)
MCR_quint2_lag4	0.82**	0.96^{**}	1.11***
	(0.36)	(0.42)	(0.42)
MCR_quint3_lag4	0.60^{**}	0.69^{**}	0.79^{***}
	(0.28)	(0.30)	(0.30)
MCR_quint4_lag4	0.35	0.36^{*}	0.44^{**}
	(0.26)	(0.21)	(0.21)
ΔBCR_quint1_lag4			-0.97***
			(0.21)
$\Delta dBCR_quint5_lag4$			0.01
			(0.18)
$AssetBtP_lag4$		1.29	-0.56
		(6.33)	(6.23)
$\ln MV_lag1$		-0.09	-0.09
		(0.12)	(0.12)
beta_lag1		0.14	0.14
		(0.33)	(0.32)
Constant	2.80^{***}	1.96	3.91
	(0.67)	(6.42)	(6.31)
Observations	$88,\!249$	62,994	62,994
Number of groups	187	179	179
\mathbb{R}^2	0.02	0.07	0.07
<u> </u>	1 1	** 0.01	** ~ ~ ~ * ~ ~ ~

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6: Returns and alphas on portfolios sorted on capital ratios and on a change in capital. Monthly returns and alphas for double-sort portfolios, first on market capital ratio $\left(MCR = \frac{MV}{MV+D}\right)$ and then on a quarterly change in the book capital ratio $\left(BDR_t - BCR_{t-3} \text{ with } BCR = \frac{CE}{CE+D}\right)$. Portfolios are formed at different time lags after fiscal quarter end. T-values correspond to a t-test on equality of means with different variances between the fifth and the first or the fifth and the third portfolio. Alphas are calculated using a 5-factor risk model according to equation 1. The Gibbons-Ross-Shanken test is reported for alphas (H0: all alphas are zero). Results reported in column and row 'mean' correspond to aggregated portfolios composed of the individual banks in the respective row or column. Portfolio-months with fewer than 3 banks are excluded. Period 1973-2019.

(a) Monthly returns (%) and alphas for portfolios formed on leverage and leverage change 1 month after accounting quarter end (e.g. formed on the first of February if fiscal quarter ends on the 31st December). Banks for which the information on leverage (quarterly reports) is not yet known are excluded.

Returns	LowMCR	2	3	4	HighMCR	Mean	Mid-Low	t	Alphas	LowMCR	2	3	4	HighMCR	Mean	Mid-Low	p(GRS)
$Decrease \Delta BCR$	0.61	0.98	0.86	0.84	0.85	0.92	0.25	-1.66	$Decrease \Delta BCR$	-1.07	-0.22	-0.33	-0.26	-0.18	-0.40	0.74	-0.07
2	1.11	1.07	1.31	1.01	1	1.18	0.21	-1.84	2	-0.28	0.01	0.13	-0.09	-0.02	-0.05	0.41	-0.49
3	1.29	1.28	1.28	1.02	0.8	1.16	-0.01	-1.9	3	0.14	0.17	0.13	-0.13	-0.14	0.04	-0.01	-0.17
4	1.18	1.28	1.29	1.04	0.66	1.15	0.11	-2.2	4	0.27	0.19	0.08	-0.07	-0.38	0.02	-0.19	-0.02
$Increase \Delta BCR$	1.51	1.25	1.25	1.1	0.9	1.25	-0.26	-3.22	$Increase \Delta BCR$	0.34	0.02	0.13	-0.03	-0.24	0.04	-0.21	-0.24
Mean	1.24	1.22	1.22	1.03	0.87		-0.02	-4.93	Mean	-0.11	0.04	0.03	-0.12	-0.19		0.14	-0.03
High-Low	0.90	0.27	0.39	0.26	0.05	0.33			High-Low	1.41	0.24	0.46	0.23	-0.06	0.45		
t	2.45	1.78	2.35	1.25	-0.01	3.79			t	0.00	-0.15	-0.01	-0.44	-0.11	0.00		0.00

(b) Portfolios formed 4 months after accounting quarter end.

Returns	LowMCR	2	3	4	HighMCR	Mean	Mid-Low	t	Alphas	LowMCR	2	3	4	HighMCR	Mean	Mid-Low	p(GRS)
$Decrease \Delta BCR$	-0.04	0.99	1.07	0.84	0.79	0.82	0.11	2.14	$Decrease \Delta BCR$	-0.97	-0.04	0.03	-0.14	-0.21	-0.25	1.01	-0.09
2	0.91	1.27	1.12	1.13	0.80	1.09	0.21	0.11	2	-0.20	0.15	0.02	0.06	-0.17	-0.02	0.22	-0.27
3	1.06	1.06	1.03	0.97	0.86	1.03	-0.03	-0.89	3	-0.01	-0.09	-0.08	-0.06	-0.09	-0.07	-0.07	-0.99
4	1.36	1.40	1.12	1.05	0.81	1.18	-0.24	-1.78	4	0.19	0.25	0.02	-0.02	-0.16	0.06	-0.17	-0.35
$Increase \Delta BCR$	0.94	1.03	1.14	1.02	0.81	1.03	0.20	-0.55	$Increase \Delta BCR$	-0.09	-0.10	0.02	-0.07	-0.25	-0.10	0.11	-0.45
Mean	0.94	1.17	1.12	1.03	0.85		0.17	-0.39	Mean	-0.21	0.03	0.00	-0.05	-0.18		0.21	-0.13
High-Low	0.98	0.04	0.07	0.18	0.03	0.21			High-Low	0.88	-0.07	-0.02	0.07	-0.04	0.15		
t	2.63	0.09	0.59	2.16	0.51	2.89			\mathbf{t}	-0.04	-0.06	-0.96	-0.75	-0.62	-0.02		0.09

(c) Portfolios formed 7 months after accounting quarter end.

Returns	LowMCR	2	3	4	HighMCR	Mean	Mid-Low	t	Alphas	LowMCR	2	3	4	HighMCR	Mean	Mid-Low	p(GRS)
$Decrease \Delta BCR$	0.08	1.19	1.03	0.87	0.80	0.86	0.95	1.32	$Decrease \Delta BCR$	-0.91	0.08	-0.04	-0.19	-0.07	-0.07	0.23	-0.74
2	0.71	1.17	1.00	0.88	0.69	0.95	0.29	-0.06	2	-0.42	0.03	-0.08	-0.23	-0.29	0.07	-0.31	-0.68
3	1.08	1.07	1.13	0.95	0.84	1.03	0.05	-0.59	3	0.25	0.04	-0.01	-0.04	-0.17	0.01	-0.26	-0.66
4	1.41	1.18	1.10	1.05	0.85	1.18	-0.31	-3.15	4	0.33	0.13	0.03	0.00	-0.13	-0.19	0.34	-0.10
$Increase \Delta BCR$	1.00	1.10	1.18	1.08	0.80	1.08	0.18	-0.14	$Increase \Delta BCR$	-0.17	-0.06	0.07	-0.11	-0.12	-0.18	0.88	-0.06
Mean	1.04	1.15	1.15	1.00	0.80		0.11	-1.14	Mean	-0.15	0.04	-0.01	-0.12	-0.16		0.15	-0.15
High-Low	0.92	-0.09	0.15	0.22	0.00	0.22			High-Low	0.75	-0.14	0.11	0.08	-0.05	0.11		
t	1.83	-0.23	1.00	0.93	0.57	2.00			t	0.00	-0.89	-0.95	-0.39	-0.50	-0.01		

Table 7: The effect of a change in capital ratios on returns. Fama-MacBeth (1973) regressions, explaining quarterly buy-and-hold returns in %. Asset BtP is defined as $\frac{TA}{TA-CE+MV}$ with TA being the total assets, CE the book value of common equity, and MV the market value of equity. ΔBCR_{quint5} is a dummy variable indicating that a bank belongs to the quintile with the largest quarterly increase in book capital ratio $\left(\frac{CE}{CE+D}\right)$ within a given

leverage quintile in a given month (Δ BCR is a second sort, after a first sort on market capital ratio $\left(\frac{MV}{MV+D}\right)$). Lags of explanatory variables are expressed in months. For example, in the case of lag 4 and a fiscal quarter-end in December, the return from the 1st May 2014 until the 30th July 2014 is explained by a change in leverage between the 30th September and the 31st December 2013. MCR_quintile5 is a dummy variable indicating that a bank belongs to the quintile with the highest market capital ratio in a given month. Δ BCRquint5*MCRquint5 is the interaction dummy variable. Betas are calculated using the CAPM over a rolling window over the preceding 2 years. Standard errors are corrected for correlation within periods and within firms (Newey-West 1987) and for the first stage estimation of betas (Shanken 1992). Period 1973-2019.

	(1)	(2)	(3)	(4)
ΔBCR quint1 lag4	-0.69***	-0.72***	-0.85***	-0.35*
	(0.26)	(0.21)	(0.21)	(0.21)
$\Delta { m BCR_quint1_lag7}$	-0.44	-0.45*	-0.39*	-0.04
	(0.27)	(0.24)	(0.22)	(0.21)
$\Delta { m BCR_quint5_lag4}$	0.12	0.02	0.13	0.06
	(0.24)	(0.23)	(0.19)	(0.19)
$\Delta { m BCR_quint5_lag7}$	0.03	-0.02	0.03	-0.03
	(0.22)	(0.21)	(0.18)	(0.18)
$\Delta BCRquint1_MCRquint1_lag4$				-1.61***
				(0.55)
$\Delta BCRquint1_MCRquint1_lag7$				-1.05**
				(0.48)
MCR_quint5_lag4		-0.91^{***}	-0.67***	-0.64**
		(0.32)	(0.25)	(0.25)
$MCR_quint51_lag7$		0.08	-0.09	0.59
		(0.44)	(0.43)	(0.40)
$AssetBtP_lag4$			3.17	2.67
			(5.96)	(5.85)
$\ln MV_lag1$			-0.11	-0.13
			(0.11)	(0.11)
$beta_lag1$			0.25	0.29
			(0.30)	(0.30)
Constant	3.37^{***}	3.55^{***}	0.99	1.46
	(0.71)	(0.73)	(6.06)	(5.96)
Observations	$88,\!249$	$88,\!249$	$62,\!994$	$62,\!994$
Number of groups	187	187	179	179
R^2	0.01	0.03	0.07	0.08

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 8: **Returns and alphas when leverage is announced.** Buy and hold returns and abnormal returns (%) over a 6-day period (J-2 until J+3) around earnings announcement for double-sorted stocks, first on market capital ratio $\left(\frac{MV}{MV+D}\right)$ and then on relative change in debt $\frac{D_t - D_{t-3}}{D_{t-3}}$. Debt is defined as the book value of all liabilities. Abnormal returns are buy-and-hold returns minus the expected return on a 5-factor model (market, size, value, momentum and term spread factor), calibrated using daily returns over a rolling window of 2 years. T-values correspond to a t-test on equality of means with different variances between the first and fifth portfolio. Results reported in column and row 'mean' correspond to aggregated portfolios composed of the individual banks in the respective row or column. Period 1973-2019.

Returns	Low M	ICR	2 I	Mid MC	CR 4	Hig	h MCR	Mean	Mid-	Low t	
DecreasedD	0.12	2	0.31	0.29	0.53	(0.49	0.36	0.1	-0.98	_
2	0.60	6	0.41	0.65	0.57	(0.57	0.57	-0.	01 -0.06	
3	0.44	4	0.65	0.51	0.63	(0.59	0.57	0.0	0.51	
4	0.8	1 (0.48	0.68	0.57	(0.67	0.63	-0.	13 -0.84	
IncreasedD	0.60	6	0.64	0.53	0.52	(0.68	0.59	-0.	13 -0.87	
Mean	0.5_{-}	4	0.49	0.53	0.56	(0.60		-0.	02 -0.29	
High-Low	0.54^{*}	<** 0.	.32**	0.24^{*}	-0.01	(0.19	0.23^{***}	* .		
t	2.7	7 2	2.21	1.79	-0.08		1.38	3.64	•	•	_
Abnormal ret	urns 1	Low MC	R 2	М	id MCR	4	High	MCR	Mean	Mid-Low	\mathbf{t}
Decreased	D	0.00	0.0)6	0.00	0.19	0.	19	0.09	0.01	0.03
2		0.39	0.1	9	0.34	0.31	0.	19	0.28	-0.05	-0.33
3		0.23	0.3	5	0.23	0.27	0.	18	0.25	-0.00	-0.04
4		0.57	0.1	.6	0.4	0.27	0.	29	0.33	-0.17	-1.17
Increased	D	0.45	0.3	8	0.19	0.13	0.	34	0.28	-0.26*	-1.80
Mean		0.34	0.2	21	0.22	0.23	0.	23	•	-0.11*	-1.82
High-Low	7	0.45^{**}	0.32	**	0.18	-0.06	0.	15 ().19***		
\mathbf{t}		2.45	2.4	2	1.49	-0.53	1.	15	3.22		

	(1)	(2)	(3)	(4)	(5)	(6)
MCR_quint1_lag4	0.41	2.23***	0.52	1.53**	0.77	1.63***
- •	(0.60)	(0.61)	(0.68)	(0.62)	(0.66)	(0.61)
MCR_quint2_lag4	0.82**	1.60***	0.96**	1.10***	1.11***	1.11***
	(0.36)	(0.38)	(0.42)	(0.40)	(0.42)	(0.39)
MCR_quint3_lag4	0.60^{**}	1.00^{***}	0.69^{**}	0.52^{*}	0.79^{***}	0.55^{*}
	(0.28)	(0.27)	(0.30)	(0.30)	(0.30)	(0.30)
MCR_quint4_lag4	0.35	0.61^{**}	0.36^{*}	0.27	0.44^{**}	0.32
	(0.26)	(0.25)	(0.21)	(0.23)	(0.21)	(0.23)
$\Delta \mathrm{BCR}_\mathrm{quint5}_\mathrm{lag4}$					0.01	0.03
					(0.18)	(0.18)
ΔBCR_quint1_lag4					-0.97***	-0.58***
					(0.21)	(0.20)
$AssetBtP_lag4$			1.29	9.60	-0.56	8.32
			(6.33)	(6.05)	(6.23)	(5.91)
$\ln MV_lag1$			-0.09	-0.09	-0.09	-0.09
			(0.12)	(0.11)	(0.12)	(0.11)
$beta_lag1$			0.14	0.52	0.14	0.51
			(0.33)	(0.33)	(0.32)	(0.32)
$Asset_growth_3 years$		3.18^{***}		3.37^{***}		3.35^{***}
		(0.37)		(0.39)		(0.38)
Constant	2.80^{***}	1.30^{*}	1.96	-7.75	3.91	-6.38
	(0.67)	(0.66)	(6.42)	(6.13)	(6.31)	(6.00)
Observations	$88,\!249$	$55,\!336$	$62,\!994$	48,737	62,994	48,737
Number of groups	187	176	179	170	179	170
\mathbb{R}^2	0.2	0.5	0.7	0.9	0.7	0.10

Table 9: Effect of leverage on returns conditional on correctly anticipating asset growth. Fama-MacBeth (1973) regressions explaining quarterly returns in %. Variables are defined as in Table 5. Asset growth is defined as $\frac{TA_{t+3y}-TA_t}{TA_t}$, explaining the return starting 4 months after time t. Period 1973-2019.

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 10: **Capital ratios and book-to-price.** Monthly returns (%) and alphas (%) for double-sort portfolios, first sorted by asset BtP, then by market capital ratio $\left(\frac{MV}{MV+D}\right)$. Asset BtP is defined as $\frac{TA}{TA-CE+MV}$ with TA being the total assets, CE the book value of common equity and MV the market value of equity. Portfolios are formed on data four months earlier. T-values correspond to a t-test on equality of means with different variances between first/third and fifth portfolio. Alphas are calculated according to equation 1. The Gibbons-Ross-Shanken test is reported for alphas (H0: all alphas are zero). Results reported in column and row 'mean' correspond to portfolios composed of the individual banks in the respective row or column. Period 1973-2019.

Returns	LowAssetBtP	2	3	4	HighAssetBtP	Mean	High-Low	t
LowMCR	0.63	0.81	1.02	0.73	0.65	0.87	0.02	0.04
2	0.88	0.94	1.06	1.31	1.12	1.10	0.23	0.61
MidMCR	0.72	1.15	1.18	1.26	1.06	1.10	0.34	0.98
4	0.88	1.01	1.10	1.15	1.14	1.08	0.26	0.82
HighMCR	0.75	0.71	1.07	1.08	1.16	0.98	0.41	1.32
Mean	0.81	0.96	1.12	1.16	1.10		0.29	0.90
Low-Mid	-0.09	-0.33	-0.16	-0.52	-0.41	-0.24		
\mathbf{t}	-0.27	-0.94	-0.42	-1.27	-0.88	-0.69		
Alphas	LowAssetBtP	2	3	4	HighAssetBtP	Mean	High-Low	p(GRS)
Alphas LowMCR	LowAssetBtP -0.48	2 -0.30	3 -0.17	4	HighAssetBtP -0.38	Mean -0.30	High-Low 0.11	p(GRS) 0.33
Alphas LowMCR 2	LowAssetBtP -0.48 -0.24	2 -0.30 -0.20	3 -0.17 -0.03	4 -0.26 0.17	HighAssetBtP -0.38 0.01	Mean -0.30 -0.06	High-Low 0.11 0.25	p(GRS) 0.33 0.42
Alphas LowMCR 2 MidMCR	LowAssetBtP -0.48 -0.24 -0.27	2 -0.30 -0.20 0.09	3 -0.17 -0.03 0.08	4 -0.26 0.17 0.17	HighAssetBtP -0.38 0.01 -0.07	Mean -0.30 -0.06 0.00	High-Low 0.11 0.25 0.21	p(GRS) 0.33 0.42 0.04
Alphas LowMCR 2 MidMCR 4	LowAssetBtP -0.48 -0.24 -0.27 -0.10	2 -0.30 -0.20 0.09 -0.04	3 -0.17 -0.03 0.08 0.08	4 -0.26 0.17 0.17 0.16	HighAssetBtP -0.38 0.01 -0.07 0.05	Mean -0.30 -0.06 0.00 0.03	High-Low 0.11 0.25 0.21 0.16	$p(GRS) \\ 0.33 \\ 0.42 \\ 0.04 \\ 0.69$
Alphas LowMCR 2 MidMCR 4 HighMCR	LowAssetBtP -0.48 -0.24 -0.27 -0.10 -0.13	2 -0.30 -0.20 0.09 -0.04 -0.30	3 -0.17 -0.03 0.08 0.08 0.00	4 -0.26 0.17 0.17 0.16 0.01	HighAssetBtP -0.38 0.01 -0.07 0.05 0.18	Mean -0.30 -0.06 0.00 0.03 -0.05	High-Low 0.11 0.25 0.21 0.16 0.31	$p(GRS) \\ 0.33 \\ 0.42 \\ 0.04 \\ 0.69 \\ 0.07$
Alphas LowMCR 2 MidMCR 4 HighMCR Mean	LowAssetBtP -0.48 -0.24 -0.27 -0.10 -0.13 -0.24	2 -0.30 -0.20 0.09 -0.04 -0.30 -0.14	3 -0.17 -0.03 0.08 0.08 0.00 0.00	4 -0.26 0.17 0.17 0.16 0.01 0.05	HighAssetBtP -0.38 0.01 -0.07 0.05 0.18 -0.03	Mean -0.30 -0.06 0.00 0.03 -0.05	High-Low 0.11 0.25 0.21 0.16 0.31 0.22	p(GRS) 0.33 0.42 0.04 0.69 0.07 0.13
Alphas LowMCR 2 MidMCR 4 HighMCR Mean Low-Mid	LowAssetBtP -0.48 -0.24 -0.27 -0.10 -0.13 -0.24 -0.21	2 -0.30 -0.20 0.09 -0.04 -0.30 -0.14 -0.39	3 -0.17 -0.03 0.08 0.08 0.00 0.00 -0.25	4 -0.26 0.17 0.17 0.16 0.01 0.05 -0.43	HighAssetBtP -0.38 0.01 -0.07 0.05 0.18 -0.03 -0.31	Mean -0.30 -0.06 0.00 0.03 -0.05 -0.30	High-Low 0.11 0.25 0.21 0.16 0.31 0.22	p(GRS) 0.33 0.42 0.04 0.69 0.07 0.13

Table 11: Capital ratios and financial distress risk. Monthly returns (%) and alphas (%) for double-sort portfolios, first sorted by S&P rating, then by market capital ratio $\left(\frac{MV}{MV+D}\right)$. S&P ratings are domestic long-term issuer credit ratings. Portfolios are formed on S&P rating during the preceding month, and market capital ratio 4 months earlier. T-values correspond to a t-test on equality of means with different variances between first/third and fifth portfolio. Alphas are calculated according to equation 1. The Gibbons-Ross-Shanken test is reported for alphas (H0: all alphas are zero). Results reported in column and row 'mean' correspond to portfolios composed of the individual banks in the respective row or column. A minority of banks are rated, portfolio-months with only one bank are omitted. Period 1986-2019. (N=25,904).

Returns	Low SPrating	Mid	High SPrating	Mean	High-Low	\mathbf{t}
LowMCR	0.57	1.04	0.34	0.72	-0.23	-0.30
2	0.42	0.77	0.76	0.73	0.34	0.52
MidMCR	1.20	1.21	0.83	1.13	-0.37	-0.68
4	0.64	0.72	0.80	0.78	0.16	0.32
HighMCR	0.77	0.94	0.93	0.89	0.16	0.36
Mean	0.77	0.98	0.85	•	0.08	0.15
Low-Mid	-0.63	-0.17	-0.49	-0.41		
t	-0.91	-0.29	-0.76	-0.75		
Alphas	Low SPrating	Mid	High SPrating	Mean	High-Low	p(GRS)
Alphas LowMCR	Low SPrating 0.16	Mid -0.35	High SPrating -0.46	Mean -0.11	High-Low -0.62	p(GRS) 0.32
Alphas LowMCR 2	Low SPrating 0.16 -0.71	Mid -0.35 -0.14	High SPrating -0.46 -0.26	Mean -0.11 -0.38	High-Low -0.62 0.45	p(GRS) 0.32 0.24
Alphas LowMCR 2 MidMCR	Low SPrating 0.16 -0.71 0.13	Mid -0.35 -0.14 0.37	High SPrating -0.46 -0.26 -0.23	Mean -0.11 -0.38 0.10	High-Low -0.62 0.45 -0.36	p(GRS) 0.32 0.24 0.11
Alphas LowMCR 2 MidMCR 4	Low SPrating 0.16 -0.71 0.13 -0.31	Mid -0.35 -0.14 0.37 -0.16	High SPrating -0.46 -0.26 -0.23 -0.02	Mean -0.11 -0.38 0.10 -0.13	High-Low -0.62 0.45 -0.36 0.28	p(GRS) 0.32 0.24 0.11 0.66
Alphas LowMCR 2 MidMCR 4 HighMCR	Low SPrating 0.16 -0.71 0.13 -0.31 -0.07	Mid -0.35 -0.14 0.37 -0.16 0.24	High SPrating -0.46 -0.26 -0.23 -0.02 -0.01	Mean -0.11 -0.38 0.10 -0.13 -0.01	High-Low -0.62 0.45 -0.36 0.28 0.06	p(GRS) 0.32 0.24 0.11 0.66 0.49
Alphas LowMCR 2 MidMCR 4 HighMCR Mean	Low SPrating 0.16 -0.71 0.13 -0.31 -0.07 -0.28	Mid -0.35 -0.14 0.37 -0.16 0.24 0.02	High SPrating -0.46 -0.26 -0.23 -0.02 -0.01 -0.14	Mean -0.11 -0.38 0.10 -0.13 -0.01	High-Low -0.62 0.45 -0.36 0.28 0.06 0.13	$p(GRS) \\ 0.32 \\ 0.24 \\ 0.11 \\ 0.66 \\ 0.49 \\ 0.19 \\$
Alphas LowMCR 2 MidMCR 4 HighMCR Mean Low-Mid	Low SPrating 0.16 -0.71 0.13 -0.31 -0.07 -0.28 0.03	Mid -0.35 -0.14 0.37 -0.16 0.24 0.02 -0.72	High SPrating -0.46 -0.26 -0.23 -0.02 -0.01 -0.14 -0.23	Mean -0.11 -0.38 0.10 -0.13 -0.01 -0.22	High-Low -0.62 0.45 -0.36 0.28 0.06 0.13	p(GRS) 0.32 0.24 0.11 0.66 0.49 0.19

Table 12: Capital ratios and the beta anomaly. Monthly returns (%) and alphas (%) for double-sort portfolios, first sorted by beta, then by market capital ratio $\left(\frac{MV}{MV+D}\right)$. Betas are calculated using the CAPM over a rolling window over the last 5 years (min 2 years). Portfolios are formed on beta available the preceding month, and market capital ratios 4 months earlier. T-values correspond to a t-test on equality of means with different variances between first/third and fifth portfolio. Alphas are calculated according to equation 1. Results reported in column and row 'mean' correspond to portfolios composed of the individual banks in the respective row or column. Period 1973-2019.

Returns	Lowbeta	2	3	4	Highbeta	Mean	High-Low	\mathbf{t}
LowMCR	1.11	0.93	1.12	1.23	0.58	1.03	-0.53	-1.13
2	1.36	1.33	1.12	1.21	1.19	1.25	-0.17	-0.45
MidMCR	1.11	1.21	1.06	1.34	1.27	1.24	0.16	0.47
4	1.11	1.13	1.23	1.24	1.08	1.16	-0.03	-0.08
HighMCR	0.88	0.97	1.08	1.06	0.96	1.04	0.08	0.24
Mean	1.24	1.16	1.17	1.26	1.07		-0.16	-0.50
Low-Mid	0.01	-0.29	0.07	-0.11	-0.69	-0.21		
\mathbf{t}	0.02	-0.83	0.18	-0.26	-1.44	-0.59		
Alphas	Lowbeta	2	3	4	Highbeta	Mean	High-Low	p(GRS)
Alphas LowMCR	Lowbeta 0.30	2 -0.10	3 0.08	4	Highbeta -0.57	Mean -0.17	High-Low -0.87	p(GRS) 0.00
Alphas LowMCR 2	Lowbeta 0.30 0.41	2 -0.10 0.34	3 0.08 -0.07	4 0.20 0.08	Highbeta -0.57 -0.01	Mean -0.17 0.05	High-Low -0.87 -0.42	p(GRS) 0.00 0.00
Alphas LowMCR 2 MidMCR	Lowbeta 0.30 0.41 0.15	2 -0.10 0.34 0.15	3 0.08 -0.07 0.00	4 0.20 0.08 0.17	Highbeta -0.57 -0.01 -0.12	Mean -0.17 0.05 0.02	High-Low -0.87 -0.42 -0.27	p(GRS) 0.00 0.00 0.07
Alphas LowMCR 2 MidMCR 4	Lowbeta 0.30 0.41 0.15 0.13	2 -0.10 0.34 0.15 0.09	3 0.08 -0.07 0.00 0.14	4 0.20 0.08 0.17 0.00	Highbeta -0.57 -0.01 -0.12 -0.10	Mean -0.17 0.05 0.02 -0.01	High-Low -0.87 -0.42 -0.27 -0.23	$p(GRS) = 0.00 \\ 0.00 \\ 0.00 \\ 0.07 \\ 0.42 = 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ $
Alphas LowMCR 2 MidMCR 4 HighMCR	Lowbeta 0.30 0.41 0.15 0.13 -0.02	2 -0.10 0.34 0.15 0.09 -0.10	3 0.08 -0.07 0.00 0.14 0.03	4 0.20 0.08 0.17 0.00 -0.03	Highbeta -0.57 -0.01 -0.12 -0.10 -0.10	Mean -0.17 0.05 0.02 -0.01 -0.09	High-Low -0.87 -0.42 -0.27 -0.23 -0.08	p(GRS) = 0.00 = 0.00 = 0.07 = 0.42 = 0.81
Alphas LowMCR 2 MidMCR 4 HighMCR Mean	Lowbeta 0.30 0.41 0.15 0.13 -0.02 0.19	2 -0.10 0.34 0.15 0.09 -0.10 0.03	$\begin{array}{c} 3 \\ 0.08 \\ -0.07 \\ 0.00 \\ 0.14 \\ 0.03 \\ 0.00 \end{array}$	4 0.20 0.08 0.17 0.00 -0.03 0.05	Highbeta -0.57 -0.01 -0.12 -0.10 -0.10 -0.24	Mean -0.17 0.05 0.02 -0.01 -0.09	High-Low -0.87 -0.42 -0.27 -0.23 -0.08 -0.43	$p(GRS) \\ 0.00 \\ 0.00 \\ 0.07 \\ 0.42 \\ 0.81 \\ 0.01$
Alphas LowMCR 2 MidMCR 4 HighMCR Mean Low-Mid	Lowbeta 0.30 0.41 0.15 0.13 -0.02 0.19 0.15	2 -0.10 0.34 0.15 0.09 -0.10 0.03 -0.26	$\begin{array}{c} 3 \\ 0.08 \\ -0.07 \\ 0.00 \\ 0.14 \\ 0.03 \\ 0.00 \\ 0.09 \end{array}$	4 0.20 0.08 0.17 0.00 -0.03 0.05 0.03	Highbeta -0.57 -0.01 -0.12 -0.10 -0.10 -0.24 -0.45	Mean -0.17 0.05 0.02 -0.01 -0.09 -0.19	High-Low -0.87 -0.42 -0.27 -0.23 -0.08 -0.43	p(GRS) 0.00 0.00 0.07 0.42 0.81 0.01

Table 13: Capital ratios and the ivol anomaly. Monthly returns (%) and alphas (%) for double-sort portfolios, first sorted by ivol, then by market capital ratio $\binom{MV}{MV+D}$. Ivol is the variance of the error term in the 3-factor F&F model on daily data as in Liu et al. (2018). Portfolios are formed on ivol available the preceding month, and market capital ratios 4 months earlier. T-values correspond to a t-test on equality of means with different variances between first/third and fifth portfolio. Alphas are calculated according to equation 1. Results reported in column and row 'mean' correspond to portfolios composed of the individual banks in the respective row or column.

Returns	LowIvol	2	3	4	HighIvol	Mean	High-Low	t
LowMCR	1.26	1.18	1.05	1.25	0.64	1.07	-0.62	-1.30
2	1.33	1.16	1.24	0.95	0.69	1.14	-0.64	-1.54
MidMCR	1.28	1.36	1.06	1.07	0.61	1.17	-0.67^{*}	-1.85
4	0.94	1.08	1.03	1.14	0.71	1.02	-0.23	-0.67
HighMCR	1.01	1.06	0.62	0.62	0.22	0.78	-0.79**	-2.27
Mean	1.15	1.17	0.99	0.90	0.39		-0.76*	-1.95
Low-Mid	-0.03	-0.17	-0.01	0.18	0.02	-0.11		
\mathbf{t}	-0.09	-0.50	-0.03	0.46	0.05	-0.32	•	
Alphas	LowIvol	2	3	4	HighIvol	Mean	High-Low	p(GRS)
Alphas LowMCR	LowIvol 0.44	2 0.12	3 -0.16	4 0.18	HighIvol -0.35	Mean -0.09	High-Low -0.79	p(GRS) 0.00
Alphas LowMCR 2	LowIvol 0.44 0.32	2 0.12 0.03	3 -0.16 0.12	4 0.18 -0.04	HighIvol -0.35 -0.37	Mean -0.09 0.01	High-Low -0.79 -0.68	p(GRS) 0.00 0.01
Alphas LowMCR 2 MidMCR	LowIvol 0.44 0.32 0.25	2 0.12 0.03 0.30	3 -0.16 0.12 -0.03	4 0.18 -0.04 0.06	HighIvol -0.35 -0.37 -0.31	Mean -0.09 0.01 0.05	High-Low -0.79 -0.68 -0.56	p(GRS) 0.00 0.01 0.01
Alphas LowMCR 2 MidMCR 4	LowIvol 0.44 0.32 0.25 -0.01	2 0.12 0.03 0.30 -0.02	3 -0.16 0.12 -0.03 -0.01	4 0.18 -0.04 0.06 0.22	HighIvol -0.35 -0.37 -0.31 -0.25	Mean -0.09 0.01 0.05 -0.07	High-Low -0.79 -0.68 -0.56 -0.24	p(GRS) 0.00 0.01 0.01 0.07
Alphas LowMCR 2 MidMCR 4 HighMCR	LowIvol 0.44 0.32 0.25 -0.01 0.03	2 0.12 0.03 0.30 -0.02 -0.05	3 -0.16 0.12 -0.03 -0.01 -0.33	4 0.18 -0.04 0.06 0.22 -0.30	HighIvol -0.35 -0.37 -0.31 -0.25 -0.53	Mean -0.09 0.01 0.05 -0.07 -0.24	High-Low -0.79 -0.68 -0.56 -0.24 -0.57	p(GRS) = 0.00 = 0.01 = 0.01 = 0.07 = 0.01 = 0.01
Alphas LowMCR 2 MidMCR 4 HighMCR Mean	LowIvol 0.44 0.32 0.25 -0.01 0.03 0.11	2 0.12 0.03 0.30 -0.02 -0.05 0.03	3 -0.16 0.12 -0.03 -0.01 -0.33 -0.15	4 0.18 -0.04 0.06 0.22 -0.30 -0.18	HighIvol -0.35 -0.37 -0.31 -0.25 -0.53 -0.63	Mean -0.09 0.01 0.05 -0.07 -0.24	High-Low -0.79 -0.68 -0.56 -0.24 -0.57 -0.74	p(GRS) 0.00 0.01 0.01 0.07 0.01 0.02
Alphas LowMCR 2 MidMCR 4 HighMCR Mean Low-Mid	LowIvol 0.44 0.32 0.25 -0.01 0.03 0.11 0.19	2 0.12 0.03 0.30 -0.02 -0.05 0.03 -0.17	3 -0.16 0.12 -0.03 -0.01 -0.33 -0.15 -0.13	4 0.18 -0.04 0.06 0.22 -0.30 -0.18 0.12	HighIvol -0.35 -0.37 -0.31 -0.25 -0.53 -0.63 -0.04	Mean -0.09 0.01 0.05 -0.07 -0.24 -0.14	High-Low -0.79 -0.68 -0.56 -0.24 -0.57 -0.74	p(GRS) 0.00 0.01 0.01 0.07 0.01 0.02

Table 14: Capital ratios and bank size. Monthly returns (%) and alphas (%) for double-sort portfolios, first on total assets, then on market capital ratio $\left(\frac{MV}{MV+D}\right)$. Portfolios are formed on data four months earlier. T-values correspond to a t-test on equality of means with different variances between first/third and fifth portfolio. Alphas are calculated according to equation 1. Results reported in column and row 'mean' correspond to portfolios composed of the individual banks in the respective row or column. Period 1973-2019.

Returns	LowTA	2	3	4	HighTA	Mean	High-Low	t
LowMCR	0.87	1.12	0.87	0.75	0.66	0.93	-0.21	-0.42
2	1.13	1.12	1.30	1.14	0.94	1.17	-0.19	-0.50
MidMCR	1.13	1.13	1.25	1.07	0.88	1.12	-0.24	-0.73
4	1.05	1.09	1.11	1.04	0.77	1.05	-0.28	-0.88
HighMCR	0.82	0.92	0.80	0.79	0.75	0.85	-0.07	-0.22
Mean	1.05	1.11	1.11	1.00	0.85		-0.20	-0.63
Low-Mid	-0.26	-0.01	-0.37	-0.32	-0.22	-0.19		
\mathbf{t}	-0.71	-0.03	-0.94	-0.71	-0.47	-0.54		
Alphas	LowTA	2	3	4	HighTA	Mean	High-Low	p(GRS)
Alphas LowMCR	LowTA 0.17	2 0.19	3 -0.09	4 -0.55	HighTA -0.62	Mean -0.19	High-Low -0.79	p(GRS) 0.04
Alphas LowMCR 2	LowTA 0.17 0.23	2 0.19 0.09	3 -0.09 0.32	4 -0.55 -0.10	HighTA -0.62 -0.34	Mean -0.19 0.04	High-Low -0.79 -0.56	p(GRS) = 0.04 = 0.05
Alphas LowMCR 2 MidMCR	LowTA 0.17 0.23 0.29	2 0.19 0.09 0.16	3 -0.09 0.32 0.21	4 -0.55 -0.10 -0.22	HighTA -0.62 -0.34 -0.40	Mean -0.19 0.04 0.00	High-Low -0.79 -0.56 -0.68	p(GRS) 0.04 0.05 0.01
Alphas LowMCR 2 MidMCR 4	LowTA 0.17 0.23 0.29 0.14	2 0.19 0.09 0.16 0.18	3 -0.09 0.32 0.21 0.06	4 -0.55 -0.10 -0.22 -0.20	HighTA -0.62 -0.34 -0.40 -0.44	Mean -0.19 0.04 0.00 -0.05	High-Low -0.79 -0.56 -0.68 -0.58	$p(GRS) \\ 0.04 \\ 0.05 \\ 0.01 \\ 0.03$
Alphas LowMCR 2 MidMCR 4 HighMCR	LowTA 0.17 0.23 0.29 0.14 0.08	2 0.19 0.09 0.16 0.18 0.00	3 -0.09 0.32 0.21 0.06 -0.25	4 -0.55 -0.10 -0.22 -0.20 -0.34	HighTA -0.62 -0.34 -0.40 -0.44 -0.36	Mean -0.19 0.04 0.00 -0.05 -0.17	High-Low -0.79 -0.56 -0.68 -0.58 -0.43	$p(GRS) \\ 0.04 \\ 0.05 \\ 0.01 \\ 0.03 \\ 0.16$
Alphas LowMCR 2 MidMCR 4 HighMCR Mean	LowTA 0.17 0.23 0.29 0.14 0.08 0.18	2 0.19 0.09 0.16 0.18 0.00 0.12	3 -0.09 0.32 0.21 0.06 -0.25 0.05	4 -0.55 -0.10 -0.22 -0.20 -0.34 -0.27	HighTA -0.62 -0.34 -0.40 -0.44 -0.36 -0.42	Mean -0.19 0.04 0.00 -0.05 -0.17	High-Low -0.79 -0.56 -0.68 -0.58 -0.43 -0.60	p(GRS) 0.04 0.05 0.01 0.03 0.16 0.01
Alphas LowMCR 2 MidMCR 4 HighMCR Mean Low-Mid	LowTA 0.17 0.23 0.29 0.14 0.08 0.18 -0.12	$\begin{array}{c} 2\\ 0.19\\ 0.09\\ 0.16\\ 0.18\\ 0.00\\ 0.12\\ 0.03 \end{array}$	3 -0.09 0.32 0.21 0.06 -0.25 0.05 -0.29	4 -0.55 -0.10 -0.22 -0.20 -0.34 -0.27 -0.33	HighTA -0.62 -0.34 -0.40 -0.44 -0.36 -0.42 -0.22	Mean -0.19 0.04 0.00 -0.05 -0.17 -0.19	High-Low -0.79 -0.56 -0.68 -0.58 -0.43 -0.60	p(GRS) 0.04 0.05 0.01 0.03 0.16 0.01

Appendix A: SIC codes

Compustat SIC codes of banks.

SIC code		frequency	%
6020	Commercial banks	164,726	71.78
6022	State commercial banks	32	0.01
6035	Savings institutions, federally chartered	42,791	18.65
6036	Savings institutions, not federally chartered	$18,\!612$	8.11
6099	Functions Related to Depository Banking, Not Elsewhere Classified	3,324	1.45

Appendix B: List of largest banks

Names of 30 largest banks included in 2015, total assets (Mio\$), market value (Mio\$) and market capital ratio $\left(\frac{MV}{D+MV}\right)$.

Name	TA	MV	MCR
JPMORGAN CHASE & CO	2,351,698	243,065	0.10
BANK OF AMERICA CORP	$2,\!144,\!316$	$175,\!242$	0.08
WELLS FARGO & CO	1,787,632	277,661	0.15
U S BANCORP	421,853	$74,\!637$	0.17
BANK OF NEW YORK MELLON CORP	393,780	$45,\!052$	0.11
PNC FINANCIAL SVCS GROUP INC	$358,\!493$	48,399	0.13
STATE STREET CORP	$245,\!192$	26,775	0.11
BB&T CORP	209,947	29,497	0.14
SUNTRUST BANKS INC	190,817	21,832	0.12
FIFTH THIRD BANCORP	141,082	15,966	0.11
CITIZENS FINANCIAL GROUP INC	138,208	$13,\!819$	0.10
REGIONS FINANCIAL CORP	126,050	12,533	0.10
M & T BANK CORP	122,788	16,152	0.13
NORTHERN TRUST CORP	116,750	$16,\!669$	0.13
KEYCORP	$95,\!133$	11,018	0.12
COMERICA INC	$71,\!877$	7,393	0.10
HUNTINGTON BANCSHARES	71,045	8,811	0.12
GRUPO FINANCIERO SANTANDER	68,394	$28,\!802$	0.32
ZIONS BANCORPORATION	$59,\!670$	5,577	0.10
FIRST REPUBLIC BANK	58,981	9,619	0.15
NEW YORK CMNTY BANCORP INC	50,318	7,914	0.15
CREDICORP LTD	$46,\!378$	7,762	0.16
SVB FINANCIAL GROUP	$44,\!687$	$6,\!123$	0.13
FIRST NIAGARA FINANCIAL GRP	39,918	$3,\!849$	0.10
PEOPLE'S UNITED FINL INC	$38,\!877$	5,010	0.13
POPULAR INC	35,770	2,936	0.09
SIGNATURE BANK/NY	$33,\!451$	7,807	0.20
EAST WEST BANCORP INC	$32,\!351$	5,981	0.17
BOK FINANCIAL CORP	31,476	4,049	0.13
FIRST CITIZENS BANCSH -CL A	31,476	2,841	0.09

Appendix C: Sorts on value-weighted portfolios

Yearly returns (%) on value-weighted portfolios of deciles sorted on market capital ratios $\left(\frac{MV}{MV+D}\right)$, book capital ratios $\left(\frac{CE}{CE+D}\right)$, Basel-adjusted capital ratios $\left(\frac{Tier1+Tier2}{TA_{riskadj}}\right)$ with CE common equity, D book value of liabilities, MV market value of equity. 1a, 1b, 2a and 2b are half-deciles. Returns are buy-and-hold returns in % including dividend payouts and delisting returns. Portfolios are formed on data four months earlier to ensure that the data is publicly available. Alpha5F, and the expected return (ExpReturn5F), are calculated using a 5-factor risk model, according to equation 1. Book to Price (BtP) is book value of common equity over its market value . Mean S&P ratings are calculated assuming equal differences between each category. ReturnS is the return minus the return on the size decile portfolio of each bank. Period 1973-2019.

MCR_decile	Return	AlphaCAPM	BetaCAPM	Alpha5F	ExpReturn 5F	BtP	SPrating	ReturnS
1a	-1.5	-6.8*	1.3	-15.0***	21.6	2.0	BB+	-11.0
1b	3.2	-3.9	1.0	-11.0***	18.9	1.6	BBB	-5.3
2a	8.4	2.3	0.9	-1.7	14.6	1.4	BBB+	-2.5
$2\mathrm{b}$	13.2	4.1	1.1	-1.8	17.4	1.2	BBB+	1.9
3	11.1	2.1	1.1	-3.2	16.7	1.1	A-	0.3
4	10.0	0.7	1.0	-4.6*	16.6	1.0	A-	-0.8
5	12.1	2.5	1.0	-2.2	15.9	0.9	А	0.5
6	10.0	0.6	1.0	-2.7	14.1	0.8	А	-1.3
7	12.3	2.9	0.9	-1.9	15.3	0.8	А	0.8
8	9.7	0.3	0.9	-3.9*	15.1	0.7	$\mathbf{A}+$	-1.7
9	8.3	-1.1	0.9	-4.7**	14.5	0.6	$\mathbf{A}+$	-3.0
10	13.4	3.6^{*}	0.9	2.0^{*}	12.0	0.5	А	1.5

(a) Returns on market capital ratio portfolios

BCR_decile	Return	AlphaCAPM	BetaCAPM	Alpha5F	ExpReturn 5F	BtP	SPrating	ReturnS
1a	4.3	-3.4*	1.1	-8.7**	17.7	1.1	BBB+	-4.5
1b	7.1	-2.0	1.1	-6.3**	16.3	1.0	A-	-3.4
2a	10.7	0.9	1.1	-3.3	16.0	0.9	A-	0.2
$2\mathrm{b}$	9.0	-0.3	1.0	-5.4**	16.6	0.9	A-	-1.6
3	9.6	-0.1	1.1	-3.5	14.9	0.9	А	-0.9
4	10.0	0.6	1.0	-3.7*	15.4	0.8	А	-0.7
5	9.8	0.3	1.0	-2.2	13.7	0.9	А	-2.0
6	9.4	0.2	0.9	-3.4	14.4	0.9	А	-2.4
7	11.8	2.5	0.9	-1.5	14.3	0.8	А	0.2
8	9.8	0.7	0.8	-4.3**	15.6	0.8	A-	-2.1
9	11.6	2.2	0.9	-2.8	15.6	0.9	A-	-0.5
10	14.8	4.8**	0.9	2.9	12.4	0.7	BBB+	1.9

(b) Returns on book capital ratio portfolios

${\rm BaselCR_decile}$	Return	AlphaCAPM	BetaCAPM	Alpha5F	ExpReturn 5F	BtP	SPrating	$\operatorname{ReturnS}$
1a	-3.3	-7.5	1.0	-10.2	12.0	0.9	BBB	-11.9
1b	4.3	-2.4	0.9	-4.6	11.1	0.8	A-	-5.3
2a	8.6	1.6	0.8	-0.5	10.4	0.7	A-	-1.6
$2\mathrm{b}$	7.3	0.8	0.9	-0.5	9.9	0.7	A-	-2.6
3	9.8	2.3	0.9	1.2	10.0	0.7	А	0.2
4	8.5	-0.2	1.1	-1.3	11.0	0.6	Α	-1.4
5	7.8	-1.0	1.1	-1.5	10.4	0.7	Α	-1.7
6	8.9	1.3	0.9	-0.5	10.5	0.7	Α	-0.6
7	9.5	1.8	0.9	1.6	8.6	0.7	A-	-0.4
8	9.5	2.1	0.9	1.0	9.5	0.7	BBB+	-0.6
9	11.9	4.0	0.8	4.1	8.3	0.7	A-	1.0
10	10.4	3.6	0.7 41	1.9	9.1	0.7	BBB	-0.7

(c) Returns on Basel capital ratio portfolios

Appendix D: Sorts on book and risk-adjusted capital ratios

Yearly returns (%) on equally weighted portfolios of deciles sorted on book capital ratios $\left(\frac{CE}{CE+D}\right)$, Merton-adjusted capital ratio $\left(\frac{MV}{MV+D_{merton}}\right)$, Basel-adjusted capital ratios $\left(\frac{Tier1+Tier2}{TA_{riskadj}}\right)$ with CE common equity, D book value of liabilities, MV market value of equity and D_{Merton} the market value of debt calculated with the Merton (1974) model. 1a, 1b, 2a, 2b are half-deciles. Returns are buy-and-hold returns in % including dividend payouts and delisting returns. Portfolios are formed on data four months earlier to ensure that the data is publicly available. Alpha5F, and the expected return (ExpReturn5F), are calculated using a 5-factor risk model, according to equation 1. Book to Price (BtP) is book value of common equity over its market value. Mean S&P ratings are calculated assuming equal differences between each category. p(GRS) reports the p-value of the Gibbons-Ross-Shanken test (H0: all alphas are zero). Period 1973-2019.

BCR_decile	Return	AlphaCAPM	BetaCAPM	Alpha5F	ExpReturn 5F	BtP	SPrating	MV	ТА
1a	2.3	-4.3	1.01	-10.1**	17.3	1.5	BBB-	856	14288
1b	13.3	4.6	0.89	-0.5	15.6	1.3	BBB+	1200	20115
2a	12.4	3.4	0.89	-3.2	17.4	1.2	BBB+	1403	19171
2b	13.4	4.1*	0.84	-1.4	16.0	1.2	BBB+	1799	19071
3	13.9	4.4**	0.84	-0.9	15.6	1.1	A-	2150	20655
4	13.9	4.6^{**}	0.78	-0.2	14.7	1.0	A-	1774	15289
5	14.4	5.1^{***}	0.78	0.4	14.5	1.0	A-	1957	17068
6	13.3	4.0^{**}	0.77	-0.3	14.1	1.0	A-	1653	14683
7	14.8	5.6^{***}	0.73	1.1	14.0	1.0	A-	1148	8917
8	11.9	3.2^{*}	0.68	-1.3	13.8	1.0	BBB+	795	5730
9	12	3.0^{*}	0.71	-1.3	13.8	1.0	BBB-	582	4052
10	13.5	4.6***	0.69	1.3	12.7	0.8	BB+	1748	2752

p(GRS)

0.095

0.019

(d)	Returns	on	book	capital	ratio	portfolios	(N=216, 476)).
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MertonCR_decile	Return	AlphaCAPM	BetaCAPM	Alpha5F	ExpReturn5F	BtP	SPrating	MV	ТА
1a	8.8	2.4	0.97	-2.3	15.4	1.9	9.4	217	8305
1b	12.0	3.8	0.90	-2.8	17.3	1.7	11.7	392	11107
2a	12.3	3.6	0.83	-1.7	15.6	1.4	13.0	645	14067
$2\mathrm{b}$	16.5	7.3^{***}	0.81	1.4	15.9	1.3	13.5	1208	19579
3	16.6	7.3^{***}	0.76	1.6	15.5	1.2	13.2	1536	17971
4	15.6	6.3^{***}	0.76	1.7	14.2	1.1	13.8	1567	16419
5	13.0	3.8^{**}	0.77	-0.8	14.4	1.0	14.2	1404	13828
6	15.2	6.1^{***}	0.73	1.1	14.5	0.9	14.5	1381	12439
7	12.8	3.7^{**}	0.75	-1.2	14.7	0.9	14.8	1445	11685
8	11.4	2.5	0.73	-1.9	14.1	0.8	15.1	1798	12179
9	9.7	0.8	0.75	-3.3**	13.9	0.8	15.3	1506	8740
10	9.1	-0.2	0.81	-3.0**	13.0	0.7	14.1	2523	5279
p(GRS)		0.000		0.000					

(e) Returns on Merton-adjusted capital ratio portfolios (N=216,476).

$BaselCR_decile$	Return	AlphaCAPM	BetaCAPM	Alpha5F	ExpReturn 5F	BtP	SPrating	MV	ТА
1a	7.8	3.0	0.74	2.40	8.3	1.1	BBB	616.0	4660.0
$1\mathrm{b}$	8.5	2.6	0.71	0.50	9.7	1.0	BBB+	1424.0	9559.0
2a	13.1	6.2^{**}	0.69	4.8^{*}	8.9	0.9	BBB+	2513.0	16888.0
2b	11.6	4.8	0.67	4.2^{*}	7.9	0.9	BBB+	3036.0	20388.0
3	12.4	5.4**	0.67	4.9^{**}	7.8	0.8	A-	2766.0	20167.0
4	12.9	5.5^{**}	0.71	3.20	9.9	0.8	A-	2978.0	22258.0
5	13.4	6.3^{**}	0.65	4.9^{**}	8.6	0.8	A-	2641.0	21062.0
6	12.8	5.8^{**}	0.65	4.4**	8.5	0.8	BBB+	2517.0	20445.0
7	12.3	5.4^{**}	0.62	4.2^{**}	8.2	0.8	BBB+	2558.0	23317.0
8	13.2	6.6^{***}	0.58	5.2^{***}	8.0	0.9	BBB	2420.0	19958.0
9	13.9	7.3^{***}	0.54	42:3***	7.5	0.9	BBB+	1215.0	9551.0
10	11.0	5.1^{***}	0.45	3.7^{**}	7.3	0.9	BBB	502.0	2611.0
n(GRS)		0.014		0.007					

p(GRS)

(f) Returns on Recol adjusted capital ratio portfolios (N-151 170)

Appendix E: Sorts during recessions and high bank volatility

Yearly returns (%) on equally-weighted portfolios sorted on deciles of market capital ratios $\left(\frac{MV}{MV+D}\right)$. Returns are yearly buy-and-hold returns in % including dividend payouts and delisting returns. Portfolios are formed on data four months earlier to ensure that the data is publicly available. Recessions are NBER recessions and highoindicates that the volatility of the value-weighted index of all bank stocks is high, beyond the 80th percentile, as in Bouwman et al. (2018). In Sub-Table 15h, alpha5F is calculated using a 5-factor risk model, according to equation 1. Alpha5F_noRecession corresponds to the risk-adjusted return in non-recessionary periods and is calculated using equation 1 augmented with a dummy variable indicating NBER recessions. Alpha5FNoRecession is the coefficient on this NBER dummy variable and can be interpreted as the difference in alpha in periods of high volatility. Similarly, Alpha5F_Low\sigma and Alpha5F_High\sigma are calculated using equation 1, augmented with a dummy variable indicating a period of high volatility. Alpha 5F&F refers to the Fama and French (2015) 5-factor model. The p(GRS) reports the p-value of the Gibbons-Ross-Shanken test (H0: all alphas are zero). Period 1973-2019.

MCR_decile	Return	${ m Return NoCrisis}$	ReturnCrisis	$Return_Low\sigma$	Return_Higho
1	7.5	9.0	-0.9	9.4	0.6
2	15.4	18.5	-1.9	18.0	6.0
3	15.4	18.4	-1.4	17.8	6.6
4	14.3	16.9	-0.4	15.4	10.1
5	13.9	16.2	0.8	15.7	7.4
6	14.4	16.4	3.3	15.0	12.3
7	14.3	16.3	2.9	14.7	13.0
8	11.8	13.6	0.8	12.2	9.9
9	10.7	12.7	-0.7	11.2	8.6
10	10.4	12.0	0.7	9.3	14.6

(g) Returns

MCR_decile	Alpha5F	Alpha5FNoRecession	Alpha5FRecession	$Alpha5F_Low\sigma$	$Alpha5F_High\sigma$	Alpha5FF	Alpha5FFNoCrisis	Alpha5FFCrisis	$Alpha5FF_Low\sigma$	Alpha5FF_High σ
1	-5.7	-5.7	-0.4	-3.1	-12.4	-4.7	-5.3	4.4	-2.9	-9.2
2	0.9	2.6	-11.6	4.2	-14.9	1.7	3.0	-8.7	4.3	-12.2
3	0.7	2.4	-11.4	3.8	-13.9	2.0	3.4	-9.0	4.5	-11.6
4	-0.0	1.4	-9.4	1.9	-9.2	0.7	1.8	-7.5	2.2	-7.2
5	-0.3	0.9	-8.3	2.3	-11.9	0.4	1.3	-6.4	2.6	-10.2
6	0.4	1.2	-5.3	1.8	-6.7	0.8	1.4	-4.1	1.8	-5.0
7	0.6	1.4	-5.5	1.8	-5.7	0.7	1.3	-4.4	1.5	-3.8
8	-1.6	-0.8	-5.6	-0.3	-6.3	-1.4	-0.8	-4.7	-0.5	-4.8
9	-2.4	-1.7	-5.1	-1.1	-6.2	-2.2	-1.6	-4.4	-1.3	-4.7
10	-1.4	-0.9	-3.6	-1.2	-1.1	-1.6	-1.3	-2.3	-1.8	0.9
p(GRS)	0.03	0.017	0.005	0.003	0.001	0.013	0.006	0.001	0.003	0.001
					(h) Alphas					

Appendix F: Sensitivity to size and sample periods

Figure 3: Yearly returns on equally-weighted portfolios sorted both on deciles of market capital ratios $\left(\frac{MV}{MV+D}\right)$ and size. Returns are yearly buy-and-hold returns in %, including dividend payouts and delisting returns. Portfolios are sorted monthly and formed on quarterly data four months earlier.



(a) Yearly returns (%) on equally weighted portfolios sorted first on deciles of market capital ratios $\left(\frac{MV}{MV+D}\right)$, then on terciles of size (market value at the end of the preceding period). Portfolio-months with less than 5 banks are omitted.



(b) Returns for different sub-periods. In 1988 the Basel I agreement starts, which sets international standards on banking safety. In 1999, the Glass-Steagall Act was appealed, allowing banks to engage in riskier banking activities. Before 1994, the dataset gradually improves coverage, increasing the dataset from 139 banks in 1973 to 817 in 1994. After 1994, banks consolidate, leading to 382 banks in 2019.

Appendix G: Bobustness to resampling

Figure 4: Yearly returns (%) on equally weighted portfolios sorted on market capital ratio $\left(\frac{MV}{MV+D}\right)$. Returns are yearly buy-and-hold returns in %, including dividend payouts and delisting returns. Portfolios are sorted monthly and formed on quarterly data four months earlier. Alpha's are based on equation 1. The results show 90% confidence intervals for 1000 Monte Carlo runs resampling the data. In the case of bootstrapping, a sample of the same size is randomly selected with replacement. In the case of 'resample 80%', each run randomly omits 20% of the data. This relates to a jackknife technique but instead of dropping 1 observation, 20% of the sample is dropped. Period 1973-2019.



(b) Alphas

Appendix H: Principal Component analysis of the residual of the 5factor model

Loadings on the three first principal components of the error in equation 1 for returns on 10 portfolios sorted on market capital ratio $\left(\frac{MV}{MV+D}\right)$. The three principal components explain respectively 63%, 14% and 5% of the variation of the error terms. The first component has loadings of similar magnitude on the different portfolios and captures common shocks to all banks. The second component has high loadings on low-capital portfolios and negative loadings on high-capital portfolios, capturing shocks that have the opposite effect for high- and low-capital banks. The third component has high loadings both on high- and low-capital banks, capturing shocks that are common for both the highest and lowest-capital banks, and have the opposite effect on banks with an intermediate capital ratios. In a similar way as PC2 in Gandhi and Lustig (2015), I construct PC2 as $PC_{2,t} = \sum_i \lambda_{2,i} r_{i,t}$, with $\lambda_{2,i}$ the loading of portfolio i on the second principal component and $r_{i,t}$ the return on portfolio i at time t. The alphas for the 5-factor model augmented with PC2 as a 6th factor is reported in model 6 of Figure 1b. Period 1973-2019.

Market capital ratio decile	First	Second	Third
1 (lowest capital ratio)	0.2092	0.5833	0.4156
2	0.2876	0.4619	0.0372
3	0.3267	0.2886	-0.1223
4	0.3452	0.1414	-0.2088
5	0.3536	-0.0159	-0.2343
6	0.3473	-0.1302	-0.0910
7	0.3462	-0.1866	-0.1472
8	0.3300	-0.2667	-0.1111
9	0.3207	-0.3358	-0.0015
10 (highest capital ratio)	0.2651	-0.3274	0.8186

(i) Loadings on the three first principal components.

Appendix I: Size-adjusted returns

Size-adjusted monthly returns (%) for double-sort portfolios first sorted on book-to-price, beta, ivol then on market capital ratios $\binom{MV}{MV+D}$. Size-adjusted returns are calculated by subtracting for each bank the return of its size portfolio, constructed on market value deciles at the end of the preceding month. Asset BtP is defined as $\frac{TA}{TA-CE+MV}$ with TA being the total assets, CE the book value of common equity, and MV the market value of equity. Betas are calculated using the CAPM over a rolling window over the last 5 years (min 2 years). ivol is the variance of the error term in the 3-factor Fama & French model on daily data as in Liu et al. (2018). Portfolios are formed on data four months earlier. T-values correspond to a t-test on equality of means with different variances between first/third and fifth portfolio. Results reported in column and row 'mean' correspond to portfolios composed of the individual banks in the respective row or column. Period 1973-2019.

	LowAssetBtP	2	3	4	${\rm HighAssetBtP}$	Mean	High-Low	t(t-test)
LowMCR	-0.33	-0.16	0.01	-0.38	-0.42	-0.17	-0.09	-0.29
2	-0.09	-0.01	0.05	0.19	-0.02	0.05	0.07	0.38
MidMCR	-0.26	0.18	0.10	0.11	-0.05	0.04	0.20	1.34
4	-0.07	-0.02	0.06	0.07	0.04	0.04	0.10	0.71
HighMCR	-0.26	-0.34	-0.01	-0.04	0.00	-0.11	0.26	1.35
Mean	-0.17	-0.04	0.07	0.03	-0.03		0.14	1.34
Low-Mid	-0.08	-0.34**	-0.08	-0.50**	-0.36	-0.21*		
t(t-test)	-0.43	-2.10	-0.42	-2.01	-1.31	-1.82		
		(j) Book-t	o-price vers	sus leverage			

	Lowbeta	2	3	4	Highbeta	Mean	High-Low	t(t-test)
LowMCR	-0.12	-0.23	-0.06	0.07	-0.50	-0.18	-0.38	-1.29
2	0.04	0.12	-0.08	0.09	0.11	0.05	0.08	0.36
MidMCR	-0.16	0.00	-0.04	0.21	0.17	0.06	0.32^{**}	2.04
4	-0.18	-0.12	0.05	0.05	0.07	0.00	0.25	1.64
HighMCR	-0.34	-0.29	0.02	0.05	-0.11	-0.08	0.23	1.15
Mean	-0.10	-0.08	-0.01	0.12	-0.03		0.07	0.57
Low-Mid	0.03	-0.23	-0.02	-0.14	-0.66**	-0.24^{*}		
t(t-test)	0.19	-1.35	-0.11	-0.66	-2.40	-1.79		

(\mathbf{k}	Beta	versus	leverage
1	(n)	Deta	versus	leverage

	Lowivol	2	3	4	Highivol	Mean	High-Low	t(t-test)
LowMCR	0.36	0.26	-0.02	0.12	-0.60	-0.01	-0.96***	-3.27
2	0.26	0.13	0.18	-0.04	-0.58	0.06	-0.84***	-3.42
MidMCR	0.17	0.26	0.09	0.04	-0.39	0.11	-0.55***	-3.08
4	-0.02	0.10	0.02	0.02	-0.43	-0.01	-0.40**	-2.21
HighMCR	-0.02	-0.08	-0.40	-0.33	-0.68	-0.23	-0.65***	-3.34
Mean	0.07	0.13	-0.03	-0.10	-0.68	•	-0.75***	-3.38
Low-Mid	0.19	0.00	-0.11	0.08	-0.21	-0.12		
t(t-test)	1.48	-0.02	-0.70	0.39	-0.67	-1.13		

(l) Ivol versus leverage

Appendix J: One dimensional sorts on S&P rating, beta and ivol

Yearly returns (%) on portfolios sorted on S&P rating groups, S&P quintiles and beta deciles. S&P ratings are domestic long-term issuer credit ratings. Betas are calculated using the CAPM over a rolling window over the last 2 years. Ivol is the variance of the error term in the 3-factor F&F model on daily data as in Liu et al. (2018). Returns are monthly buy-and-hold returns in % including dividend payouts and delisting returns. Portfolios are formed on information available at the end of the preceding month. Alpha5F, and the expected return (ExpReturn) are calculated using a 5-factor risk model, according to equation 1. MCR corresponds to market capital ratio $\left(\frac{MV}{MV+D}\right)$

and BaselCR corresponds to Basel-adjusted capital ratios $\left(\frac{Tier1+Tier2}{TA_{riskadj}}\right)$.

$SPrating_group$	Return	AlphaCAPM	BetaCAPM	Alpha5F	ExpReturn 5F	MCR	BaselCR	# obs
AAA, AA+, AA-	6.7	-1.7	1.05	-3.9	14.0	0.17	0.14	2697
A+	11.0	1.5	1.03	-0.1	13.9	0.26	0.13	2630
Α	10.9	0.9	0.98	-2.7	16.8	0.36	0.13	4212
A-	11.8	3.5	0.84	-0.0	14.3	0.21	0.13	4650
BBB+	10.2	2.3	0.85	-2.5	16.0	0.16	0.13	3488
BBB, BBB-	9.5	1.1	0.95	-3.1	16.2	0.15	0.14	6169
BB+, BB, BB-	9.6	-1.0	1.11	-6.3	22.0	0.14	0.16	2366
B+, B, B-	1.8	-5.7	1.49	-13.9	30.1	0.15	0.16	928

(m) Returns on S&P rating groups. S&P ratings are only available for a subset of banks from December 1986 onwards (86 banks in 1986, 110 in 1988 and 59 in 2015). Therefore, portfolio-months with less than 3 banks were excluded.

SPrating quintile	Return	AlphaCAPM	BetaCAPM	Alpha5F	ExpReturn 5F	MCR	BaselCR	# obs
5	10.2	0.5	1.05	-1.8	14.9	0.28	0.14	5502
4	11.9	3.1	0.90	-0.1	14.6	0.19	0.13	5499
3	12.3	3.9	0.87	-0.8	15.9	0.16	0.13	5495
2	10.5	1.9	0.94	-2.5	16.4	0.16	0.14	5501
1	8.7	0.0	1.16	-3.2	17.0	0.15	0.15	5464

(n) Returns on S&P rating quintiles. S&P ratings are only available for a subset of banks from December 1986 onwards.

beta decile	Return	AlphaCAPM	BetaCAPM	Alpha5F	ExpReturn 5F	MCR	BaselCR
1	13.4	5.0	0.49	1.4	12.8	0.12	0.2
2	14.9	5.9	0.55	1.1	14.7	0.11	0.2
3	14.6	5.2	0.61	0.7	15.0	0.11	0.2
4	14.8	5.0	0.67	0.5	15.6	0.12	0.2
5	15.6	5.6	0.68	1.0	15.8	0.12	0.2
6	15.2	5.3	0.70	-0.0	16.8	0.12	0.1
7	16.8	6.1	0.79	1.2	17.1	0.13	0.1
8	17.1	6.0	0.86	1.2	17.8	0.12	0.1
9	15.8	4.8	0.90	0.4	17.8	0.12	0.1
10	13.5	1.9	1.11	-3.8	21.6	0.17	0.2

(o) Returns on CAPM Beta portfolios. Period 1973-2019.

Ivol decile	Return	AlphaCAPM	BetaCAPM	Alpha5F	ExpReturn 5F	MCR	BaselCR
1	13.0	4.9	0.55	1.4	12.4	0.12	0.2
2	15.0	6.0	0.70	1.6	14.6	0.11	0.2
3	14.4	5.5	0.71	0.7	15.1	0.11	0.2
4	14.8	5.7	0.74	0.3	16.0	0.11	0.2
5	13.5	4.5	0.75	-0.2	15.3	0.11	0.2
6	13.8	4.8	0.75	-0.1	15.6	0.10	0.2
7	14.6	5.5	0.75	1.0	15.1	0.10	0.2
8	13.2	4.6	0.73	0.1	14.9	0.09	0.2
9	12.3	3.7	0.75	-1.4	15.9	0.09	0.2
10	7.6	-0.2	0.86	-5.1	16.7	0.09	0.1

(p) Returns on Ivol portfolios. Period 1973-2019.