Does stricter capital requirement raise the cost of capital of banks?

A theoretical and empirical study of banks in the US

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Number of Pages: 70

A thesis submitted in partial fulfillment of the requirements for the degree of
MSc. in Advanced Economics and Finance (cand.oecon)

Copenhagen Business School
May 15, 2020

Acknowledgements

This master thesis is the final work for obtaining the degree of MSc in Advanced Economics and Finance at Copenhagen Business School. I would like to express my sincere gratitude to everyone who supported me throughout this thesis work. It is not going to be possible without your help and guidance.

Firstly, I would like to give special thanks to my supervisor David Lando. His supervision, inspiration and critical judgements help me to find out present short-comings and provide guidance for improvements.

I would like to thank the lecturers in my master program. From their lectures I have learned so much knowledge in Finance and Economics. I would also like to thank Jens Dick-Nielsen, for his help with data and explaining his work to me.

Last but not least, I would like to thank my parents and my boyfriend, for their endless love and support.

Roskilde, Denmark
May 15, 2020
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Abstract

This thesis examines the impacts of increased capital requirement on the cost of capital of banks. We revisit the work by Baker and Wurgler [2015] and Dick-Nielsen et al. [2019] that propose different models to measure the cost of capital and then investigate the impacts of the heightened capital requirement on banks. In the former study, the cost of equity is measured by the CAPM which is adjusted by a low risk anomaly. Meanwhile, the debt is assumed to be riskless. We reproduce the tests and find the stricter capital requirement will lead to a significant increase in the total cost of capital in banks when applying this approach. We further relax the riskless debt assumption to include the risk of debt in the modeling framework. After this modification, we find the predicted increase in the total cost of capital using the original approach is too large. In the latter study by Dick-Nielsen et al. [2019], the cost of equity is measured by the implied cost of capital and the cost of debt is modeled through the interest expenses of banks. Then the regressions of cost of equity, cost of debt and total cost of capital on the capital ratio are performed. We reproduce the tests and find the stricter capital requirement will lead to a large decrease in the cost of equity and a moderate decrease in the cost of debt. These effects will finally balance out which means the total cost of capital will not increase significantly. We also extend this approach by an additional regression of implied cost of capital on the multiplicative inverse of capital ratio, rather than on the capital ratio. The proposed regression predicts a much smaller decrease in the cost of equity due to the same amount of increase in the capital ratio, compared to the original regression. This result indicates that the estimation of the change in the total cost of capital might be understated in the original approach. From the two proposed methods, we have a consistent conclusion that the stricter capital requirement will lead to a moderate increase in the total cost of capital for banks with the current level of leverage.

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Chapter 1

Introduction

The stability of banks is of vital importance for the financial stability of the society. The Basel I in 1988 marked the start of the international standards for bank regulation. Since then, there has been an evolutionary process of bank regulation. In response to the financial crisis of 2007–08, the recent regulation on banks has been moving towards a stricter framework with refined requirements to further improve the financial stability. One basic principle in the Basel Accords is the capital adequacy of financial institutions. According to the latest agreement in Basel III, the total Tier 1 capital of banks must be at least 6% (which is 4% before Basel III) of the risk weighted asset (RWA) at all times (Hull [2018]). The Tier 1 capital is the core capital of a bank, which is mainly consisted of the common equity and the retained earnings. The risk weighted asset is a bank's assets weighted according to different categories of risks. Thus, the ratio of Tier 1 capital over RWA, which is called the Tier 1 capital ratio, measures the financial strength of a bank. Apart from raising the Tier 1 ratio, the Basel III also introduces two capital buffers: the capital conservation buffer (CCoB) and the counter-cyclical capital buffer (CCyB). The CCoB is an additional capital requirement on top of the Tier 1 ratio. When this additional requirement is not satisfied, an automatic constraint on the capital distribution will be imposed to replenish the buffer. The CCyB is a more macroprudential approach, which will be activated by the authorities when they judge the aggregate credit growth to be excessive. So, the CCyB can protect the banking sectors from the system-wide risks (BIS [2020]).

The updated regulation is forcing banks to reduce the reliance on debt financing, which ensures the stability of banks by directly improving the capital adequacy. But it also raises concerns about the impacts on the funding costs of banks. Many bankers argued that equity is expensive and debt is cheap, thus a higher capital requirement will make the total financing more costly. However, some researchers (e.g. Miller [1995], Admati and Hellwig [2014]) pointed out that when the bankers claim the total funding is more expensive because of using more equity capital, they have ignored the reduced risks carried by the banks. Because banks with higher capital adequacy will bear lower risks, their expected return of equity should be lower.

The lowered cost of equity can balance out the effect of the increased weight of equity. As a result, a higher capital ratio will not increase the total cost of funding. This argument is also supported by the irrelevance of capital structure in the Modigliani–Miller (MM) theorem.

Apart from the theoretical arguments, some existing literature investigated this problem empirically based on the data of banks. For example, Baker and Wurgler [2015] explored the relationship between risk, leverage, and total cost of capital of banks in the US. They showed that a higher capital requirement does increase the total cost of capital significantly. However, Dick-Nielsen et al. [2019] explored the relationships between the implied cost of capital, the expected cost of debt and leverage of banks. Their results empirically confirmed the MM irrelevance theorem in banks.

The motivation of this thesis origins from the debates on whether the capital structure of banks can affect the total cost of capital. In the existing literature, the conclusions from the empirical tests with different theoretical models and assumptions using similar data could be completely different. So, this thesis is to investigate the extent of the influence of the capital structure on the cost of capital. Firstly, the relevant literature is reviewed to provide the theoretical basis for the investigation. Then, the empirical tests by Baker and Wurgler [2015] and Dick-Nielsen et al. [2019] are reproduced with updated datasets. Some additional tests based on modified or alternative models proposed in this thesis are also performed. Finally, the results from different tests are compared and the conclusion is made.

The thesis is structured as follows: Section 2 reviews the literature. Section 3 describes the major methodologies that Baker and Wurgler [2015] and Dick-Nielsen et al. [2019] applied as well as the approaches proposed in this thesis. Section 4 introduces the datasets involved in the analysis with a brief inspection of them. Section 5 utilizes the different models and datasets to perform the various tests and then analyzes the results. Section 6 draws the conclusions of the thesis.

Chapter 2

Literature Review

This chapter is divided into three parts for a better overview of the theoretical basis applied in this thesis. Section 2.1 reviews the literature on the capital structure of firms in general, which is not limited to banks. Section 2.2 reviews the literature of two traditional measures of the cost of capital: the Capital Asset Pricing Model (CAPM) and the Implied Cost of Capital (ICC). Section 2.3 focuses on the banking literature and explains the particularity of the bank industry.

2.1 Capital structure theories

The literature on capital structure commenced with the famous paper by Modigliani and Miller [1958], which is the theoretical cornerstone of the modern corporate finance. It states in a frictionless condition with a stable investment policy and in the absence of taxes, transaction costs, asymmetric information and arbitrage opportunities, there is no optimal capital structure. The firm value and total cost of capital will remain constant regardless of the composition of debt and equity. The conclusion originates from the unrealistic condition that all of the five assumptions are satisfied. Thus, a large number of further studies are built on the MM theorem by relaxing one or more of these assumptions. These studies are characterized by a dominant dichotomy between asymmetric information models and trade-off models.

The asymmetric information models take into account the information discrepancies between different parties, e.g. shareholders and managers, corporate insiders and outside investors. For instance, Ross [1977] proposed that if the firm managers have access to the inside information, the firm can signal its quality by issuing more debt. This signal is credible due to the potential bankruptcy costs. Another contribution to the asymmetric information model is by Myers and Majluf [1984]. They proposed that the firms facing the adverse selection issues will prefer internal financing over outside financing, because of the absence of issuing costs and information costs of the internal cash flows. When the internal funding is insufficient, issuing debt is preferred rather than equity. This is because the equities can be over- or under-valued. The firm managers with inside information will be reluctant to issue new equities if the equities are undervalued. Inversely, if the managers choose to issue new equities, it can be interpreted as a consequence of the equities being overvalued. Hence, the investors who have correctly anticipated the overvalued equities are not willing to pay the high price. So the managers will prefer to issue debts over equities. Hence, a descending pecking order consisting of retained earnings, debt and equity emerges. The pecking order theory provides support to the argument that equity capital is more expensive.

The trade-off model was firstly attributed to Kraus and Litzenberger [1973] who argued that the optimal capital structure should balance the tax benefits against the financial distress costs of debt. Because the interest on debt is a tax-deductible expense for firms, relying on debt funding can create tax shields. Meanwhile, more debt can cause the firm to be more fragile and generate direct and indirect financial distress costs. Thus, the firms should trade off the benefits and costs induced by debt. These two effects of debt are quantitatively investigated by Andrade and Kaplan [1998] and later by Graham [2000]. Graham tried to answer the question of "How big are the tax benefits of debt?", and he concluded that, the tax benefits of debt equal to 9.7% of the firm value on average (4.3% when taking the personal taxes into account). Despite the significance of tax shields, exploring the direct impact of tax shields in banks, however, is a complicated task. Andrade and Kaplan tried to answer the question of "How costly is financial (not economic) distress?". They observed evidence from the highly leveraged transactions and concluded that the financial distress costs approximately equal to 10% to 20% of the firm value. These studies provide straightforward numbers showing the magnitude of the frictions regarding the capital structure.

The trade-off theory as well as the asymmetric information theories reflect the relevance of the capital structure on the firm value under various conditions. These theories could also interpret why the banks still hold a certain amount of equity in the absence of strict bank regulation in the early years, despite many bankers claim that equity capital is too expensive.

2.2 Cost of capital theories

In order to answer the research question of whether the cost of capital can be affected by the capital structure change due to the regulation, it is necessary to appropriately measure the two variables. The capital structure variables can be obtained from the balance sheet or the supplementary balance sheet, but the cost of capital cannot be directly obtained.

The (total) cost of capital is usually referred to the weighted average of the cost of equity capital (r_e) and the cost of debt capital (r_d), which is commonly noted as WACC or r_a. It is the rate that a firm is expected to pay on average to all of its security holders to finance itself.

$$r_a = \frac{E}{D+E} r_e + \frac{D}{D+E} r_d \tag{2.1}$$

In the equation of WACC, the weights are the ratios of the equity capital (E) and the debt capital (D) over the total capital ($D+E$). As implied by the MM theorem, if more equity capital is used ($\frac{E}{D+E}$ rises), the risk of the capital carried by the firm will fall. Since the required return of an asset can be partly considered as the compensation for bearing the corresponding risk, the reduced risk will cause the return of expected equity to fall. This will balance out the effect of the increased weight of equity capital. In the previous argument, the positive correlation between return and risk is used, but the risk is not explicitly shown in Equation 2.1. Driven by this relationship, Kashyap et al. [2010] as well as later Baker and Wurgler [2015] utilized the CAPM to measure the cost of capital in banks through risks. In addition, Baker and Wurgler [2015] observed a low risk anomaly in banks which distorted the CAPM prediction. To better understand these studies and properly apply these theoretical tools in this thesis, some relevant papers are reviewed.

2.2.1 CAPM and low risk anomaly

The CAPM (Sharpe [1964], Lintner [1965]) is a theoretical pillar of the asset pricing theories. It predicts the expected return of an asset (single asset or single portfolio) to be proportional to its systematic risk. Letting $\mathbb{E}(r_i)$ and $\mathbb{E}(r_m)$ denote the expected return of asset i and the market; letting r_f denote the risk-free rate and β_i denote the systematic risk of asset i, the CAPM has the model equation:

$$\mathbb{E}(r_i) = r_f + \beta_i[\mathbb{E}(r_m) - r_f] \tag{2.2}$$

However, the results from a series of empirical tests are having large discrepancies with the CAPM prediction. Fama and French [2004] did a comprehensive review of the logic behind the CAPM and the previous relevant tests. One of the earliest tests is to regress a cross-section of the asset returns ($\mathbb{E}(r_i)$) on asset betas (β_i). As implied by Equation 2.2, the slope of such a regression should be equal to the market excess return over the risk-free rate $\big(\mathbb{E}(r_m) - r_f\big)$. But there are two problems in this type of regression. Firstly, the true beta (β_i) of an individual asset is unknown. Only a proxy of the beta ($\hat{\beta}_i$) estimated from the historical returns could be obtained. In Section 3, the estimation of beta is described in detail. This estimation process generates measurement errors which can affect the test results. Secondly, the regression residuals have common sources of variation, which can lead to a downward bias of the estimated slope.

To solve the problem of measurement errors, some researchers worked with portfolios rather than single assets in the regression. For example, Black et al. [1972] showed the estimated beta of a diversified portfolio ($\hat{\beta}_p$) is more precise than that of an individual asset ($\hat{\beta}_i$). However, forming portfolios largely reduces the number of observations, which will reduce the statistical power of the regression. This is mitigated by sorting the individual assets according to the individual betas ($\hat{\beta}_i$) and then grouping them into portfolios.

To mitigate the common source of residual problem, Fama and MacBeth [1973] proposed to perform the month-by-month cross-section regressions of returns on betas, instead of performing a single cross-section regression. Meanwhile, they described an important regression phenomenon induced by the beta sorting procedure. When estimating the individual betas, a high risk asset tends to have $\hat{\beta}_i$ exceeding the corresponding true β_i, while a low risk asset tends to have a $\hat{\beta}_i$ lower than its true β_i. On this basis, the phenomenon will also exist in the portfolios. This problem can be mostly mitigated by the modified grouping procedure proposed by Fama and MacBeth [1973]: ranking the individual assets based on the value of $\hat{\beta}_i$ computed from the data within one time period but computing the value of $\hat{\beta}_p$ of the portfolios within another time period. This procedure is now standard in testing the CAPM theories. It was applied by Baker and Wurgler [2015] and will also be used in this thesis.

Alternative to the cross-section regression, Jensen [1968] proposed a time-series regression of returns on betas:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \epsilon_{i,t} \tag{2.3}$$

In the regression, α_i is the intercept (called Jensen's alpha or alpha) which should be zero if the CAPM holds. With this regression method and the aforementioned grouping procedure, Black et al. [1972] empirically confirmed that the alpha is non-zero and accordingly rejected the CAPM. The value of alpha is greater than zero for the low-beta assets and smaller than zero for the high-beta assets. This phenomenon is called the low risk anomaly. Fama and French [2004] updated the test result using data covering a longer time interval and illustrated it in a plot as shown in Figure 2.1. The dots in the figure represent the realized returns of the beta-sorted portfolios. The returns of the corresponding betas predicted by the CAPM will lie on the solid line. The dots of the portfolios with lower betas are above the line, which indicates positive alphas. Meanwhile, the dots of the portfolios with higher betas are below the line, which indicates negative alphas.

The low risk anomaly is further investigated and interpreted. One explanation is that many investors are constrained by their abilities of borrowing. So, these investors will seek high returns by trading high risk assets. As a result, the high-beta assets will have relatively high prices (with low returns) due to the higher demand (Frazzini and Pedersen [2014]). Alternatively, Baker et al. [2011] explained the anomaly with the theory of behavioural finance. Some investors may have a preference for lotteries and might be overconfident, resulting in an irrational high demand of high risk assets in the market.

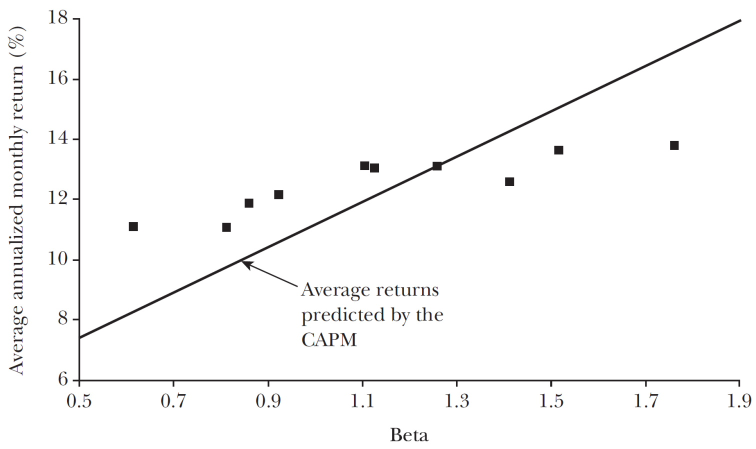

Figure 2.1: The illustration of the low risk anomaly. The firms are sorted into ten portfolios in each period according to the beta. For each portfolio, the return and beta are computed and plotted as the dots. The solid line illustrates the expected return, for given value of beta, predicted by the CAPM. Visually, the slope of the CAPM line is larger than the slope of the trend of the dots. The high-beta portfolios have their realized returns lower than the CAPM predictions, while low-beta portfolios have realized returns over the CAPM predictions.

Source: Fama and French [2004]

The interpretations vary in different papers, but the anomaly does exist in the firms within many industries. Baker and Wurgler [2015] confirmed its existence in banks with even larger strength than other industries. Following their method, this thesis will also apply the standard grouping procedure in testing the CAPM and examine the low risk anomaly in banks.

2.2.2 Implied cost of capital

As argued by Elton [1999], the realized return is too noisy to be a good measure of the expected return. Thus, some researchers utilized the asset pricing models, such as the CAPM, to measure the expected return. But the CAPM is still heavily relying on the noisy realized returns. In addition, the failure of the CAPM in the empirical tests raised concerns about the precision in further research regarding the expected return (Hou et al. [2012]). Besides the CAPM, the implied cost of capital (ICC) is an increasingly popular class of proxies for the expected return of equity. It is defined as the internal rate of return letting the current stock price to be equal to the discounted expected future dividends. It is an ex-ante approach that one can infer the return from the current price and the expected future dividends. Thus, the ICC does not rely on the noisy realized returns as in the CAPM or some other asset pricing models.

There have been several ICC variants based on different assumptions, e.g., Gordon and Gordon [1997], Ohlson and Juettner-Nauroth [2005] and Easton [2004]. The common aspect behind the listed three variants is to use the analysts' forecasts of the firm's performance to model and estimate the expected future dividends.

2.3 Capital structure and cost of capital in banks

The literature on the capital structure and cost of capital of the banks, which belong to a specific category of firms, is reviewed in this section. It coincides with the focus of the research topic in this thesis.

In the US, most of the non-financial firms have their liabilities less than 50% of the total assets. But for banks, the liabilities usually account for more than 80% of the total assets (see Figure A.2 in Appendix A). Generally, banks are making profits by selling liabilities (e.g., deposits) and using the proceeds to buy assets (e.g., loans). During this process, banks also offer services such as check clearing, record keeping and so forth (Mishkin [2013]). The business model and capital structure of banks are different from the non-financial firms, which cause researchers and bankers to ask: Do the MM propositions apply to banks? Bankers suggest that equity capital is more expensive than debt capital, higher equity financing increases the total cost of capital and harms the growth of the banking business. Instead, Miller [1995] argued that the cost of equity capital is not a fixed number but a function depends on the risk of the banks. He concluded that the enhanced capital requirement will reduce the risk of banks. Meanwhile, it will be the cheapest solution in the regulatory framework.

To find evidence from the historical data, many researchers related the banks' capital structure to the cost of capital through the CAPM theories. Kashyap et al. [2010] estimated the systematic risk (beta) of single banks, and tested the relationship between leverage and beta. They argued that if the CAPM holds, the cost of equity will increase proportionally to leverage. According to their calculation, the estimated increase in the WACC of banks is around 25 basis points (bps) per year corresponding to a ten percentage points increase in the capital ratio. Miles et al. [2013] used the UK banks' data to investigate the same problem. Rather than assuming the CAPM holds strictly, they performed a series of regressions to estimate the effects of leverage on beta as well as on the cost of equity. They concluded that even if the amount of equity capital is doubled, the average cost of bank funding will only increase by about 10-40 bps per year. In addition, they used a shock model to show that a higher portion of equity capital structure will reduce the probability of a banking crisis. The increased stability is beneficial to the banks and the society.

Baker and Wurgler [2015] utilized a modified CAPM with a low risk anomaly to measure the cost of equity. The strength of the anomaly was further estimated to show to what extent the stricter capital requirement will increase the total cost of capital. They concluded that ten percentage points of increase in the capital requirement will lead to about 85 bps of increase in the total cost of capital per year. Thus, it is costly for banks to cut down debt financing due to stricter regulations.

Deviating from the above studies based on the CAPM, Dick-Nielsen et al. [2019] used an

ICC model to estimate the expected cost of equity and used the real interest expenses to model the expected cost of debt. They observed that reducing leverage does reduce both the ICC of equity and the expected cost of debt. These effects will finally be balanced out which means the capital structure is irrelevant with the total cost of funding.

Chapter 3

Methodology

3.1 Baker and Wurgler's two-step approach

In this section, the two-step approach applied by Baker and Wurgler [2015] (noted as BW) is described. The approach builds on a modified CAPM which takes the low risk anomaly into consideration. In the first step, the positive correlation between equity risk (measured by beta) and the leverage of banks is established. In the second step, it is argued the reduced equity risk, contrary to the CAPM's prediction, will raise the cost of equity capital due to a low risk anomaly. Then the change in the total cost of capital is estimated based on the strength of the low risk anomaly.

There are two reasons of using the two-step approach instead of directly analyzing the correlation between the cost of capital and the capital structure. Firstly, using a proxy to measure the cost of capital can mitigate the problem of the noisy realized returns, which has been mentioned in Section 2.2.2. Secondly, using beta as a proxy can give a lower boundary of the ultimate effect of leverage on the cost of capital, which will be explained in Section 3.1.4.

3.1.1 Estimating equity beta and alpha

According to the CAPM, beta describes how an asset's return responds to swings in the market. It is calculated by dividing the covariance of the asset's return (r_i) and the market's return (r_m) by the variance of the market's return.

$$\beta_i = \frac{cov(r_i, r_m)}{var(r_m)} \tag{3.1}$$

Alpha is a measure of the excess return earned by an asset compared to the return suggested by the CAPM, the value of alpha could be either positive or negative or zero.

$$\alpha_i = r_i^{ex} - \beta_i r_m^{ex} \tag{3.2}$$

The true beta (noted as β, the subscript i is not specified when referring to all banks) is unknown, but a proxy of it can be estimated from the historical returns. The estimated beta ($\hat{\beta}$) changes with the time horizon. Baker and Wurgler [2015] estimated the beta using a time horizon of 24-60 months (also suggested by e.g., Black et al. [1972] and Fama and MacBeth [1973]). In addition, there is a difference between using backward and forward returns. On one hand, the backward beta can capture the information which is already available in the market. On the other hand, the forward beta utilizes the future information which is unknown at a certain time point.

The backward beta at time t using n ($24 \leq n \leq 60$) past monthly returns is defined as:

$$\hat{\beta}_{i,t}^{n} = \frac{\sum_{t-n+1}^{t}(r_{m,t} - \bar{r}_m)(r_{i,t} - \bar{r}_i)}{\sum_{t-n+1}^{t}(r_{m,t} - \bar{r}_m)^2} \tag{3.3}$$

The forward beta at time t using h ($24 \leq h \leq 60$) future monthly returns is defined as:

$$\hat{\beta}_{i,t}^{h} = \frac{\sum_{t}^{t+h-1}(r_{m,t} - \bar{r}_m)(r_{i,t} - \bar{r}_i)}{\sum_{t}^{t+h-1}(r_{m,t} - \bar{r}_m)^2} \tag{3.4}$$

In practice, the betas are estimated by applying the OLS regression with a linear model of $r_i^{ex} = \alpha_i + \beta_i r_m^{ex}$ (the superscript ex means excess return over risk-free rate). The slope of this regression will be almost identical to the definition in Equation 3.3 and 3.4, although the dependent variable and independent variable are both excess returns, instead of returns. Using this method, the intercept from the OLS regression directly corresponds to the definition of alpha. Otherwise, if the original returns are used to perform the regression, the alpha needs to be calculated by subtracting the risk-free rate from the intercept of the regression.

3.1.2 Step 1: Reducing leverage reduces equity beta

A theoretical analysis starts from the asset beta (β_a, unlevered beta), which describes the systematic risk of a firm's underlying business. It is a weighted average of the equity beta (β_e) and the debt beta (β_d). The weights are the fraction of equity ($e \equiv \frac{E}{D+E}$) and the fraction of debt ($1 - e = \frac{D}{D+E}$).

$$\beta_a = e\beta_e + (1 - e)\beta_d \tag{3.5}$$

By rearranging the equation, β_e is shown to be a weighted average of β_a and β_d:

$$\beta_e = \frac{1}{e}\beta_a + (1 - \frac{1}{e})\beta_d \tag{3.6}$$

There are two assumptions proposed to derive the relationship between leverage (measured by $\frac{1}{e}$) and equity beta.

Assumption BW1: The debts held by banks are riskless.

This assumption implies that $\beta_d = 0$. As a result, Equation 3.6 becomes:

$$\beta_e = \frac{1}{e}\beta_a \tag{3.7}$$

From Equation 3.7, the equity beta (β_e) is linearly proportional to the leverage. Since the focus is only on banks, the underlying business is the same. So, the second assumption is made on the asset beta (β_a), which is the slope between the equity beta (β_e) and leverage ($\frac{1}{e}$).

Assumption BW2: The systematic risk of banks' underlying asset (β_a) is constant for all banks across all months.

Hence, the linear relationship in Equation 3.7 can be illustrated by the dashed line in Figure 3.1 (left), which strictly crosses the origin with the slope of β_a. Apart from the linear relationship, Baker and Wurgler [2015] predicted some deviations in the extreme situations. Firstly, high leverage banks tend to have riskier debt, with positive-valued β_d. According to Equation 3.6, the effect of β_d will appear in these banks. Thus, the slope ($\frac{\partial \beta_e}{\partial \frac{1}{e}}$) will deviate from β_a and become flattered when the leverage ($\frac{1}{e}$) is large. Secondly, an endogeneity problem could come into effect in the extreme high or low leverage banks. Because high equity beta banks tend to lower the leverage, and low equity beta banks tend to increase the leverage, the predicted positive correlation will become weaker. Banks with extreme leverage will suffer more from this endogeneity selection problem, thereby the slope becomes flattered. To conclude, the predicted relationship between equity beta and leverage is illustrated in Figure 3.1 (left). Without the deviations, the predicted relationship is the dashed line with a slope equal to β_a. After considering the deviations in the extreme leverage banks, the linear relationship changes into non-linear, which is illustrated with the S-shape solid line in Figure 3.1 (left).

To confirm the predictions, a linear regression and a kernel regression are applied respectively (see Figure 3.1, right). The two regressions are reproduced using data from the same source and period as Baker and Wurgler [2015]. The details of obtaining the data will be described in Section 4. The dependent variable β_e is the forward equity beta. The independent variable $\frac{1}{e}$ is the (multiplicative) inverse of Tier 1 ratio instead of the equity to asset ratio. This is because the Tier 1 ratio conveys information from a regulator's point of view, which mirrors the equity to asset ratios but is not proactively adjusted by banks. Thus, it can mitigate the aforementioned endogeneity problem by using the Tier 1 ratio to measure the capital ratio (e), which is the denominator of the independent variable. For the linear regression, the intercept is forced to zero to be consistent with the riskless debt assumption. The result is plotted as the dashed line in Figure 3.1 (right), which has a positive slope confirming the equity risk is increasing in leverage. The result of the kernel regression is plotted as the solid line in Figure 3.1

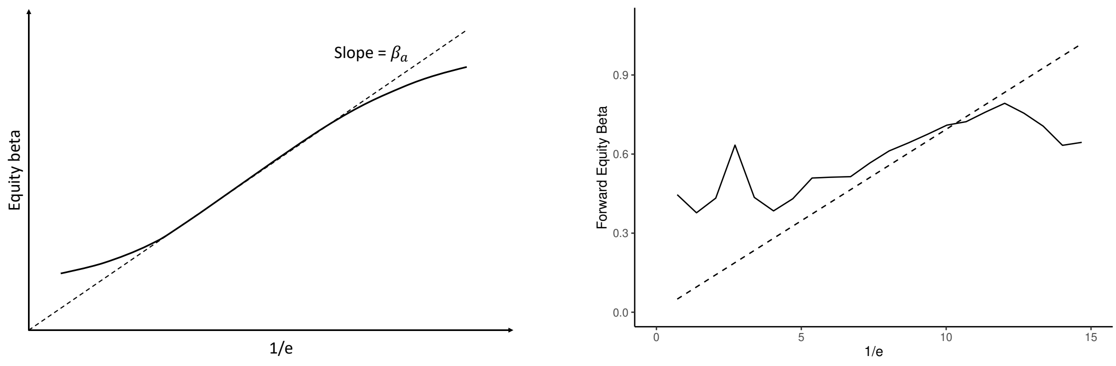

Figure 3.1: The relationship between equity beta and leverage. The left plot is the predicted relationship and the right plot shows the empirical test results. The dashed line in the predictions (left) shows that equity beta is linear in leverage with a slope of β_a. It crosses the origin since debt is assumed to be riskless. The solid line takes the endogeneity problem into account, so the slope becomes flattered in extreme leverage banks. To empirically prove these predictions, a linear regression of forward equity beta on the inverse of Tier 1 ratio with zero intercept is firstly performed. The positive slope confirms that higher leverage results in higher equity beta. Then a kernel regression (solid line, local polynomial regression using an Epanechnikov kernel, with bandwidth of 0.3 and grid size of 30) is fitted, which reflects the endogeneity problem.

(right). It confirms the predicted deviations in extreme (high or low) leverage banks since the slope becomes flattered in these banks as explained by Baker and Wurgler [2015]. The details of the regressions are described in Section 5.

3.1.3 Step 2: Reducing beta increases the total cost of capital

According to the CAPM in Equation 2.2, a lower equity beta will lead to a lower expected return of equity. But when taking the low risk anomaly into consideration, this conclusion may not necessarily hold. The CAPM is then adjusted accordingly:

$$\mathbb{E}(r_i) = \alpha(\beta_i) + r_f + \beta_i[\mathbb{E}(r_m) - r_f] \tag{3.8}$$

Rewriting the equation with simpler notations, where the subscript i and the symbol of the expected value are omitted, and the subscript e representing equity is included:

$$r_e = \alpha(\beta_e) + r_f + \beta_e r_m^{ex} \tag{3.9}$$

In order to show the banks exhibit a low risk anomaly, Baker and Wurgler [2015] performed a regression of alphas on betas of banks. Instead of performing a pooled OLS regression on the panel data, they applied the grouping procedure suggested by Fama and MacBeth [1973]. For the observations in each month, the banks are sorted into three groups (top 30%, middle 40%

and bottom 30%) based on their backward beta. Two portfolios are then formed within each group: the EW portfolio takes the equal weighted average of returns, and the VW portfolio takes the market capitalization value weighted average of returns. Thus, for each month there are six portfolios, which will form six time series of returns covering the whole time period. Applying the OLS regression method on each of these portfolios, a pair of alpha and beta is computed.

Finally, a linear regression is performed on the six pairs of alpha and beta, the estimated slope ($\frac{\partial \alpha}{\partial \beta_e}$) is the key variable of interest. The sign of the slope should be negative if the low risk anomaly exists. The absolute value of the slope measures the strength of the anomaly, where a larger absolute value means a stronger anomaly. If the anomaly is strong enough, the trend of the data points of realized return on beta will have a negative slope, instead of having a positive slope as shown in Figure 2.1. The negative slope of realized return on beta means riskier stocks will have lower returns. The alpha-beta regression is reproduced using the data from the same source and covering the same time period as Baker and Wurgler [2015] and is shown in Figure 3.2. The negative and significant slope proves that the low risk anomaly exists in banks.

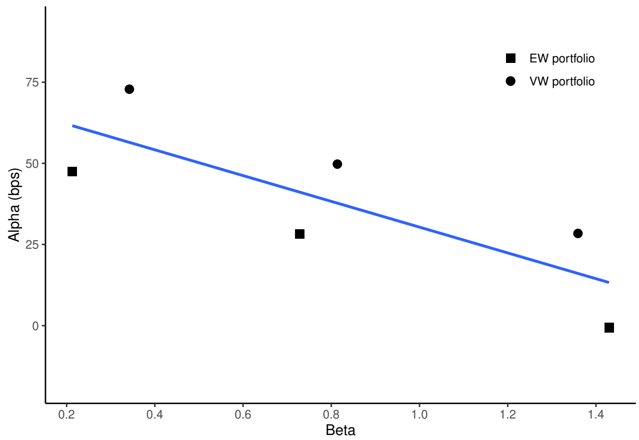

Figure 3.2: The strength of the low risk anomaly in banks. To obtain the data points in this figure, a grouping procedure is utilized. The banks in each month are sorted by their backward beta into three groups: top 30%, middle 40% and bottom 30%. Each group forms two portfolios: the EW portfolio takes the equal weight average of returns within a group, the VW portfolio takes the market capitalization value weighted average of returns within a group. Then, there are six time series of portfolio returns. With the calculated alpha and beta for the six portfolios, the regression of alphas on betas is shown by the blue line.

To explore the extent of the effect of the anomaly on the cost of capital, Baker and Wurgler [2015] specified the expression of α as a function of β_e.

Assumption BW3: The equity of banks exhibits a low risk anomaly in the form:

$$\alpha(\beta_e) = \gamma_e(\beta_e - 1) \tag{3.10}$$

In Equation 3.10, α is linear in β_e with a slope γ_e, which is $\frac{\partial \alpha}{\partial \beta_e}$. The reason of using the expression of $\beta_e - 1$ is because the market portfolio with beta equal to one will have alpha equal to zero. Applying this specific expression of $\alpha(\beta_e)$, Equation 3.9 becomes:

$$r_e = \gamma_e(\beta_e - 1) + r_f + \beta_e r_m^{ex} \tag{3.11}$$

Assumption BW4: The cost of debt in banks is determined by the CAPM, with no anomaly.

$$r_d = r_f + \beta_d r_m^{ex} \tag{3.12}$$

Since the total cost of asset r_a is the weighted average of the cost of equity r_e and the cost of debt r_d, the equation of r_a is rewritten in the following form.

$$\begin{aligned} r_a &= er_e + (1-e)r_d \\ &= e\big(r_f + \gamma_e(\beta_e - 1) + \beta_e r_m^{ex}\big) + (1-e)(r_f + \beta_d r_m^{ex}) \\ &= r_f + \beta_a r_m^{ex} + \gamma_e(\beta_a - e) \end{aligned} \tag{3.13}$$

If there is no anomaly ($\gamma_e = 0$) in the equity capital, the total cost of asset will only contain the first two terms in Equation 3.13, without the explicit dependency on e. However, since the anomaly is confirmed by a negative γ_e, both γ_e and e will influence r_a. Suppose the capital ratio increases from e to e^* ($e^* > e$), the change in the cost of asset will be:

$$\Delta r_a = r_a^* - r_a = -\gamma_e(e^* - e) \tag{3.14}$$

For given value of γ_e and $e^* - e$, the change of total cost of capital can be obtained with Equation 3.14. Baker and Wurgler [2015] used this equation and predicted that the total cost of capital (r_a) would increase at least 85 basis points (bps) per year if the equity ratio (e) increases by ten percentage points.

3.1.4 Using beta as a proxy can provide a lower boundary

An important reason of using the two-step approach, which is from leverage to beta and then from beta to return, instead of directly from leverage to return is to answer the research question (do strict capital requirements raise the total cost of capital?) more precisely. It has been shown there exists an endogeneity problem that high risk banks tend to lower their leverage and vice versa, which results in the S-shape relationship in Figure 3.1. Fitting a linear regression on the non-linear relationship will underestimate the true slope between leverage and beta in the linear region. It is illustrated by the blue dotted line with a flattered slope compared to the real slope in Figure 3.3. Then, in the first step the reduced leverage leads to a reduction in the equity beta, but the magnitude of this reduction is underestimated due to the flattered slope. It is illustrated in Figure 3.4. Since the equity beta is reduced less, it suffers less from the low risk anomaly. Thus, the estimated effect of reduced leverage on the cost of equity and the total cost of capital is understated. The final result of the change in the total cost of capital in Equation 3.14 from the whole estimation process will then be a lower boundary. If the regression between return and leverage is performed directly, the endogeneity problem still exists. But the direction of the bias is unclear and may lead to wrong conclusions.

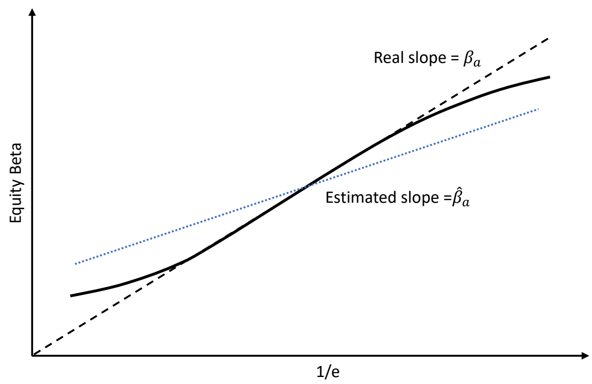

Figure 3.3: The illustration of the underestimated slope in the regression of equity beta on leverage. Due to the endogeneity problem, the relationship between beta and leverage will be non-linear and in S-shape as shown by the solid line. Fitting a linear regression on this relationship will produce a flattered slope (blue dotted line) than the true slope of β_a in the linear region (black dashed line).

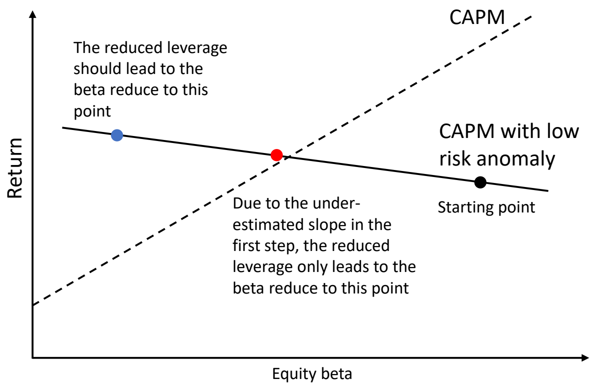

Figure 3.4: The illustration of underestimated effect of leverage on cost of equity. In the first step, the slope between the leverage and the equity beta is underestimated due to the endogeneity problem. As a result, the reduced leverage should have reduced the equity beta from the black point to the blue point, but it only leads to the equity beta reduce to the red point which has larger beta than the blue point. In the second step, the reduced beta will increase the return of equity as argued by Baker and Wurgler [2015]. And the red point has less increase in the return of equity than the blue point. Thus, it will lead to an understated effect on the cost of equity and finally on the total cost of capital.

3.2 A proposed model based on the BW two-step approach

The derivation of the two-step method by Baker and Wurgler [2015] relies on four assumptions. The Assumption BW1 of riskless debt is very strong and is unrealistic to be applied for all banks. In this section, we propose a modified two-step method with this assumption relaxed. The modified method utilizes the option pricing theory and follows the two-step approach with the remaining three assumptions.

3.2.1 Beta of call option

The theoretical relationship between leverage and beta borrows ideas from the option pricing theories.* A firm's equity could be viewed as a call option underlying on the firm's assets (Merton [1974]). This call option will have the strike price equal to the value of debt (D) and will have the payoff equal to the larger value between the residual value of asset net of debt ($A - D$) and zero. The beta of equity can thus be derived from the beta of the call option. Black and Scholes [1973] discovered an important insight of the replicating portfolio when valuing the options. A replicating portfolio is a portfolio consisted of other securities that has exactly the same value as the option (Berk and DeMarzo [2007]). Using this idea, the beta of equity of the firm can be derived from its replicating portfolio. The value of equity (E) is replicated by a portfolio with Δ shares of the firm's asset (A) and one share of risk-free bond (B):

$$E = A\Delta + B$$

Then the beta of equity (β_e) is the weighted average of the beta of asset (β_a) and beta of the risk-free bond (β_B):

$$\begin{aligned} \beta_e &= \frac{A\Delta}{A\Delta + B}\beta_a + \frac{B}{A\Delta + B}\beta_B \\ &= \frac{(D+E)\Delta}{E}\beta_a + \frac{B}{A\Delta + B} \times 0 \\ &= \frac{1}{e}\Delta\beta_a \end{aligned} \tag{3.15}$$

Applying the Black-Scholes-Merton model (Black and Scholes [1973], the details of deriving the value of Δ are in Appendix B), the Δ in Equation 3.15 is:

$$\Delta = \Phi(d_1) \tag{3.16}$$

$$\text{where} \quad d_1 = \frac{\ln[A/D]}{\sigma\sqrt{T}} + \frac{\sigma\sqrt{T}}{2}$$

*Acknowledgement: The argument and derivations in this section are highly inspired by David Lando, Professor of Finance at Copenhagen Business School.

The value of Δ equals to $\Phi(d_1)^*$, which is a probability between 0 and 1. Cox et al. [1979] explained this term and stated that the product of the underlying asset price and $\Phi(d_1)$ is the present value of receiving the asset if and only if the call option finishes in-the-money. So, the term $\Phi(d_1)$ can be viewed as a measure of the probability of the call option finishes in-the-money.

3.2.2 Step 1: Leverage and beta

With the concepts from option beta, the relationship between equity beta and the leverage is obtained by combining Equation 3.15 and 3.16.

$$\beta_e = \Phi(d_1)\beta_a \frac{1}{e} \tag{3.17}$$

Comparing to the original method, the difference in the relationship between leverage and beta is the term of $\Phi(d_1)$. Here, the risk of debt is included and the assumption of riskless debt is relaxed.

With the Assumption BW2 which states that β_a is constant for all banks across all months, we can make an alternative prediction of the relationship between the equity beta and the leverage. Firstly, when the leverage is very low, the debt is close to riskless ($\beta_d \to 0$). The probability of the option being in-the-money will be very high ($\Phi(d_1) \to 1$). Equation 3.17 becomes $\beta_e \approx \beta_a \frac{1}{e}$, which is the same as the original prediction in the BW model. Secondly, as the leverage increases, the debt will become riskier and the probability term $\Phi(d_1)$ will gradually decrease. As a result, the slope will become flattered, but remains positive.

The predicted relationship between the equity beta and the leverage ignoring the endogeneity problem is illustrated in Figure 3.5. It is different from the BW model ignoring the endogeneity, which has a linear relationship. Despite Baker and Wurgler [2015] also argued the effect from risky debt, the risk of debt was not included in their final model of the change in the total cost of capital in Equation 3.14.

The predicted relationship between equity beta and leverage in the modified method can also be confirmed by the kernel regression in Figure 3.1. For the banks with moderate leverage, the linear relationship is confirmed. For the banks with high leverage, the flattered slope is observed. For the low leverage banks, the slope from the regression is having spikes and fluctuating. Because most of the banks rely heavily on debt financing, the number of observations with low leverage is very small. It is not convincing to conclude the slope is either linear or flattered.

If the endogeneity for the extreme (high or low) leverage banks is considered, the modified method will also predict an S-shape and the final Δr_a will also be a lower boundary. The arguments are the same as that for the original BW method in Section 3.1.4.

$^*\Phi(.)$ is the cumulative distribution function of the standard normal distribution

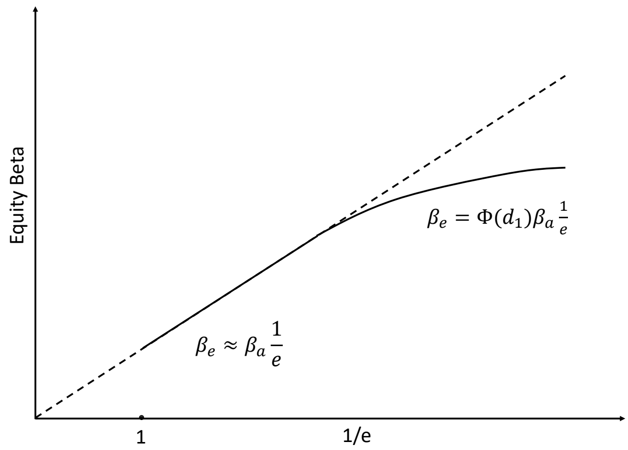

Figure 3.5: The relationship between equity beta and leverage predicted by the modified two-step method. Since the equity ratio e is between 0 and 1, the leverage $\frac{1}{e}$ is equal or larger than 1. When the leverage is very low, the equity beta is linear in leverage with a constant slope of β_a. As the leverage increases, the probability of the option being in-the-money falls. Thus, the slope as well as the value of $\Phi(d_1)\beta_a$ become lower as the leverage increases.

3.2.3 Step 2: Beta and the cost of capital

In the second step, the final change in the total cost of capital (Δr_a) due to an increase in the capital ratio (e) is estimated with the riskless debt assumption relaxed. In addition, the change in the cost of equity capital is derived. The two assumptions of Assumption BW3 and BW4 as in the original model are used.

The change in the total cost of capital can be derived similarly with the BW method. In the original derivation in Equation 3.13, the relationship of $\beta_a = e\beta_e$ is applied under the assumption of $\beta_d = 0$. In the modified method, we consider the risk of debt.

$$\begin{aligned} r_a &= er_e + (1-e)r_d \\ &= e\big(r_f + \gamma_e(\beta_e - 1) + \beta_e r_m^{ex}\big) + (1-e)(r_f + \beta_d r_m^{ex}) \\ &= r_f + \beta_a r_m^{ex} + \gamma_e(\underbrace{e\beta_e}_{\text{diff.}} - e) \end{aligned} \tag{3.18}$$

Denoting the term $\gamma_e(e\beta_e - e)$ in Equation 3.18 as y. The influence of e on r_a will be identical with the influence of e on y. Inserting Equation 3.17 in y:

$$\begin{aligned} y \equiv \gamma_e(e\beta_e - e) &= \gamma_e\big(e\Phi(d_1)\beta_a \frac{1}{e} - e\big) \\ &= \gamma_e \Phi(d_1)\beta_a - e\gamma_e \end{aligned} \tag{3.19}$$

Suppose the capital ratio increases from e to e^*, the change in total cost of capital is derived (the term with superscript of $*$ corresponds to e^*).

$$\begin{aligned}\Delta r_a &= y^* - y \\ &= \underbrace{[\Phi(d_1^*) - \Phi(d_1)]\beta_a\gamma_e}_{\text{additional term}} \underbrace{-\gamma_e(e^* - e)}_{\text{original term}} \quad (3.20)\end{aligned}$$

Compared to the final result of Δr_a in the original method, there is an additional term which is negative. As has been discussed in Step 1, the probability term $\Phi(d_1)$ will decrease when the leverage ($\frac{1}{e}$) increases. Thus, if the capital ratio increases from e to e^* (leverage decreases), the probability term will increase ($\Phi(d_1^*) > \Phi(d_1)$). In addition, since γ_e is negative confirmed by the data, the additional term is then negative. As a result, the change in the total cost of capital will be less than the original prediction by Baker and Wurgler [2015].

In addition to Δr_a, the change in the cost of equity capital can also be derived. Taking the derivative on both sides of Equation 3.9 with respect to $\frac{1}{e}$:

$$\begin{aligned}\frac{dr_e}{d(1/e)} &= \frac{d\alpha}{d\beta_e}\frac{d\beta_e}{d(1/e)} + r_m^{ex}\frac{d\beta_e}{d(1/e)} \\ &= (\gamma_e + r_m^{ex})\frac{d\beta_e}{d(1/e)} \quad (3.21)\end{aligned}$$

In Equation 3.21, γ_e is the strength of the low risk anomaly which can be estimated as in the original BW method. The value of r_m^{ex} can be estimated from the historical market returns. And the term of $\frac{d\beta_e}{d(1/e)}$ is the slope of β_e on $\frac{1}{e}$, which will be estimated using linear regressions in Section 5.

3.2.4 Summary of the modified and original BW two-step approach

To sum up, the modified method relaxes the riskless debt assumption and modifies the relationship between leverage and risk. Then, the ultimate effect of leverage on the cost of capital is modified by including the risk of debt through the option pricing theory. The difference between the original BW approach and the modified approach is summarized in Table 3.1.

Table 3.1: The difference between the original and modified BW two-step approach.

	BW two-step approach	Modified BW two-step approach
Assumption	Debt is riskless	Debt is almost riskless, when leverage is low Debt is risky, when leverage is high
Step 1	$\beta_e = \beta_a\frac{1}{e}$	$\beta_e \approx \beta_a\frac{1}{e}$, when leverage is low $\beta_e = \Phi(d_1)\beta_a\frac{1}{e}$, when leverage is high
Step 2	$\Delta r_a = -\gamma_e(e^* - e) > 0$	$\Delta r_a = Y - \gamma_e(e^* - e) \gtreqless 0$, where $Y = [\Phi(d_1^*) - \Phi(d_1)]\beta_a\gamma_e < 0$

3.3 The approach based on the ICC and expected return of debt

In this section, the approach applied by Dick-Nielsen et al. [2019] (noted as DGT) is described. Deviating from the BW approaches, the DGT approach does not rely on the CAPM to measure the cost of capitals. Instead, it measures the cost of equity capital with the implied cost of capital (ICC) as has been introduced in Section 2.2.2. Meanwhile, the cost of debt is modeled by the interest expenses of debt rather than by CAPM. The models of cost of debt and cost of equity will be firstly introduced. Then, the regression method applied in the DGT approach will be described.

3.3.1 ICC variants and the principle of ICC

The ICC is relying on the analysts' forecasts of the future performance of firms. In practice, the forecasting data is usually obtained from the Institutional Brokers' Estimate System database (I/B/E/S). Two of the ICC variants used by Dick-Nielsen et al. [2019] are derived by Ohlson and Juettner-Nauroth [2005] and Easton [2004]. The expression of the ICC variant by Ohlson and Juettner-Nauroth (noted as OJ) is:

$$ICC^{OJ} = A + \sqrt{A^2 + \frac{eps_1}{P_0} \times [STG - (\gamma - 1)]} \tag{3.22}$$

$$\text{where } A = \frac{1}{2}[(\gamma - 1) + \frac{dps_1}{P_0}], \text{ and } STG = \sqrt{\frac{eps_2 - eps_1}{eps_1} \times LTG}$$

Easton suggested a simplified version of the OJ model and is noted as PEG model:

$$ICC^{PEG} = \sqrt{\frac{eps_1}{P_0} \times STG} \tag{3.23}$$

In the above formulas, the forecasts of one- and two-year ahead earnings per share are noted as eps_1 and eps_2. The forecast of one-year ahead dividends per share is noted as dps_1. The forecasts of long term (five-year ahead) growth and short term growth of eps are noted as LTG and STG, respectively. The expected long term (permanent) momentum of the eps growth is noted as $\gamma - 1$ (for details, see Appendix C).

Apart from these two ICC variants, Dick-Nielsen et al. [2019] utilized two additional ICC variants based on the residual income model. The average of the four variants is defined as the robust ICC. Then the regressions of the robust ICC on the capital ratios are performed to analyze their relationship.

The principle of ICC models

The principle of the ICC models is described using the ICC variant of the Gordon Growth Model (GGM), which relies on very strong assumptions. The OJ model and the PEG model are extended from this basic model with one or more assumptions relaxed. The notations and derivations are following the work by Gode and Mohanram [2003].

P_0: price per share at time zero
dps_t: expected dividends per share of future time t, predicted at time zero
eps_t: expected earnings per share of time t, predicted at time zero
$r = R - 1$: discount rate or cost of equity capital

There are three basic assumptions:
Assumption GGM1: The current stock price is determined by discounting the future dividends.
Assumption GGM2: The payout policy is stable.
Assumption GGM3: The dividends are growing at a constant rate of g, which is smaller than the discount rate r ($0 \leq g < r$).

The assumption of $g < r$ on the growth rate indicates the price will not explode through the discounting process. With these assumptions, the price per share is given by:

$$P_0 = \mathrm{PV}(\sum_{t=1}^{\infty} dps_t) = \frac{dps_1}{r - g} \tag{3.24}$$

The special case of a full payout policy ($eps = dps$) is examined to derive the ICC. By adding and then subtracting the term of $\frac{eps_1}{r}$ in the right-hand-side of Equation 3.24:

$$\begin{aligned} P_0 &= \frac{eps_1}{r} - \frac{eps_1}{r} + \frac{eps_1}{r-g} \\ &= \frac{eps_1}{r} + \frac{g \times eps_1}{r(r-g)} \end{aligned} \tag{3.25}$$

Since the growth rate (g) is constant in every future period, it can be replaced by the short-term growth rate $(eps_2 - eps_1)/eps_1$. Then, the price per share (P_0) is expressed with the known short-term forecasts and the value of r (ICC) can be solved for given value of P_0 as well as the forecasts. The derivation of the OJ model and PEG model is very similar with this method.

3.3.2 The expected return of debt capital

Following the DGT approach, the expected return of debt capital for bank i at time t is given by:

$$r_{i,t}^{d} = \frac{\sum_{k=0}^{3} \text{Interest expense}_{i,t-k}}{\frac{1}{4}\sum_{j=1}^{4} \text{Debt}_{i,t-j}} \tag{3.26}$$

where t denotes the quarter; Interest $\text{expense}_{i,t}$ is the interest expense of bank i of quarter t; $\text{Debt}_{i,t}$ is the total debt of bank i at quarter t.

Intuitively, the equation has the numerator of the interest expenses over the last year (sum of four quarters). And the denominator is the average of the total debt over the last year. Because most banks have a short average maturity on their liabilities, the one-year horizon of estimation could be a good proxy for the annual cost of debt. This model equation relies on the realized interest expenses to back up the cost of debt, rather than relying on the senior bond rates, because the senior debt usually accounts for only a small fraction of banks' liability.

3.3.3 Relating the cost of capital to capital structure

After obtaining the valid ICC and expected cost of debt, the total cost of capital is calculated based on the formula of WACC (Equation 2.1). And linear regressions are performed to explore the relationship between different kinds of cost of capital and capital ratio:

$$\begin{aligned}\text{Cost of capital} = \text{a} + \text{b} \times \text{Capital ratio} \\ &+ \text{Bank fixed effects} + \text{Time fixed effects} \\ &+ \text{Other control variables} + \epsilon \end{aligned} \tag{3.27}$$

3.4 A proposed method based on DGT approach

According to the analysis in the BW approach, when ignoring the endogeneity problem there is a linear relationship between the equity beta (β_e) and the leverage ($\frac{1}{e}$) instead of the capital ratio (e). In addition, the CAPM predicts a linear correlation between the cost of equity (r_e) and the equity beta (β_e). So, the relationship between r_e and $\frac{1}{e}$ predicted from the BW method has a linear region. Then the predicted relationship between r_e and e will be non-linear. With this concern, the previous regression model with the dependent variable of r_e in the original DGT method in Equation 3.27 might produce biased estimation with a misspecified model equation. Thus, we propose a modified regression. When the dependent variable is r_e (measured by ICC), we replace the dependent variable of capital ratio (e) in the linear regression by the inverse of capital ratio ($\frac{1}{e}$).

$$\begin{aligned}\text{Cost of equity capital} &= \text{a} + \text{b} \times \text{Inverse of capital ratio}\\ &\quad + \text{Bank fixed effects} + \text{Time fixed effects}\\ &\quad + \text{Other control variables} + \epsilon \end{aligned} \tag{3.28}$$

3.5 A proposed data-based approach

In Section 3.1.4, it is explained that if directly applying the regression between realized return and leverage, there will be an unclear bias due to the endogeneity problem. Apart from the method of using proxies, the endogeneity problem can be mitigated by some econometric methods, e.g., utilizing an instrumental variable (IV). Thus, in this section we propose a direct IV regression approach of the realized return of equity on the capital ratio as shown in Equation 3.29.

The IV for the endogenous independent variable in Equation 3.29 has to satisfy two requirements. Firstly, the IV should be correlated with the inverse of equity capital ratio ($\frac{1}{e}$). Secondly, the IV should be uncorrelated with the error term of ϵ.

$$\text{Realized cost of equity capital} = \text{a} + \text{b} \times \text{ Inverse of capital ratio} + \epsilon \tag{3.29}$$

Flannery and Rangan [2008] applied IV regressions to analyze the correlation between capital ratio and risk in banks. They used some time dummy variables as the IV for their analysis. Inspired by their approach, the time dummy of D_1 is chosen in the following form.

$$D_1 = \begin{cases} 0, & \text{if time before 1993} \\ 1, & \text{otherwise} \end{cases} \tag{3.30}$$

The reason is that the Basel I took effect in 1993, since then the regulation policy could have direct impacts on the equity capital ratio of banks. Meanwhile, the regulation cannot directly affect the cost of capital or the risk of banks. Thus, the chosen time dummy based on Basel I satisfies the two requirements of a valid IV. But the dependent variable of this regression is the realized return of equity, which suffers significantly from the noisy problem. We will compare the regression results with the other regressions in which the cost of equity is measured by CAPM, CAPM with anomaly and the ICC in Section 5.

Chapter 4

Data

To empirically investigate the research question, the relevant data of capital structure and cost of capital is required. This chapter describes how to acquire data from different databases and then preliminarily inspects the data. The chapter proceeds as follows. Section 4.1 introduces a commonly-used method of distinguishing the banks from the generalized firms in the database. Section 4.2 presents the process of acquiring data and calculating beta, followed with a preliminary visualization of the dynamics of beta. Section 4.3 describes how to acquire the capital structure data of banks from two different databases, followed with a brief visualization of the capital structure data. Section 4.4 describes the data acquisition of the analysts' forecasts of the banks' performance and how to use them to calculate the implied cost of capital. Section 4.5 calculates the expected return of debt using the model introduced in the DGT method.

4.1 Distinguishing banks

Before the data acquisition, it should be clear how to distinguish the objective firms: the banks in the US. Fama and French assigned each NYSE, AMEX and NASDAQ stock to an industry category based on its four-digit Standard Industrial Classification (SIC) code. The details of the industrial classification are available in Kenneth R. French Data Library, banks have SIC code of 6000-6199. Concerning the research purpose, not all of these banks are included. For example, the Foreign banks (SIC: 6080-6082) and Federal Reserve banks (SIC: 6010-6019) are weeded out. Besides the banks (SIC: 6000-6199), the bank holding companies (SIC: 6710-6719) are also included in the analysis. A bank holding company is a corporation that owns several different companies, and it can engage in activities related to banking (Mishkin [2013]). So, their behaviours are also important in investigating banks. Appendix A (Table A.2) shows the details of the selected banks and their corresponding SIC codes.

4.2 Return and beta

In Baker and Wurgler's two-step approach, the beta of each individual equity is firstly estimated from the historical returns. Using the SIC code as the identifier, the relevant variables for calculating beta are obtained in Center for Research in the Security Prices database (CRSP): monthly return (RET), closing price (PRC: bid/ask average price if the closing price is not available) and number of shares outstanding (SHROUT). These variables are available from 1926. But in the early years, there are too few observations, so they are not covered. Following the work by Baker and Wurgler [2015], the data is collected from Jan 1970 and to Dec 2019, which is an updated version of their data (from Jan 1970 to Dec 2011). The market return is also required. So, the monthly market excess return (MKTRF) and the risk-free return (RF) are collected from the Kenneth R. French Data Library. The summarized statistics of the above variables are listed in Appendix A (Table A.3).

With these basic ingredients, betas are calculated by regressing the individual stock's excess return on market excess return as discussed in Section 3.1.1. The calculation is using a rolling window process. To calculate one valid beta, at least 24 months of returns are required, and the maximum window size is 60 months. For example, suppose a bank has monthly returns from Jan 1970 to Dec 2019, then the calculation of the backward beta and forward beta in each month is illustrated in Table 4.1.

Table 4.1: An example of calculating the betas of a bank using the rolling window process, supposing it has the observations of monthly returns from Jan 1970 to Dec 2019. In order to calculate the backward beta, at least 24 months of past returns are required. So, in the first 23 months (from Jan 1970 to Nov 1971), we cannot calculate the backward beta. From the 24th month (Dec 1971), we have enough 24 observations. After that, we can have more and more available past returns, but we use at most 60 months of returns. So, since Dec 1974 we only use 60 past months returns. The principle of calculating forward beta is very similar.

Time	Backward beta	Time	Forward beta
Jan 1970 ˜ Nov 1971	Not Available	Jan 1970 ˜ Dec 2014	Using 60 future months
Dec 1971	Using 24 past months	Jan 2015	Using 60 future months
Jan 1972	Using 25 past months	Feb 2015	Using 59 future months
...	...	...	...
Dec 1974	Using 60 past months	Jan 2018	Using 24 future months
Jan 1975 ˜ Dec 2019	Using 60 past months	Feb 2018 ˜ Dec 2019	Not Available

After calculating valid backward betas for all banks, there are 320,655 months' observations left. The mean and median of the backward beta over the whole time period are 0.73 and 0.65, which are not very large (see Table 4.2).

To visualize the dynamics of beta within the time period, the averaged backward beta of all banks in each month is calculated. The equal weighted (EW) average and the market capitalization value weighted (VW) average of backward beta from Dec 1971 to Dec 2019 are

Table 4.2: The summarized statistics of the forward and backward beta.

	Obs.	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Backward beta	320655	-2.7073	0.3345	0.6530	0.7286	1.0331	6.8621
Forward beta	320655	-4.7752	0.3558	0.6711	0.7401	1.0434	6.9770

shown in Figure 4.1. From the figure, the EW averaged beta is below one in most times, but the VW averaged beta is fluctuating around one and mostly above the EW average. The VW averaged beta gives more weights to the large banks. As a result, a higher VW average over EW average indicates that larger banks have higher equity betas. In addition, there is a sudden increase in VW averaged beta in 2009. This is possibly caused by the 2008 Financial crisis. During the crisis (around 2007 to 2009), the banks' returns and the market's returns co-moved a lot, leading to some extremely correlated observations within that time period. So, when a sufficient amount of extreme observations are included in the rolling window (during 2009), the beta sharply increases. When these extreme observations are excluded from the rolling window (during 2014, because the maximum window size is five years), the beta decreases sharply. This phenomenon is less pronounced in the EW averaged beta, indicating the larger banks suffer more from the crisis.

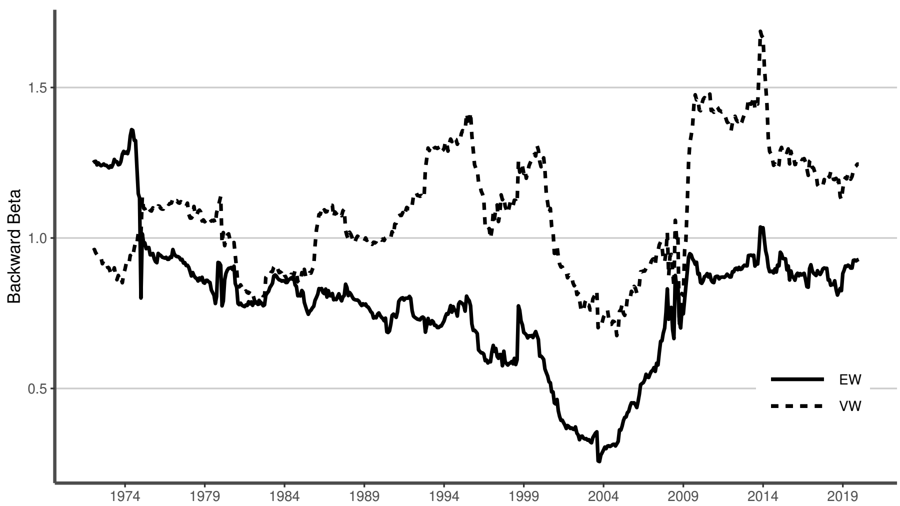

Figure 4.1: The equal weighted (EW) and market capitalization value weighted (VW) average of backward beta, 1971-2019. The VW average is higher than the EW average in most time, indicating the larger banks may have higher betas. There is a sudden increase during 2009 and a sharp decrease during 2014 in the VW average, which are possibly caused by the 2008 Financial crisis and the rolling window method. The effect is less pronounced in the EW average.

Due to the large difference in EW and VW average betas, a further analysis is made by dividing the banks in each month into groups (top 30%, middle 40% and bottom 30%) based on their market capitalization. Figure 4.2 and 4.3 show the EW and VW average of betas of each group. It is not surprising that the VW average of the whole sample is almost the same with the top 30% group (Figure 4.3), which means the largest banks are dominating the VW average beta.

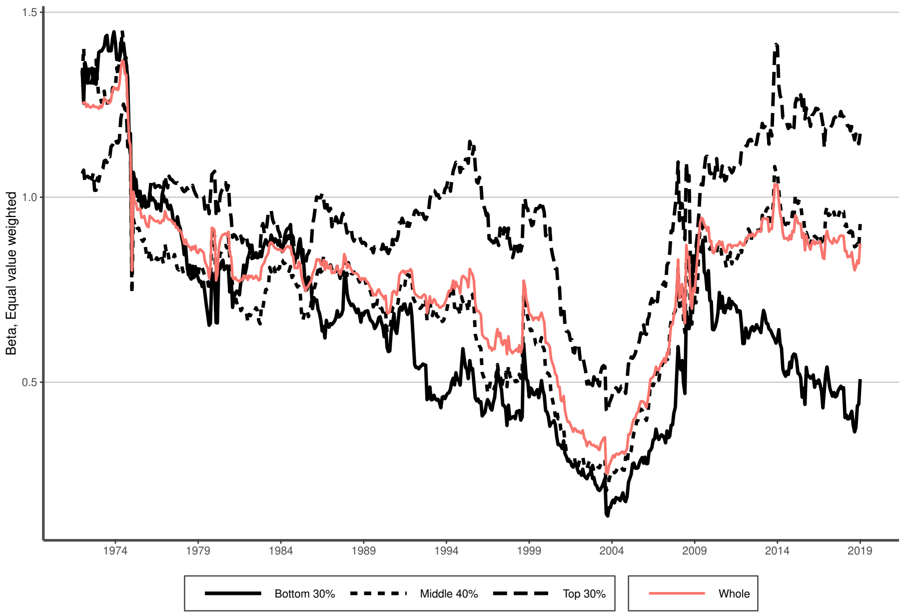

Figure 4.2: The equal weighted (EW) average of backward beta of the top 30%, middle 40% and bottom 30% (sorted by market capitalization) portfolios, 1971-2019. The red line is the EW average of backward beta of all banks within each month.

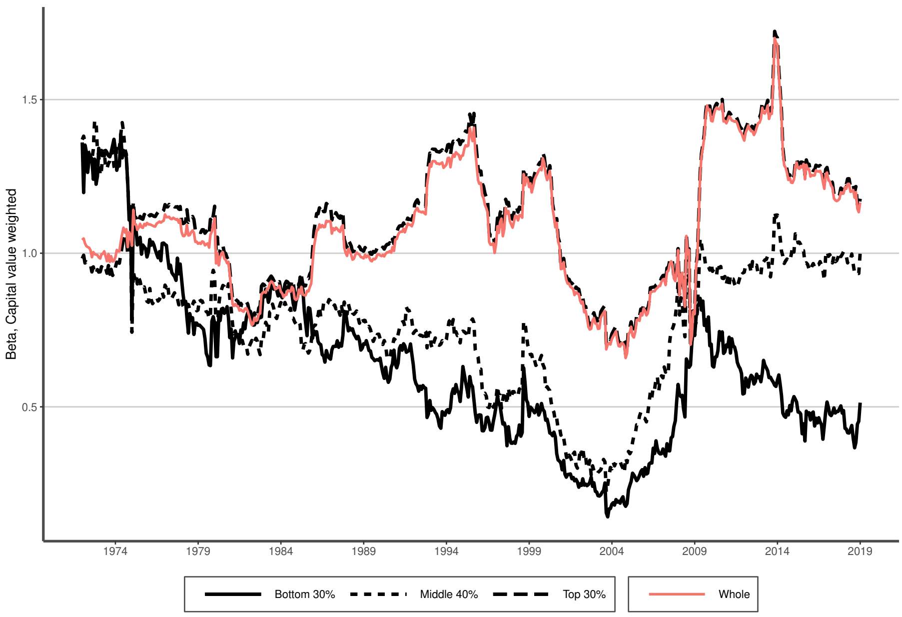

Figure 4.3: The market capitalization value (VW) weighted average of beta of the top 30%, middle 40% and bottom 30% (sorted by market capitalization) portfolios, 1971-2019. The red line is the VW average of beta of all banks within each month.

A similar analysis is made by plotting the EW and VW average of backward beta of the top 30%, middle 40% and bottom 30% groups sorted by backward beta. The results are shown in Figure 4.4 and 4.5 which are the updated version of the figures in Baker and Wurgler [2015]'s work. From the figures, we can see significant dispersion between groups, where the spread between the top group and the bottom group is around one.

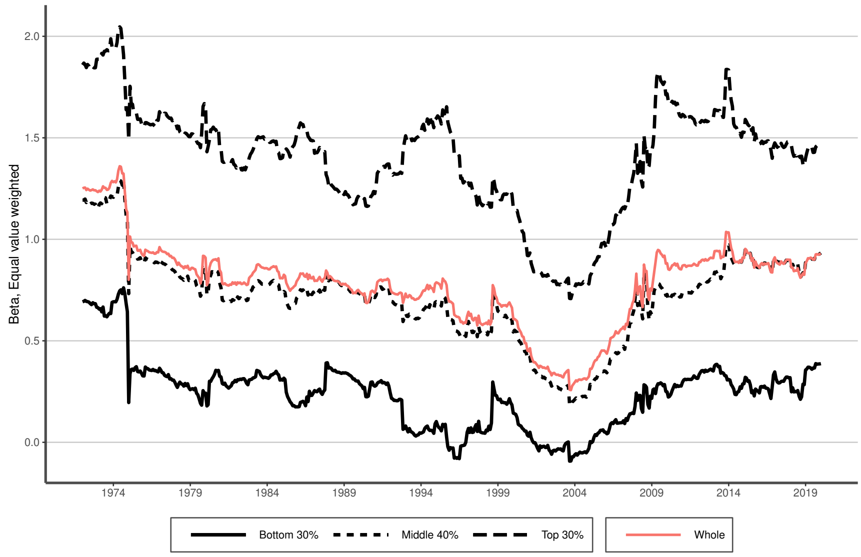

Figure 4.4: The equal weighted (EW) average of backward beta of the top 30%, middle 40% and bottom 30% (sorted by backward beta) portfolios, 1971-2019. The red line is the EW average of backward beta of all banks within each month.

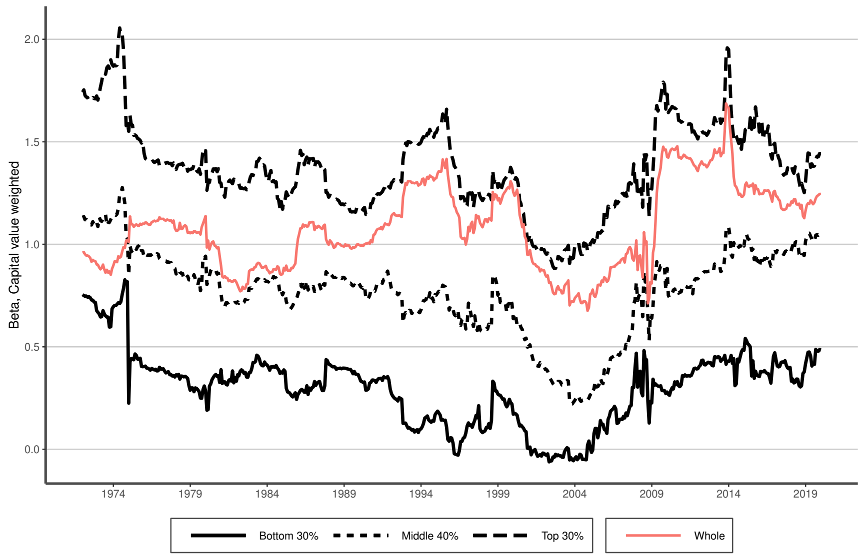

Figure 4.5: The market capitalization value (VW) weighted average of beta of the top 30%, middle 40% and bottom 30% (sorted by backward beta) portfolios, 1971-2019. The red line is the VW average of beta of all banks within each month.

4.3 Capital structure

4.3.1 Compustat dataset

To analyze the capital structure of banks, the data from the financial statements are required. The quarterly or annual financial statement contains the balance sheet of a firm, which records the firm's asset, liability and equity at a given time point. The Compustat database provides annual and quarterly financial statements data of US banks after 1961. Using the SIC identifying method, the relevant variables: common equity (CEQ), total liability (LT), total asset (AT) and total deposit (DPTC) can be obtained from Jan 1970 to Dec 2019. In addition, since Basel I defined the Tier 1 ratio, the data of Tier 1 ratio (CAPR1) and Tier 2 ratio (CAPR2) can be obtained from the Compustat database after 1993.

To have a preliminary understanding of banks' capital structure, the annual capital data is firstly collected. Furthermore, some capital ratios are defined and visualized:

$$\text{Book capital ratio} = (\text{Total asset - Total liability})/ \text{ Total asset} \tag{4.1}$$

$$\text{Common equity ratio} = \text{Common equity } / \text{ Total asset} \tag{4.2}$$

$$\text{Book leverage ratio} = \text{Total liability } / \text{ Total asset} \tag{4.3}$$

$$\text{Deposit liability ratio} = \text{Total deposit } / \text{ Total liability} \tag{4.4}$$

Figure 4.6 shows the distribution of the book capital ratio in each year from 1970 to 2019. The figure is taking the form of box plot to illustrate the main features of the ratio in each year. A detailed explanation of the box plot is shown in Appendix A (Figure A.1). The whole period average of the book capital ratio is about 9%, which is very low compared to non-financial firms. Having a closer look at the trend of the distribution in Figure 4.6, there are three significant increases. The first increase appeared during 1993 which is consistent with the time point that Basel I took effect. Secondly, during 2011 when the Basel II.5 took effect and the Basel III started negotiating higher capital requirements. Thirdly in 2019, when the Basel III took effect, the book capital ratio increased. These increases indicate that the tightened regulation has significant impacts on the bank capital structure. The box plots of the common equity ratio, the book leverage ratio, and the deposit liability ratio are shown in Appendix A, Figure A.2 to Figure A.4.

There is very tiny difference between the book capital ratio and the common equity ratio by comparing Figure 4.6 and A.3, but the difference between the book capital ratio and the Tier 1 ratio is large (see Figure 4.6 and 4.7). The definition of Tier 1 ratio takes into consideration not only the on-balance-sheet information, but also about the risks of banks, which are reflected in the denominator of Tier 1 ratio:

$$\text{Tier 1 ratio} = \text{Tier 1 capital} \ / \ \text{Risk weighted assets} \tag{4.5}$$

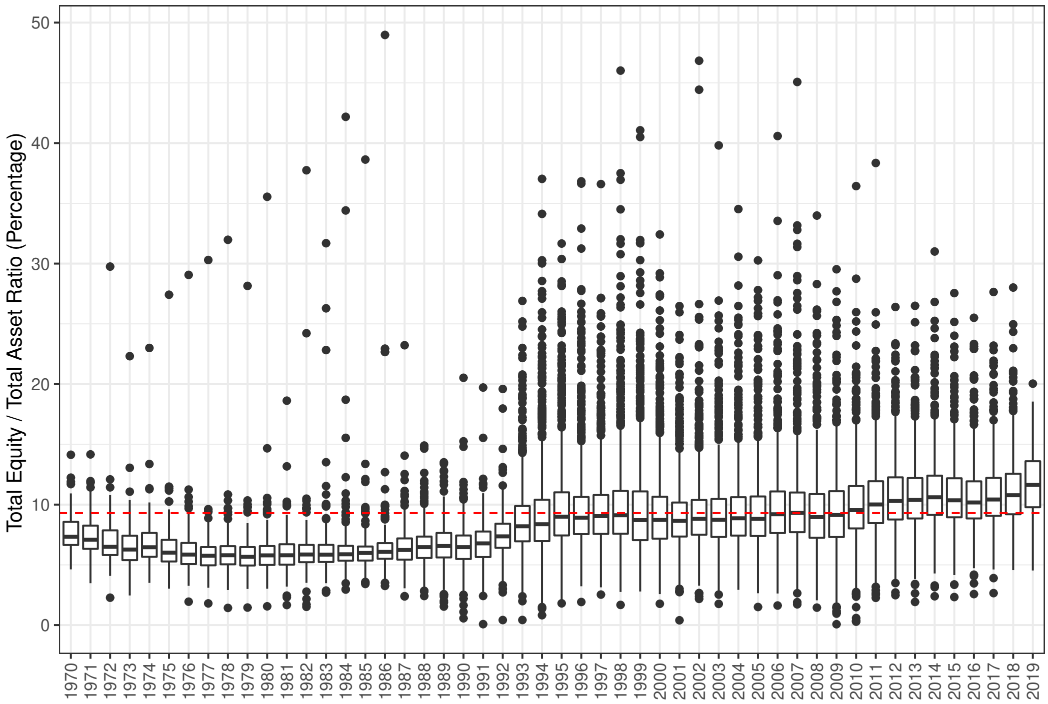

Figure 4.6: The yearly distribution of book capital ratio (Total equity / Total asset), 1970-2019. The figure takes the form of a box plot. The red dashed line is the whole sample average of the ratio, which is around 9%.

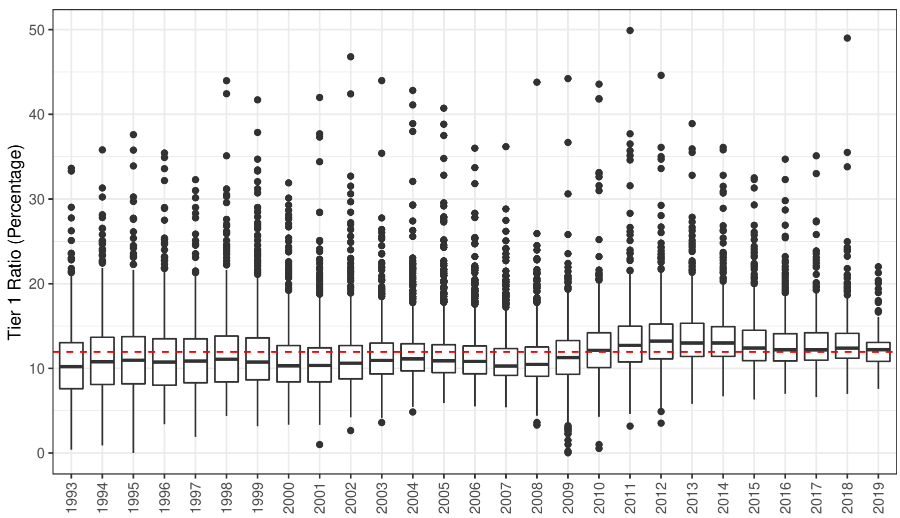

Figure 4.7: The yearly distribution of Tier 1 Ratio, 1993-2019. The figure takes the form of a box plot. The red dashed line is the average value of the Tier 1 ratio of the whole time period, which is around 12%.

Figure 4.7 is the distribution of the Tier 1 ratio from 1993 to 2019. The whole period average is about 12%, higher than the current regulatory requirement. But it is surprising that there is no significant increase in 2019 (when the Basel III took effect), contrary to the observation that the book capital ratio increases a lot. Thus, we further investigate the relationship between the two ratios. The correlation between the book capital ratio and the Tier 1 ratio from 1993 to 2019 is calculated and plotted in Figure 4.8. Before 2011, the correlation remains relatively high (over 0.55). But after 2011, the correlation is continuously decreasing to a very low level of about 0.2 in 2019. These facts indicate that the Tier 1 ratio conveys information about capital structure from a regulator's point of view, but it is not exactly the same as the on-balance-sheet capital ratio. This is one reason why Baker and Wurgler [2015] used the Tier 1 ratio as a measure of the capital ratio. Banks can adjust the on-balance-sheet capital ratio easily, but they rarely proactively adjust the Tier 1 ratio. Thus, using the Tier 1 ratio to proxy the capital ratio could mitigate the potential endogeneity problem as described in Section 3.1.

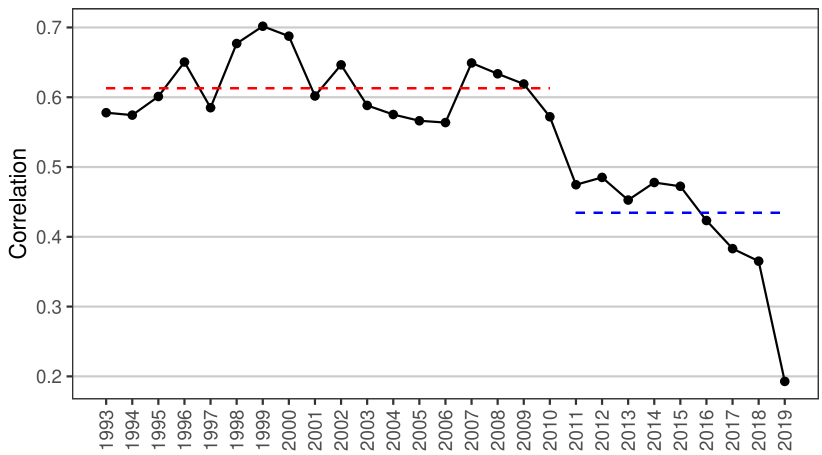

Figure 4.8: The correlation between the book capital ratio and the Tier 1 ratio, 1993-2019. The red dashed line is the average of the correlations from 1993 to 2010. The blue dashed line is the average of the correlations from 2011 to 2019.

The above figures and discussion focus on the yearly distribution of capital ratios of all banks. In Section 4.2, we have seen that when banks are divided into groups based on the market capitalization, there is a large dispersion in betas across the different groups. Similarly, there might exist dispersion in the capital ratios across different groups. Thus, banks are sorted and placed into three groups (top 30%, middle 40% and bottom 30%) according to the total asset value in each year. Figure 4.9 plots the averaged common equity ratio (left) and the averaged Tier 1 ratio (right) of each group. In the earlier years before 2008, the bottom group has the highest common equity ratio and Tier 1 ratio, and the top group consisted of the largest banks has the lowest capital ratios. This phenomenon can partly explain why the largest banks are riskier and have larger betas in Figure 4.3: the large banks rely more heavily on debt financing, the high leverage structure leads to higher risk. However, in the recent years especially after the financial crisis (from 2008 to 2019), the difference between the capital ratios of the three groups becomes smaller.

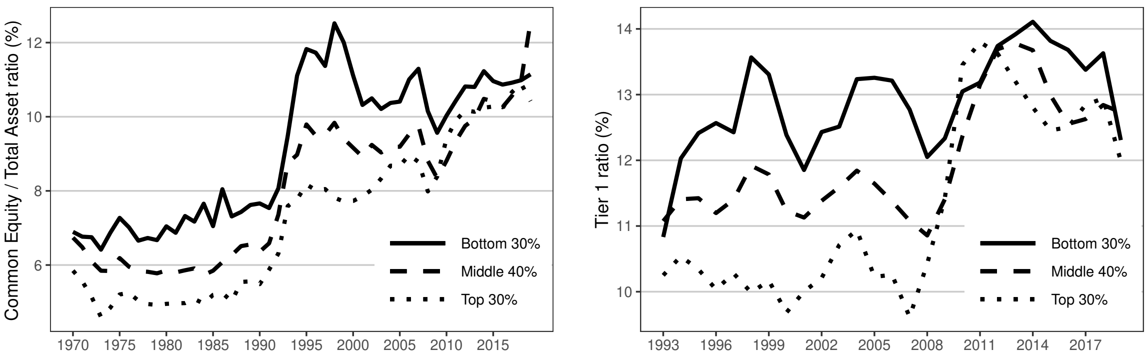

Figure 4.9: The average of common equity ratio (left) and Tier 1 ratio (right) of the groups sorted by total asset. In both plots, the bottom 30% group has the highest capital ratios in early years before 2008. But in recent years (2008-2019), the difference between groups has fallen.

In order to quantitatively relate the capital structure with the betas and returns, the more frequent data of capital structure is required. Thus, the quarterly financial statement data is collected from 1970 to 2019. Usually, the financial reports are released shortly after the quarter-end, in which the balance sheet reports the state of capital structure at the time point of the corresponding quarter-end. So, this quarter-end balance sheet also best describes the corresponding month-end state. To mimic the fact that investors do not know the accounting data until the reports are released, the quarter-end data is spanned two months forward. Table 4.3 illustrates how to span the quarterly data into monthly data used in this thesis.

Table 4.3: The illustration of how to span quarterly data into monthly data. To mimic the fact that investors do not know the accounting data until the financial reports are released, we span the quarter-end data two months forward.

Quarter end	Month	Quarter end	Month	Quarter end	Month	Quarter end	Month
31/03	March April May	30/06	June July August	30/09	September October November	31/12	December January February

The spanned monthly capital structure dataset is then combined with the monthly CRSP dataset (where the data is also reported at month-end). In the combining process, the two datasets cannot be linked by the identifier SIC code, because the SIC code is not unique for each bank. The unique firm identifier in CRSP is called PERMNO and the unique firm identifier in Compustat is called CUSIP. The Wharton Research Data Services (WRDS) provides the link table between the two identifiers. Thus, the two datasets are combined through the link table.

4.3.2 Bank Regulatory dataset

Apart from the Compustat database, the database of Bank Regulatory also provides the relevant capital data of banks and bank holding companies, but most of the data is only available after 1996. Baker and Wurgler [2015] used the capital structure data from this database to report the results and did a robustness check using the Compustat dataset (but not reported). To replicate their calculation, we also collect the data from the Bank Regulatory database. The SIC identification method applied in the CRSP and Compustat database is not feasible here because this database does not report the SIC code. Instead, the unique identifier of RSSD ID in the Bank Regulatory database is used. To collect the data, the unique firm identifiers PERMNO and PERMCO are firstly exported from the CRSP dataset. Secondly, they are transformed into RSSD IDs according to a link table provided by the Federal Reserve Bank of New York. Thirdly, the relevant variables, which are the Tier 1 capital and the risk weighted asset are collected in the Bank Regulatory database using RSSD IDs. Finally, the quarterly data is spanned into monthly data and combined with the CRSP dataset.

In the Bank Regulatory database, the data series are categorized into various main series and then various sub-series with possible segmented mnemonics. The series are labeled with a four-letter mnemonics (e.g. RCFD) followed by a four-digit (possible letters representing numbers larger than 9, e.g. 8274, A223) item number. For the two data series of interest, the Tier 1 capital and the risk weighted asset are with the item number of 8274 and A223 respectively. The mnemonic of the banks and bank holding companies are RCFD and BHCK respectively. The mnemonic of RCFD is in the main series of CALL and representing Consolidated (domestic and foreign offices) balance sheet items. The mnemonic of BHCK is in the main series of BHCF and representing Consolidated Financial Statements for Bank Holding Companies.

For banks, the Tier 1 capital is reported using the form FFIEC 031 in the series of RCFD8274 from 1994-03 to 2014-12 and then in the series of RCFA8274 from 2014-03 onwards. The risk weighted asset is reported using the same reporting form, in the series of RCFDA223 from 1996-03 to 2014-12 and then in RCFAA223 from 2014-03 onwards.

For the bank holding companies, the Tier 1 capital and the risk weighted asset are reported in the form FR Y-9C in the series of BHCK8274 and BHCKA223 respectively. The data series are from 1996-03 to 2014-12. And then from 2014-03 onwards, the data series are BHCA8274 and BHCAA223 respectively.

The series of RCFD and BHCK are available but RCFA and BHCA are not available, i.e., the relevant data after 2014 is not available (possibly due to the student account access limitation). Because of the data availability, the data from the Bank Regulatory database will only be used to reproduce the BW methods covering the time period of 1996 to 2011, which is the same as Baker and Wurgler [2015].

4.4 Implied cost of equity capital

Estimating the ICC heavily relies on the expected earnings, dividends and long term growth. The Institutional Brokers' Estimate System (I/B/E/S) database contains analysts' forecasts on firms' performance, including the *eps*, *dps* and long-term growth.* It is not possible to directly obtain data from I/B/E/S with the identifier SIC code. To collect the target banks' data, the CUSIPs of banks in the combined CRSP-Compustat dataset are firstly exported. They are then transformed into the unique identifier in I/B/E/S: International Securities Identification Number (ISIN). An ISIN (12-digit) is consisted of a 2-digit country code (e.g., "US"), a 9-digit national security identifier (9-digit CUSIP, e.g., "46625H100" for JPMorgan) and a check digit. The check digit can be computed from the country code combined with CUSIP using the Luhn algorithm, thus the entire ISINs are computed. For example, JPMorgan's check digit is 5 and its ISIN is "US46625H1005".

With the ISINs of target banks, the forecasting data is collected from 1993 to 2019. Following the work by Dick-Nielsen et al. [2019], the median forecasting measures are chosen to mitigate the impacts of extreme observations. The variables required in the database of I/B/E/S are DPS1MD, EPS1MD, EPS2MD, LTMD, IBP. They correspond to the variables of $dps1$, $eps1$, $eps2$, LTG and P_0 in Equation 3.22, respectively.

The elements contained in Equation 3.22 and 3.23 for calculating the ICC are all available from the I/B/E/S raw data, except the variable γ ($1 \leq \gamma \leq R$). There is no direct forecasting of this growth rate from the database. Following the work by Mohanram and Gode [2013] and Dick-Nielsen et al. [2019], the value of $\gamma - 1$ is set to be equal to the ten-year treasury rate minus 3%. The treasury rate can be collected from the CRSP database.

The monthly forecasting data in I/B/E/S is reported in each month-start (e.g., 2020/01/01), but the monthly ten-year treasury rate is reported in each month-end. Thus, to match the treasury rate with the I/B/E/S data, the value of $\gamma - 1$ at each month-start is set to be equal to the value at each previous month-end (e.g., 2019/12/31).

In practice, the forecasting on *dps* has very limited number of data points. As a result, in the months without valid $dps1$, it is necessary to find proxies for them. Dick-Nielsen et al. [2019] used the most recent available payout ratio ($\frac{\text{dividend}}{\text{income}}$, from the Compustat database) to mimic the $dps1$. In the case that the income is negative, the payout ratio is also negative, instead, $dps1$ is replaced by a modified payout ratio ($\frac{\text{dividend}}{0.06\times\text{asset}}$, from the Compustat database).

Thus, all the ingredients in Equation 3.22 and 3.23 are now available, the ICCs are calculated with the OJ model and PEG model, and the robust ICC is calculated as the average of the two ICC variants. The other two ICCs based on the residual income model applied by Dick-Nielsen

*Acknowledgement: I would like to thank Jens Dick-Nielsen, Associate Professor of Finance at Copenhagen Business School, for his help with this database and explaining his work in Dick-Nielsen et al. [2019].

et al. [2019] are not used in this thesis. The median and mean of the ICC through 1993 to 2019 are 9% and 9.37% (similar to the 9% and 9.26% calculated by Dick-Nielsen et al. [2019]). In Figure 4.10, the monthly distribution of ICC is plotted (an updated version of Figure 1 in Dick-Nielsen et al. [2019]). The dispersion between groups is not very large, the spread between the 90th percentile and the 10th percentile is around 5%.

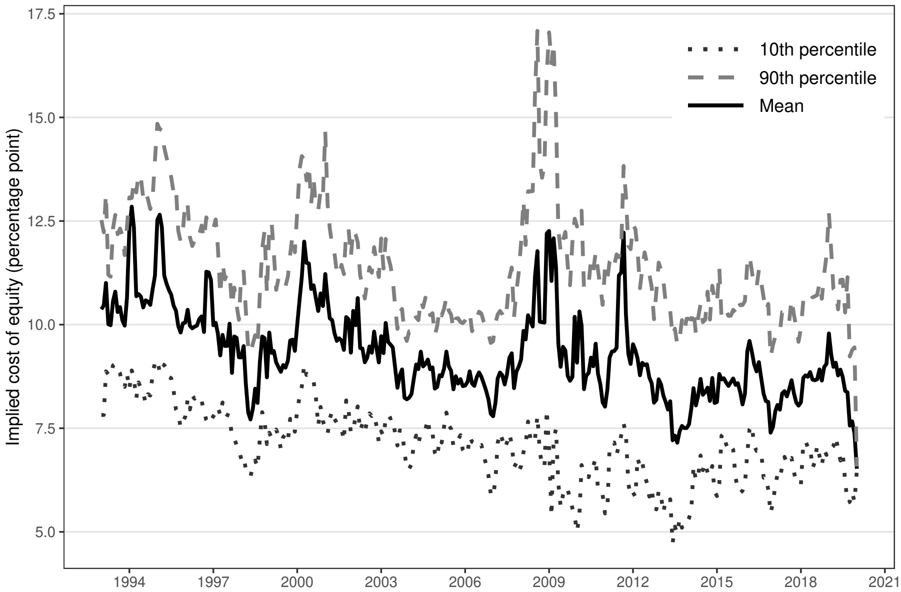

Figure 4.10: The monthly distribution of implied cost of equity capital, 1993-2019. The ICC of each bank is the average of ICCs calculated by the OJ model and PEG model. Then, in each month, the 10th percentile, mean and 90th percentile are calculated among the banks. The ICC shown in this figure is an annual rate of return.

4.5 Expected cost of debt capital

To calculate the expected cost of debt capital defined in Equation 3.26, we need the time series data of interest expenses and debt. It is possible to directly obtain the two variables in the database of Compustat: the interest expense is reported with the symbol of XINT and the debt (total liability) is reported with the symbol of LT. Following Equation 3.26, the cost of debt is calculated and plotted in Figure 4.11. The annual cost of debt is lower than the annual ICC in Figure 4.10. In addition, the averaged cost of debt is significantly lower after 2010, corresponding to the recent low-interest-rate environment. However, we encounter a problem when calculating the cost of debt that the number of observations of debt is very small. In addition, calculating one valid data point of cost of debt requires four observations of debt, which makes the number of calculated cost of debt even smaller. This problem was solved by manually collecting the annual and quarterly data from the financial reports by Dick-Nielsen et al. [2019]. Due to the time constraints of this thesis work, we only use the available data from the database, leading to the data insufficiency in many months. Figure 4.12 shows the histogram of the time distribution of the calculated expected returns of debt, they are heavily distributed after 2008. During this period when the returns of debt become relatively lower as shown in Figure 4.11. The calculated median and mean of the cost of debt capital are 0.9% and 1.5%, which are much lower than the calculation reported by Dick-Nielsen et al. [2019] of 2.86% and 2.81%. The difference is possibly due to the insufficiency of data, especially in the earlier years before 2010 when the cost of debt is relatively high.

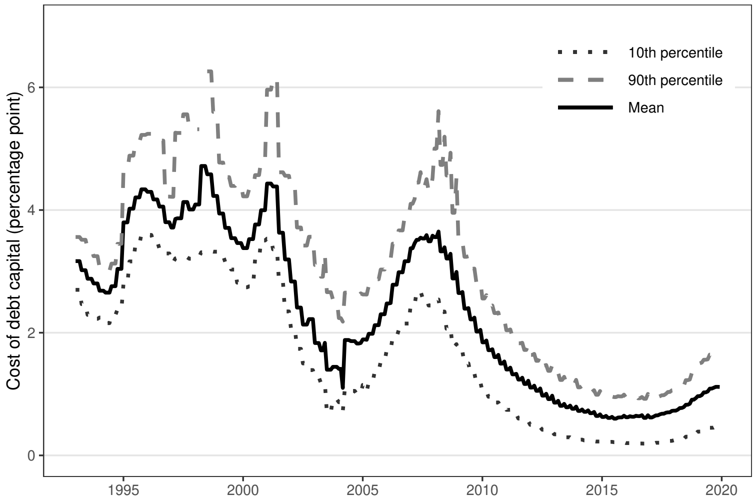

Figure 4.11: The monthly distribution of the cost of debt capital, 1993-2019. The average of the cost of debt capital is calculated across all banks in a given month. In addition, the 10th and 90th percentiles in each month are also calculated. The cost of debt is computed using the interest expenses and the total debt and it is an annual rate.

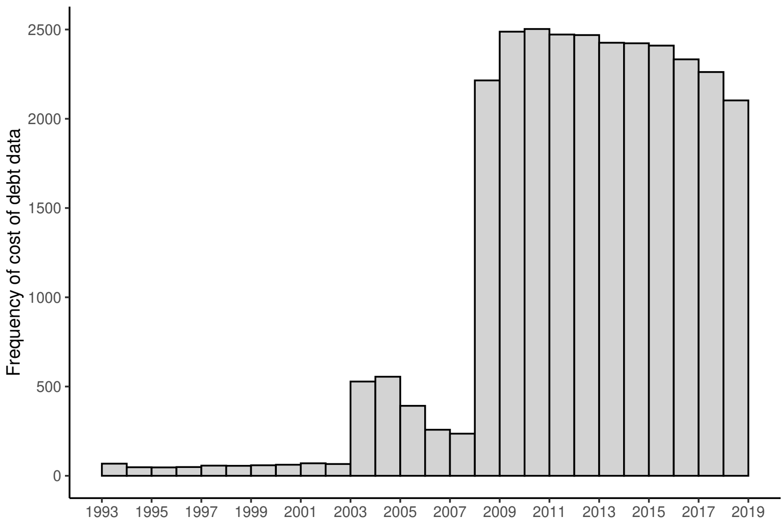

Figure 4.12: The histogram of the frequency of cost of debt data, 1993-2019. The frequency is much larger after the year 2008. The cost of debt becomes lower after 2010, thus the median and mean of cost of debt in the whole sample are relatively low.

Chapter 5

Results and Analysis

In this chapter, the results of applying the methods introduced in Chapter 3 are presented. Section 5.1 to 5.3 are the empirical results of the original and modified BW methods. These sections present the empirical tests of the correlations between leverage and beta, beta and cost of equity, as well as leverage and total cost of capital in banks. Through the discussion in the three sections, we conclude that a ten percentage points increase in the capital ratio will lead to 62.4 bps increase in the annual total cost of capital applying the original BW method, and 39.3 bps applying the modified BW method. Section 5.4 reports the regression results of ICC on the capital ratio as well as the (multiplicative) inverse of capital ratio, following the original and modified DGT approach. Section 5.5 reports the regression results of the cost of debt and the total cost of capital on the capital ratio, following the original DGT approach. The regression results predict that a ten percentage points increase in the capital ratio will lead to 11 bps increase in the annual total cost of capital under a low-interest-rate environment when applying the original DGT approach. Section 5.6 reports the regression of the realized return of equity on the inverse of capital ratio with a time dummy as instrumental variable (IV). Finally in Section 5.7, we separately analyze the correlation between the capital ratio and the cost of equity capital measured by different models.

5.1 Beta and leverage

In this section, the positive correlation between equity beta (β_e) and leverage ($\frac{1}{e}$) established in the BW two-step approaches will be examined empirically. The forward and backward β_e of banks are calculated from the return data obtained in the CRSP database using the rolling window process as described in Section 4.2. The process of acquiring the leverage data from the Compustat database and the Bank Regulatory database is described in Section 4.3.

Thus, a series of tests can be performed with the obtained leverage and forward beta. Firstly, a grouping procedure is utilized to roughly inspect and assess the trends of the relevant variables.

Secondly, we reproduce and update the linear regression and kernel regression by Baker and Wurgler [2015] to more precisely confirm the positive correlation. Thirdly, we propose a piecewise regression as an alternative method to assess the correlation. Finally, we perform a robustness check by replacing the forward beta with the backward beta in the regressions.

5.1.1 The grouping procedure

The relationship between leverage and beta could be roughly assessed by a grouping method, which is similar with the grouping procedure used to test the CAPM by Fama and MacBeth [1973]. Firstly, the banks are ranked by their capital ratio within each month, and placed into ten equal-sized portfolios. The portfolio with larger index is with a higher portion of equity-financing in the capital structure. Then, the equal weighted (EW) average and market capitalization value weighted (VW) average of returns, betas and equity ratios within each portfolio are calculated. By observing the trends of EW average and VW average of the three variables of interest, the relationship between these variables can be roughly examined. The results are divided into two panels due to the different measures of the capital ratio and are summarized in Table 5.1.

In Panel A, the equity ratio is measured by the common equity ratio. With the grouping principle, both the EW and VW columns of the equity ratio are increasing from portfolio 1 to 10. The realized return columns do not have clear trends across the portfolios, indicating an ambiguous relationship between the realized return and the common equity ratio. For both EW backward beta and forward beta, they are decreasing with the increase of the common equity ratio. This confirms the prediction that lower leverage reduces the risk. However, in the VW columns of backward beta and forward beta, the betas are not monotonously decreasing in the leverage. This may be caused by the heavier weights on the larger banks which generally have higher leverage. As discussed in the BW approaches, the correlation between beta and leverage becomes weaker for high leverage banks.

For Panel B which measures the equity ratio with Tier 1 ratio, the trends of realized return as well as beta on leverage are very similar with those in Panel A.

The results from the simple grouping method and the corresponding trends shown in Table 5.1 cannot provide a precise relationship between the variables of interest. Thus, further regressions are performed in order to better examine the predictions.

Table 5.1: Portfolios sorted by capital ratio (Panel A: common equity ratio; Panel B: Tier 1 ratio). In each month, the banks are sorted into ten equal-sized portfolios based on their capital ratios. The portfolios with small indices are those with low capital ratio and high leverage. The equity weighted average (EW) is calculated by taking the average within a portfolio. The capital value weighted average (VW) is using the market capitalization value as weights. The EW and VW average of the returns have ambiguous trends across the portfolios. For the EW columns of backward beta and forward beta, the betas are decreasing with the decrease of leverage. For the VW columns of betas, the monotonous relationship is not observed.

Panel A: Portfolios sorted by common equity ratio

Index	Mkt.Cap.	Equity ratio		Realized return		Backward beta		Forward beta	
	EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
1	1492257.0	0.047	0.048	0.008	0.015	0.846	1.301	0.879	1.337
2	1645667.9	0.063	0.071	0.013	0.017	0.733	1.131	0.798	1.090
3	2622952.9	0.070	0.081	0.013	0.015	0.686	1.068	0.750	0.950
4	2249622.0	0.076	0.083	0.013	0.014	0.681	0.966	0.752	1.094
5	2145659.3	0.081	0.091	0.013	0.009	0.652	1.058	0.743	1.074
6	2813006.1	0.086	0.095	0.014	0.014	0.653	1.126	0.719	1.105
7	1691969.8	0.092	0.101	0.013	0.015	0.642	0.904	0.706	1.006
8	1231409.8	0.099	0.108	0.012	0.014	0.605	0.855	0.698	0.899
9	763782.2	0.110	0.119	0.012	0.013	0.585	0.847	0.652	0.877
10	737836.0	0.156	0.157	0.011	0.011	0.573	0.895	0.599	0.901

Panel B: Portfolios sorted by Tier 1 ratio

Index	Mkt.Cap.	Equity ratio		Realized return		Backward beta		Forward beta	
	EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
1	1737205.8	0.069	0.074	0.009	0.003	0.726	0.777	0.740	1.041
2	4182587.4	0.083	0.083	0.011	0.010	0.673	0.857	0.728	1.098
3	3680027.1	0.091	0.093	0.011	0.013	0.682	1.070	0.744	1.048
4	3110617.7	0.099	0.105	0.011	0.017	0.668	1.235	0.744	1.093
5	2743919.5	0.107	0.116	0.011	0.015	0.641	1.127	0.706	1.117
6	1609223.2	0.114	0.119	0.012	0.012	0.629	1.074	0.705	1.051
7	1568164.2	0.122	0.126	0.012	0.011	0.609	1.185	0.660	1.061
8	2718206.3	0.131	0.135	0.012	0.020	0.584	1.155	0.649	0.922
9	1117551.6	0.146	0.147	0.012	0.016	0.557	1.083	0.607	1.005
10	614167.6	0.192	0.183	0.012	0.011	0.525	0.986	0.582	0.937

5.1.2 Reproducing and updating the BW regressions

A linear regression and a kernel regression were applied by Baker and Wurgler [2015] to verify the linear and non-linear relationships between beta and leverage. We reproduce the two regressions using the same data source covering the same time period (from 1996 to 2011) as Baker and Wurgler [2015]. The independent variable is the forward equity beta, and the dependent variable is the inverse of Tier 1 ratio (from the database of Bank Regulatory). The fitted lines of the two reproduced regressions have been shown in Figure 3.1. From the figure, we can confirm the prediction that reducing leverage will reduce the equity risk. Furthermore, we report the result of the linear regression in the first column in Table 5.2 (Panel A). The estimated slope is 0.069, which is very close to the value of 0.074 estimated by Baker and Wurgler [2015]. As explained in Section 3.1.4, the slope estimated from the linear regression with Equation 3.7 is an inferred lower boundary of the asset beta (β_a) of a typical bank, which is an important value in the later calibration.

In addition, a robustness check is done by using the capital structure data from the Compustat database, with the same time coverage (from 1996 to 2011). The regression result is summarized in the second column in Table 5.2 (Panel A). The estimated slope is 0.061 which is slightly lower than that from the previous regression (with the slope of 0.069) using the capital structure data from the Bank Regulatory database. This robustness check is also done by Baker and Wurgler [2015], but is not reported in detail. They only mentioned in their online appendix that the slope estimated using data from the Compustat database is lower than that from the Bank Regulatory database. This statement coincides with the reduced slope in our reproduced regression when using the Compustat database.

In the original regression by Baker and Wurgler [2015] as well as the reproduced regressions, the most recent data (from 2012 to 2019) is not covered. Due to the data availability in the Bank Regulatory database, which is explained in Section 4.3.2, the updated regression covering the period from 1996 to 2019 is only done using the Compustat database. The result is summarized in the third column of Table 5.2 (Panel A). The slope from this regression is 0.068, which is slightly higher than the slope obtained from the same database but with shorter time coverage (0.061).

5.1.3 Proposed piecewise linear regression

The modified BW approach predicts that when the leverage of banks is low, there is a linear relationship between the leverage and equity beta. As the leverage grows, the slope will gradually decrease and the relationship becomes non-linear, which has been illustrated in Figure 3.5. The kernel regression shown in Figure 3.1 can describe the non-linear features.

We propose to use a piecewise linear regression as an alternative method to examine the non-linear features. Firstly, the banks are sorted into ten equal-sized groups in each month based on their inverse of Tier 1 ratio. Within each group, there is the same number of data points. Then, the linear regression of forward beta on the inverse of Tier 1 ratio with forced zero intercept as in the BW method is performed within each group.

An illustration of the piecewise regression is shown in Figure 5.1. The blue solid curve is the non-linear relationship between leverage and beta derived from the option pricing theory, which is: $\beta_e = \Phi(d_1)\beta_a \frac{1}{e}$ as in Equation 3.17. The term of $\Phi(d_1)\beta_a$ will decrease as the leverage increases, indicating the slope of the blue curve will decrease. This term is actually equal to the ratio of the equity beta (β_e) over leverage ($\frac{1}{e}$) instead of the slope of the curve. Thus, its mean level within each group can be approximated by the slope of the piecewise linear regression with zero intercept (black solid lines). The estimated ratios from the regressions can show the trend of the term of $\Phi(d_1)\beta_a$ and the relationship between equity beta and leverage can then be inferred accordingly.

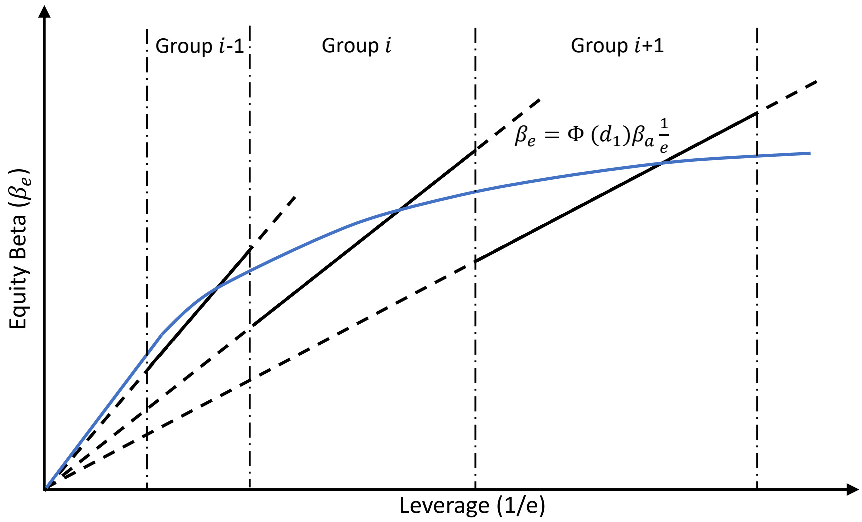

Figure 5.1: The illustration of the proposed piecewise regression. The blue curve is the established relationship between equity beta and leverage in the proposed BW modification: $\beta_e = \Phi(d_1)\beta_a \frac{1}{e}$. The black solid lines are the piecewise linear regression of β_e on $\frac{1}{e}$ with forced zero intercept, which have the extensions (black dashed lines) crossing the origin. To perform the piecewise regression, the observations are divided into equal-sized groups according to the leverage ($\frac{1}{e}$). For each month, there is the same number of data points within each group. The slopes from these regressions are to estimate the term of $\Phi(d_1)\beta_a$ (the ratio of β_e over $\frac{1}{e}$). With the increase in leverage, the estimated ratio is expected to decrease.

The slopes of the piecewise linear regressions within each group are summarized in Table 5.3 (Panel A). Due to the ranking method, the group with larger index is with higher leverage. The slope from the piecewise regression, which is the estimation of $\Phi(d_1)\beta_a$ within each group, is decreasing as the leverage increases. This confirms the predictions from the modified BW model.

5.1.4 Using the backward beta as dependent variable

The reason of using forward beta instead of backward beta as the dependent variable in the first step is not explicitly explained by Baker and Wurgler [2015]. One possible interpretation is: because in the second step, the banks are sorted by the backward beta to estimate the strength of the low risk anomaly. Based on the standard grouping procedure by Fama and MacBeth [1973], the regression of alpha on beta should utilize another time period (e.g., forward beta) to avoid the common source of residuals. Thus, in order to link the first step's effect (leverage and beta) to the second step (forward beta and forward alpha), the forward beta should also be used in the first step.

However, the link between the first and the second step is through the low risk anomaly, as shown in Equation 3.14. Once the strength of the anomaly is obtained, the anomaly can then be viewed as an existing phenomenon in banks. Thus, the dependent variable in the first step is not necessary to be the forward beta as a link to the second step, unless it can better describe the current risk level.

With this concern, we perform all the previous regressions of beta on leverage again, but using backward beta as the dependent variable. The results are summarized in Table 5.2 (Panel B). All three estimated slopes in Panel B are lower than the corresponding ones in Panel A. This indicates a slightly weaker correlation between backward beta and leverage compared to forward beta and leverage. However, the results can still confirm the positive correlation between beta and leverage. In Panel B, for the updated regression covering a longer time period, the slope is slightly larger than the one with shorter time coverage. This phenomenon is also observed in Panel A. In addition, the piecewise linear regressions are performed with backward beta and the results are shown in Table 5.3 (Panel B). The trend is the same as in Panel A with forward beta.

These additional regressions with dependent variable being backward beta can be viewed as a robustness check for the original regressions using forward beta. Since the beta with either the past information or the future information is similarly correlated with the leverage, the estimations are then more robust.

Table 5.2: The results of the reproduced and updated linear regression in the first step of the BW methods. The first column is regressing the banks' forward beta on the inverse of Tier 1 ratio with a time coverage of 1996 to 2011, which produces a slope of 0.069, very close to BW estimation of 0.074. The second column uses the Tier 1 ratio data from the database of Compustat, with the same time coverage as the first column. The third column updates the second regression by covering the time period from 1996 to 2019.

Panel A: Dependent variable is forward beta			
Capital structure database	Bank Regulatory	Compustat	Compustat (Updated)
Inverse Tier 1 ratio	0.069***	0.061***	0.068***
	(0.0002)	(0.0002)	(0.0002)
Observations	63,829	77,360	105,724
R^2	0.594	0.564	0.595
Adjusted R^2	0.594	0.564	0.595
Residual Std. Error	0.507 (df = 63828)	0.539 (df = 77359)	0.542 (df = 105723)
Panel B: Dependent variable is backward beta			
Capital structure database	Bank Regulatory	Compustat	Compustat (Updated)
Inverse Tier 1 ratio	0.054***	0.050***	0.061***
	(0.0002)	(0.0001)	(0.0001)
Observations	67,183	92,337	131,570
R^2	0.559	0.570	0.571
Adjusted R^2	0.559	0.570	0.571
Residual Std. Error	0.428 (df = 67182)	0.445 (df = 92336)	0.513 (df = 131569)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5.3: The results of slope from the piecewise regression of forward beta (Panel A) and backward beta (Panel B) on inverse of Tier 1 ratio. The banks in each month are divided into ten groups based on their inverse of Tier 1 ratio (leverage). The group index of 1 to 10 measures the magnitude of the leverage, where a higher index means a higher leverage. Then, the regressions with zero intercept of β_e on leverage $1/e$ are performed for each group, and the slopes are reported. The highlighted data in Panel A are group index 1 and 8, they will be further used to estimate the impacts of increased capital on the total cost of capital, because the difference between the averaged Tier 1 ratio of the two groups is around 10%.

Panel A: Dependent variable is forward beta										
Index	1	2	3	4	5	6	7	8	9	10
Slope	0.103	0.086	0.084	0.079	0.078	0.073	0.071	0.066	0.058	0.05
Panel B: Dependent variable is backward beta										
Index	1	2	3	4	5	6	7	8	9	10
Slope	0.093	0.078	0.073	0.070	0.067	0.065	0.062	0.060	0.053	0.047

5.2 Cost of equity capital and beta

In the previous section, tests are performed to confirm the positive correlation between leverage and equity beta. The next step in both the original and modified BW approaches is to assess the existence and strength of the low risk anomaly.

In this section, the standard grouping procedure with different number of groups is applied to assess the low risk anomaly. Then, the strength of the anomaly is utilized to estimate its effect on the cost of equity.

5.2.1 Strength of low risk anomaly

Applying the methods introduced in Section 3.1.3, we examine the existence and significance of the low risk anomaly by regressing the alpha on beta using a grouping procedure with three portfolios (top 30%, middle 40%, bottom 30%). We firstly reproduce this regression covering the same time period from 1971 to 2011. Then, we update the regression covering the time period from 1971 to 2019. Finally, some additional regressions with different group sizes as well as a pooled OLS regression are performed covering the time period from 1971 to 2019. The results of the regressions are summarized in Table 5.4.

The reproduced regression is reported in the first column of the table and it has also been illustrated in Figure 3.2. The estimated slope is around -50 bps, which has a lower absolute value compared to the estimation of -68 bps by Baker and Wurgler [2015]. The significant and negative slope confirms the existence of the low risk anomaly. The smaller absolute value of the slope in the reproduced regression indicates the low risk anomaly is having less strength in our estimation. The result of the updated regression with data until 2019 is summarized in the second column of the table, with almost the same slope as that of the previous regression in column 1.

Other grouping methods can be used for the regressions. In the work by Fama and French [2004], firms are sorted into ten equal-sized portfolios. The same grouping method is also applied as a robustness check. After sorting the banks into ten portfolios based on their backward beta, the EW and VW average of returns and the portfolio betas are calculated with the method described in Section 3.1.3. In addition, another regression is done with 20 (instead of 10) portfolios grouped according to backward beta. The results are summarized in column 3 and 4 of Table 5.4. The results show that using either of the three grouping methods, the estimated strength of the low risk anomaly is very similar to each other. The estimated strength is then confirmed to be a robust estimation.

The fifth regression is a pooled OLS regression of backward alpha on backward beta. Despite the estimated slope is close to the results from the grouping regressions, the result is not convincing due to the very low value of R^2. Nevertheless, the advantage of the grouping procedure is then obvious from the comparison.

The results of grouping regressions with three, ten and twenty portfolios are plotted in Figure 5.2-5.4. The right-hand-side plots describe the relationship between alpha and beta and are in the same form as Figure 3.2. The data of each portfolio is plotted in dots and the estimated linear regression of the portfolios is plotted in solid lines. The results of the EW portfolios are plotted in red (dots and lines) and the results of the VW portfolios are plotted in black. For each method, the lines of linear regressions from EW and VW portfolios are almost parallel, which indicates using EW-VW mixed regressions and the separate regressions will have very similar results of the slope.

The left-hand-side plots describe the relationship between the excess return and beta, and are in the similar form as Figure 2.1. The data of EW portfolios is plotted in red dots. The red lines are the corresponding linear regressions, and the black lines are the CAPM-predicted excess returns corresponding to the given betas. The slope from the linear regression is flattered compared to the CAPM due to the confirmed existence of the anomaly. But the slope is still positive, which is different from the estimations and arguments by Baker and Wurgler [2015] (reducing risk will increase the return of equity, indicating a negative slope). This is because in our estimation the low risk anomaly is not strong enough to change the sign of the relationship between return and beta from positive to negative.

Table 5.4: The regression of alpha on beta. The first column reproduces the regression by Baker and Wurgler [2015]. It utilizes the grouping procedure by dividing the banks into three groups based on the backward beta (top 30%, middle 40% and bottom 30%) and each group generates two portfolios (EW and VW portfolio). For each portfolio, a pair of alpha and beta is calculated. Finally, regressing the portfolios' alpha on beta produces the result in the table. The second column uses a same method as that in the first column, except the time coverage is longer (1971-2019). The third and fourth columns divide the banks into ten and twenty equal-sized groups, and utilize the same method to run the regressions from 1971 to 2019. The fifth column dose not utilize the grouping procedure. Instead, it is a pooled OLS regression of backward alpha on backward beta. The results correspond to monthly rate.

	Dependent variable: alpha [bps]				
	(1)	(2)	(3)	(4)	(5)
	1971-2011	1971-2019	1971-2019	1971-2019	1971-2019
	BW portfolios	BW portfolios	Ten portfolios	Twenty portfolios	Pooled OLS
beta	-49.797^{**}	-49.797^{**}	-52.497^{***}	-51.685^{***}	-42.366^{***}
	(11.975)	(11.975)	(7.143)	(5.587)	(0.462)
intercept	78.655^{***}	78.655^{***}	81.407^{***}	82.071^{***}	63.804^{***}
	(11.266)	(11.266)	(6.712)	(5.286)	(0.426)
Observations	6	6	20	40	320,655
R^2	0.812	0.812	0.750	0.692	0.026
Adjusted R^2	0.765	0.765	0.736	0.684	0.026
Residual Std. Error	13.271 (df = 4)	13.271 (df = 4)	15.527 (df = 18)	17.712 (df = 38)	148.130 (df = 320653)

Note: *p<0.1; **p<0.05; ***p<0.01

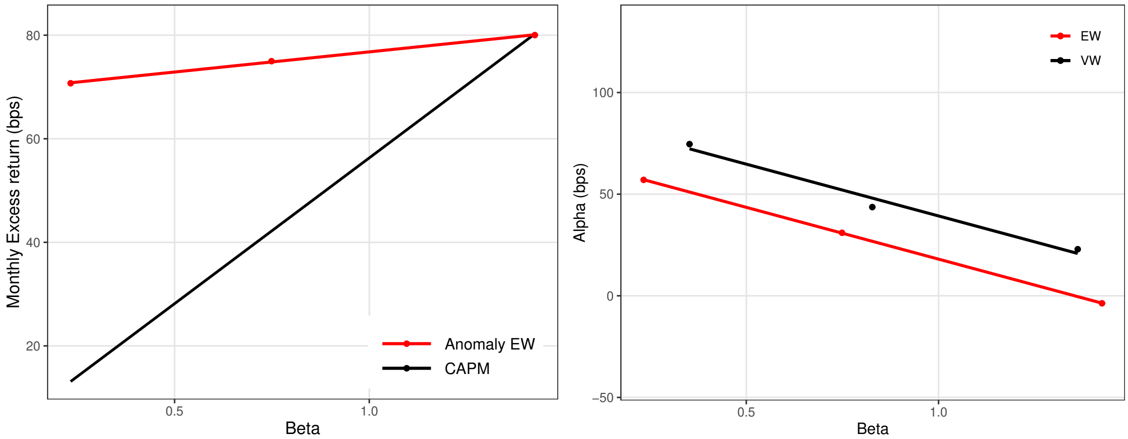

Figure 5.2: The illustration (left) and the strength (right) of the low risk anomaly. The banks are sorted into bottom 30%, middle 40% and top 30% according to the backward beta. The results correspond to monthly rate.

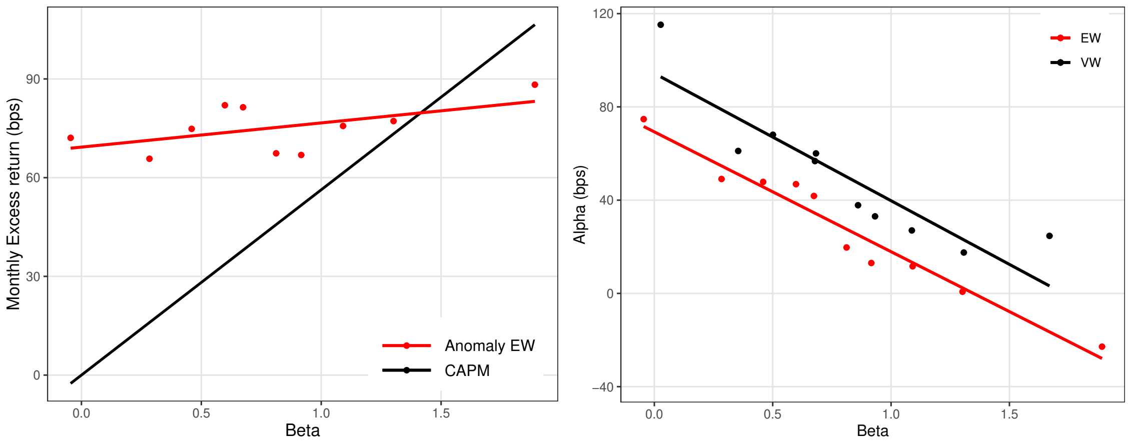

Figure 5.3: The illustration (left) and the strength (right) of the low risk anomaly. The banks are equally sorted into ten portfolios according to the backward beta. The results correspond to monthly rate.

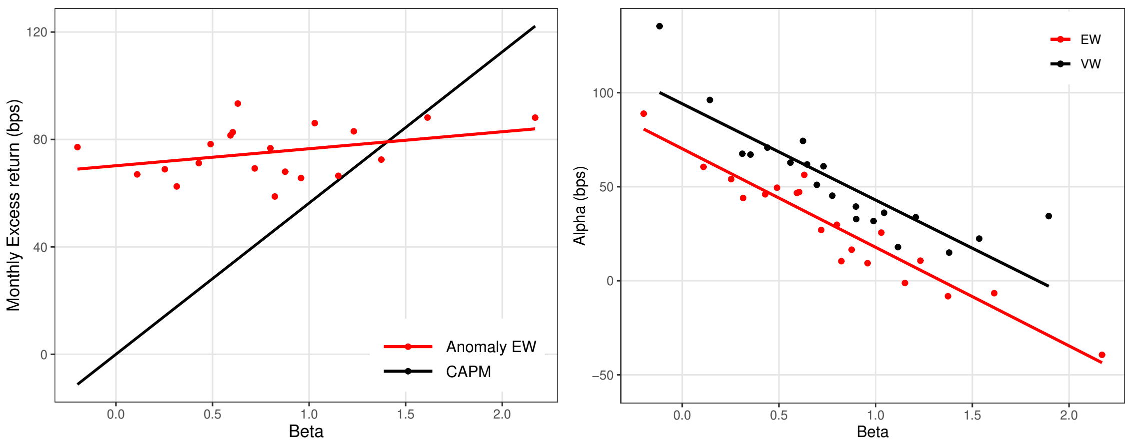

Figure 5.4: The illustration (left) and the strength (right) of the low risk anomaly. The banks are equally sorted into twenty portfolios according to the backward beta. The results correspond to monthly rate.

5.2.2 Reducing risk reduces the cost of equity

According to the figures in the previous section, reducing the banks' risk will reduce their cost of equity capital. To show the magnitude of this effect, the derivations in Section 3.2 are utilized. According to Equation 3.21:

$$\frac{dr_e}{d(1/e)} = (\gamma_e + r_m^{ex})\frac{d\beta_e}{d(1/e)} \tag{5.1}$$

In the equation, γ_e is the slope of beta in Table 5.4, which is estimated to be -52 bps in monthly unit (column 3 and 4). The market excess return (r_m^{ex}) is estimated by the average of the monthly market excess returns from 1971 to 2019, which equals 56 bps (see Table A.3). The last term $\frac{d\beta_e}{d(1/e)}$ is not a constant value. As discussed in the modified BW method, this slope will decrease with the increase of leverage, but will remain positive. From Table 5.2, the slope of the updated regression (0.068), when the dependent variable is forward beta, is used as an approximation of the representative level of $\frac{d\beta_e}{d(1/e)}$ of all banks, which should correspond to a typical bank. This approximation of $\frac{d\beta_e}{d(1/e)}$ will be lower than that of the low leverage banks and will be higher than that of high leverage banks.

Inserting all the ingredients into the above equation, the estimated derivative in monthly unit is as follows.

$$\frac{dr_e}{d(1/e)}|_{\text{considering anomaly}} = (-52 \text{ bps} + 56 \text{ bps}) \times 0.068 = 0.27 \text{ bps} \tag{5.2}$$

In this estimation, the cost of equity is positively correlated with leverage, but the correlation is very weak. According to the MM theorem, the reduced cost of equity can balance out the effect of the increased weight of equity capital. If the magnitude of the reduced cost of equity is not strong enough due to the low risk anomaly, the effect from the increased weights of equity will dominate, which means the total cost of capital will increase.

The case of ignoring the low risk anomaly (assuming the CAPM holds strictly) is also examined here. Letting the value of γ_e equal to zero, Equation 5.1 becomes:

$$\frac{dr_e}{d(1/e)}|_{\text{without anomaly}} = (0 + 56 \text{ bps}) \times 0.068 = 3.81 \text{ bps} \tag{5.3}$$

In absence of low risk anomaly, the CAPM can hold strictly, indicating the effect of reduced risk by reducing leverage will be entirely transformed to the cost of equity, instead of counteracted by the low risk anomaly. As a result, the estimation without the anomaly in Equation 5.3 is much larger than that in Equation 5.2 which considers the anomaly. According to the two estimations, we will further simulate the change in the cost of equity due to an increase in the equity ratio (e), rather than due to a decrease in leverage ($\frac{1}{e}$) in Section 5.7.

5.3 The final effect of leverage on the total cost of capital based on the BW two-step approaches

Based on the two steps of the original and modified BW approaches discussed in the previous two sections, the ultimate effect of the reduced leverage on the total cost of capital from the BW methods is estimated in this section.

In Section 3.1 and 3.2, the formulas of Δr_a are derived by the original and modified BW approaches. For the original BW method, the change of total cost of capital per year corresponding to ten percentage point increase of equity ratio can be calculated with Equation 3.14. Using the estimated strength of low risk anomaly ($\gamma_e = -52$ bps, in monthly unit) in Section 5.2.1:

$$\Delta r_a = -\gamma_e(e^* - e) \times 12 \text{ (months)} = 52 \text{ bps} \times 0.1 \times 12 = 62.4 \text{ bps} \tag{5.4}$$

It means based on the estimation using the original BW method, a ten percentage points increase in the equity capital ratio will lead to 62.4 bps increase in the total cost of capital annually. It is lower than the estimation of 85 bps per year by Baker and Wurgler [2015].

Applying the estimation from the modified BW method in Equation 3.20:

$$\begin{aligned} \Delta r_a &= [\Phi(d_1^*) - \Phi(d_1)]\beta_a\gamma_e \times 12 \text{ (months)} - \gamma_e(e^* - e) \times 12 \text{ (months)} \\ &= [\Phi(d_1^*) - \Phi(d_1)]\beta_a \times (-52 \text{ bps}) \times 12 + 62.4 \text{ bps} \end{aligned} \tag{5.5}$$

In Equation 5.5, the term of $\Phi(d_1)$ is difficult to estimate in practice. However, the term of $\Phi(d_1)\beta_a$ is equal to the ratio of β_e over $\frac{1}{e}$ according to Equation 3.17. This coincides with the definition of the slope of the piecewise linear regression with zero intercept introduced in Section 5.1.3. As a result, the difference of the slopes in the piecewise linear regressions corresponding to a ten percentage points increase in the capital ratio can be utilized as an approximation of $[\Phi(d_1^*) - \Phi(d_1)]\beta_a$.

The corresponding averaged Tier 1 ratio of each group in Table 5.3 (Panel A) is calculated and shown in Table 5.5. The group with the index of 8 has the averaged Tier 1 ratio of 9.34%. The group 1 has the lowest leverage, and the averaged Tier 1 ratio of it is 19.26%. The difference between the two groups' Tier 1 ratios is 9.92%, which is very close to 10 %. In addition, the averaged level of the Tier 1 ratio of all banks is around 12%, which is close to the value in group 8. Thus, the difference between the estimated slopes of group 1 and group 8, $0.103 - 0.066 = 0.037$ (see highlighted cells in Table 5.3), can be used as the approximation of $[\Phi(d_1^*) - \Phi(d_1)]\beta_a$.

$$\Delta r_a = 0.037 \times (-52 \text{ bps}) \times 12 \text{ (months)} + 62.4 \text{ bps} = 39.3 \text{ bps} \tag{5.6}$$

Table 5.5: The results of the averaged Tier 1 ratio within each group from the piecewise linear regression in Section 5.1.3. The highlighted cells are used in the analysis.

Index	1	2	3	4	5	6	7	8	9	10
Ave. Tier 1 ratio(%)	19.26	14.61	13.15	12.26	11.51	10.82	10.11	9.34	8.50	7.27

However, it should be kept in mind that $[\Phi(d_1^*) - \Phi(d_1)]\beta_a$ is changing in the leverage. As the leverage becomes lower, $[\Phi(d_1^*) - \Phi(d_1)]\beta_a$ will approach zero because the value of $[\Phi(d_1)]\beta_a$ will remain almost constant when the risk is very low. Thus, with the decrease of leverage, the influence of risk of debt on the total cost of capital will decrease and gradually approach zero.

Until now, the main tests and results from the original and modified BW approaches have been presented. We summarize the major findings in Table 5.6, where the key results in the work by Baker and Wurgler [2015] are also shown for reference. To conclude, the annual change in the total cost of capital (Δr_a) corresponding to ten percentage points in the capital ratio is 62.4 bps using the original BW method calculated in this thesis, and is 39.3 bps using the modified BW method. The empirical results confirm the analytical arguments that when considering the risk of debt, the increase in the total cost of capital is less than the prediction by Baker and Wurgler [2015] but still being positive.

Table 5.6: The summarized main results of the BW approaches. The results from the current thesis work as well as from the work by Baker and Wurgler [2015] are listed. The results of high interests are highlighted.

	This thesis	Baker and Wurgler
Slope of β_e on $\frac{1}{e}$, 1996-2011 (Bank Regulatory)	0.069	0.074
Slope of β_e on $\frac{1}{e}$, 1996-2019 (Compustat)	0.068	
Strength of low risk anomaly, γ_e (monthly), 1971-2011	-50 bps	-68 bps
Strength of low risk anomaly, γ_e (monthly), 1971-2019	-52 bps	
Original BW, annual Δr_a when e increases 10%	62.4 bps	85 bps
Modified BW, annual Δr_a when e increases 10%	39.3 bps	
Considering low risk anomaly, $\frac{dr_e}{d(1/e)}$ (monthly)	0.27 bps	
Without low risk anomaly, $\frac{dr_e}{d(1/e)}$ (monthly)	3.81 bps	

5.4 ICC and leverage

Different from the BW approaches which indirectly obtain the relationship between the leverage and the cost of capital, the DGT method can directly examine this correlation. In this section, the results of the relevant tests will be presented. Firstly, we reproduce the regressions of ICC on the Tier 1 ratio following the work by Dick-Nielsen et al. [2019]. Then, we conduct some modified regressions of ICC on the inverse of Tier 1 ratio, instead of directly on the Tier 1 ratio.

5.4.1 The regression of ICC on Tier 1 ratio

To perform the regression of cost of equity (measured by ICC), the data covering the time period of 1993-2019 is used, which is an update of the time period in the study by Dick-Nielsen et al. [2019] (1993-2016)*. The results of the regression of the annual ICC on Tier 1 ratio are summarized in Table 5.7 (Panel A). The first column in Panel A has the slope of Tier 1 ratio equal to -0.071 (in yearly unit), the negative sign confirms the prediction of the MM theorem that higher capital ratio will reduce the cost of equity. In addition, the magnitude of the slope is very close to the estimation by Dick-Nielsen et al. [2019] of -0.076 (it is reported as -7.619 by them because their dependent variable is in the percentage points). The slope of Tier 1 ratio remains almost unchanged when including the Tier 2 ratio and also deposit ratio (defined as $\frac{deposit}{asset}$) as the explanatory variable. So, the estimated slope of Tier 1 ratio is robust.

5.4.2 The regression of ICC on inverse of Tier 1 ratio

As proposed in the modified DGT method, the Tier 1 ratio can be replaced by the inverse of Tier 1 ratio due to the derived linear relationship between the cost of equity (r_e) and the leverage ($\frac{1}{e}$) in the BW approaches. The regression results are summarized in Table 5.7 (Panel B). There is a positive correlation between the ICC and the inverse of Tier 1 ratio, indicating that higher leverage will increase the cost of equity. Similar to the original DGT method in Section 5.4.1, the slope of the inverse of Tier 1 ratio is robust because including the inverse of Tier 2 ratio and deposit ratio will not change the result.

The slope of the annual ICC on the inverse of Tier 1 ratio is about 3.2 bps. It cannot be directly compared to the slope in Panel A where the independent variable is the Tier 1 ratio. In Section 5.7, we will derive the effect of capital ratio (e) on the cost of equity (r_e) from a known relationship between r_e and $\frac{1}{e}$. The result in Panel A and Panel B can then be compared.

However, the slope of ICC on the inverse of Tier 1 ratio can be compared to the modified BW method, where the $\frac{dr_e}{d(1/e)}|_{\text{considering anomaly}} = 0.27$ bps is derived and estimated through β_e. The slope of 3.2 bps in Panel B has an annual unit, we roughly transformed it into a monthly unit through dividing the value by 12 months, which equals to 0.27 bps. The value is the same as the estimation using the modified BW method when considering the low risk anomaly.

*Strictly speaking, the data used in the reproduced original DGT method and the proposed modified method should have the time span until 2016 to be consistent with Dick-Nielsen et al. [2019]. However, we discover the results are almost identical with that using the data until 2019. In order to compare with other methods used in this thesis which also cover data until 2019, we only report the results until 2019 in this section.

Table 5.7: The regression of ICC on capital ratios. Panel A is the regression of ICC on Tier 1 ratio. Panel B is the regression of ICC on inverse Tier 1 ratio. The results correspond to annual rate.

Panel A	*Dependent variable:*		
	Implied cost of equity capital		
	(1)	(2)	(3)
Tier 1 ratio	-0.071^{***}	-0.071^{***}	-0.072^{***}
	(0.009)	(0.009)	(0.009)
Tier 2 ratio		-0.009	-0.010
		(0.014)	(0.014)
Deposit ratio			-0.002
			(0.004)
Time effect	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes
Observations	50,328	50,171	50,325
R^2	0.860	0.860	0.860
Adjusted R^2	0.857	0.857	0.857
Residual Std. Error	0.039 (df = 49200)	0.039 (df = 49042)	0.039 (df = 49196)
F Statistic	266.110^{***}	265.872^{***}	265.633^{***}

Panel B	*Dependent variable:*		
	Implied cost of equity capital		
	(1)	(2)	(3)
Inverse of Tier 1 ratio	0.0003^{***}	0.0003^{***}	0.0003^{***}
	(0.0001)	(0.0001)	(0.0001)
Inverse of Tier 2 ratio		-0.00000	-0.00000
		(0.00000)	(0.00000)
Deposit ratio			-0.0004
			(0.004)
Time effect	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes
Observations	50,109	50,109	50,109
R^2	0.860	0.860	0.860
Adjusted R^2	0.856	0.856	0.856
Residual Std. Error	0.039 (df = 48981)	0.039 (df = 48980)	0.039 (df = 48980)
F Statistic	265.864^{***}	265.637^{***}	265.396^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

5.5 The remaining regressions in the DGT approach

Apart from the regression of ICC on the capital ratio, the DGT approach also performs the regression of cost of debt and total cost of capital on the capital ratios. Table 5.9 shows the results of the two types of regressions. To be noted, the results correspond to annual rates. The results of the regressions with dependent variable of cost of debt (r_d) are summarized in the first three columns in Table 5.9. The slopes of the Tier 1 ratio from these three regressions are all negative and significant, indicating that higher capital requirements will lower the cost of debt. However, comparing the slope of the Tier 1 ratio (-0.011, in column 3) with the same regression by Dick-Nielsen et al. [2019] (-0.023), the magnitude is approximately halved.

The results of the regressions with dependent variable of total cost of capital (r_a) are summarized in column 4-6 in Table 5.9. The slope of the Tier 1 ratio in column 4 is insignificant, indicating that capital requirement is irrelevant. However, when considering the Tier 2 ratio (column 5) and both the Tier 2 ratio and the deposit ratio (column 6), the slopes of Tier 1 ratio become significant. It means that the capital structure has impacts on the total cost of capital, despite the impact is small. Comparing the slope of Tier 1 ratio in column 6 (0.008, significant) with the result by Dick-Nielsen et al. [2019] (-0.007, not significant), the predicted impact is much larger.

The large difference between the reproduced regressions in Table 5.9 with the results by Dick-Nielsen et al. [2019] is possibly due to the insufficient amount of data in the early years (before 2008) as have been discussed in Section 4.5. With this concern, we conduct the two types of regressions again but only with the data after 2011. This is because the comparable regressions have been performed by Dick-Nielsen et al. [2019], where a series of regressions are performed including an interaction variable in the explanatory variables (Tier 1 ratio × Binary time dummy $\mathbf{1}_{\geq 2011}$[*]). Their intention of performing these regressions is to show the impacts of the low-interest-rate environment after 2011. The currently available calculated cost of debt has high and similar number of data points after 2011 as shown in the histogram in Figure 4.12. Thus, we can use the data of this time period to perform the regressions of the cost of debt and the total cost of capital on the capital ratio in order to compare them with the corresponding results by Dick-Nielsen et al. [2019].

The results are shown in Table 5.10. The slopes of the Tier 1 ratio with the dependent variable of cost of debt (r_d) (in column 1-3) are negative but have slightly larger magnitude than the corresponding ones in the previous table. Comparing the slope of Tier 1 ratio in column 3 (-0.012, significant) with the same regression by Dick-Nielsen et al. [2019] (-0.01), the results are very similar now. The regressions of the total cost of capital (r_a) on the capital ratios

[*]The indicator function is defined as $\mathbf{1}_{\geq 2011} = \begin{cases} 0, & \text{before 2011} \\ 1, & \text{2011 and onwards} \end{cases}$

are shown in column 4 to 6. Comparing the slope of Tier 1 ratio (0.011, significant) in column 6 with the same regression by Dick-Nielsen et al. [2019] (0.07), they are also similar now. But we have to keep in mind that this estimation is built upon the low-interest-rate environment. Since the banks rely heavily on the deposit financing, the low interest rate makes the cost of debt in banks especially cheap. In this sense, the estimation after 2011 might overstate the overall effect of capital requirement on the total cost of capital.

We also compare our reproduced regression of total cost of capital (r_a) on the capital ratio with different time coverage summarized in Table 5.9 (column 6) and 5.10 (column 6). The regression covering data after 1993 is having a smaller slope of Tier 1 ratio than that covering data after 2011. This might be attributed to the low-interest-rate environment after 2011. The data used in this study has very low frequency before 2008 as shown in Figure 4.12. If we had sufficient data throughout the whole time period (e.g., manually collected as Dick-Nielsen et al. [2019]), the slope of the regression using data after 1993 in our estimation might be even smaller and insignificant. Thus we infer our regression result could eventually converge to that as Dick-Nielsen et al. [2019] that the capital structure is irrelevant with the total cost of funding.

The main results of the original and modified DGT methods are summarized in Table 5.8.

Table 5.8: The summarized main results of the DGT approaches. The results from the current thesis work as well as the work by Dick-Nielsen et al. [2019] are listed. The results correspond to annual rate.

	This thesis	Dick-Nielsen et al.
Slope of ICC on Tier 1 ratio, after 1993	-0.071	-0.076
Slope of r_d on Tier 1 ratio, after 1993	-0.011	-0.023
Slope of r_a on Tier 1 ratio, after 1993	0.008	-0.007
Slope of r_d on Tier 1 ratio, after 2011	-0.012	-0.010
Slope of r_a on Tier 1 ratio, after 2011	0.011	0.007
Annual Δr_a when e increases 10%, after 2011	11 bps	7 bps
Slope of ICC on inverse of Tier 1 ratio $\frac{dr_e}{d(1/e)}$, after 1993	3.2 bps	

Table 5.9: The regression of cost of capital on capital ratios, 1993-2019. The first three columns have the dependent variable of cost of debt capital, which is calculated from the total interest expenses and the total debt value of banks. The last three columns have the dependent variable of total cost of capital, which is the weighted average of cost of debt and the ICC. The results correspond to annual rate.

	Dependent variable:					
	Cost of debt capital			Total cost of capital		
	(1)	(2)	(3)	(4)	(5)	(6)
Tier1 ratio	-0.006^{***}	-0.006^{***}	-0.011^{***}	0.003	0.010^{***}	0.008^{***}
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Tier2 ratio		-0.00001	-0.00001		0.050^{***}	0.046^{***}
		(0.00002)	(0.00001)		(0.005)	(0.005)
Deposit ratio			-0.009^{***}			-0.008^{***}
			(0.001)			(0.002)
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,789	24,688	24,674	16,961	16,936	16,936
R^2	0.965	0.965	0.965	0.924	0.924	0.924
Adjusted R^2	0.963	0.963	0.963	0.921	0.921	0.921
Residual Std. Error	0.003	0.003	0.003	0.007	0.007	0.007
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 5.10: The regression of cost of capital on capital ratios, 2011-2019. The first three columns have the dependent variable of cost of debt capital, which is calculated from the total interest expenses and the total debt value of banks. The last three columns have the dependent variable of total cost of capital, which is the weighted average of cost of debt and the ICC. The results correspond to annual rate.

	Dependent variable:					
	Cost of debt capital			Total cost of capital		
	(1)	(2)	(3)	(4)	(5)	(6)
Tier1 ratio	-0.009^{***}	-0.009^{***}	-0.012^{***}	0.001	0.012^{***}	0.011^{***}
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
Tier2 ratio		−0.00000	−0.00000		0.064^{***}	0.062^{***}
		(0.00001)	(0.00001)		(0.007)	(0.007)
Deposit ratio			-0.008^{***}			-0.006^{**}
			(0.001)			(0.003)
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,635	18,572	18,564	11,740	11,730	11,730
R^2	0.956	0.957	0.957	0.863	0.863	0.863
Adjusted R^2	0.954	0.954	0.955	0.858	0.859	0.859
Residual Std. Error	0.003	0.003	0.003	0.007	0.007	0.007
Note:				*p<0.1; **p<0.05; ***p<0.01		

5.6 Realized return of equity and leverage

Apart from the CAPM-based BW method and the DGT method based on the ICC and expected return of debt, a data-based method is proposed in Section 3.5 which utilizes an instrumental variable (IV) to mitigate the endogeneity problem in the regression of realized return on the leverage. A time dummy variable is chosen based on the implementation time of Basel I. Thus, in the regression of realized return on leverage, the inverse of Tier 1 ratio cannot be used as the independent variable since it was also introduced in the Basel I. Instead, the inverse of common equity ratio is used to measure the leverage ($\frac{1}{e}$). The regression of the realized return of equity on the inverse of common equity ratio is summarized in Table 5.11. The estimated slope $\frac{dr_e}{d(1/e)}$ is 6.7 bps (in monthly unit) and significant, indicating a strong positive correlation between the leverage and cost of equity.

In addition, two diagnostic tests are performed to check the validity of the IV. Firstly, the weak instruments test with a null that the IV has a low correlation with the endogenous dependent variable is applied. It shows that the null is significantly rejected. Thus, the chosen IV can satisfy the first of the two requirements of IV mentioned in Section 3.5. Secondly, the Wu-Hausman test with the null stating that the IV regression is just as consistent as the OLS regression is applied. If the null cannot be rejected, the IV regression is inefficient. From the test result, this inefficiency null is also rejected, indicating that using the OLS regression cannot be more efficient than the IV regression. As a result, the validity of the IV is confirmed.

Table 5.11: The IV regression of realized return on inverse of common equity ratio. The weak instruments test and the Wu-Hausman test are done and confirm the validity of the IV. The results correspond to monthly data.

	Dependent variable: Realized return of equity
Inverse of common equity ratio	6.7e-04***(0.0001)
Intercept	2.5e-03***(0.002)
Observations	219,017
R^2	-0.735
Residual Std. Error	0.133 (df = 219015)
Diagnostic tests:	p-value
Weak instruments	<2e-16***
Wu-Hausman	6.23e-14***
Note:	*p<0.1; **p<0.05; ***p<0.01

5.7 The effect of increased capital ratio on the cost of equity

From the proposed methods, there have been different estimations of the correlation between the cost of equity and leverage (measured by $\frac{dr_e}{d(1/e)}$). This section aims to have an intuitive illustration of the extent of the capital ratio's effect (instead of leverage's effect) on the cost of equity. The change in the cost of equity corresponding to a ten percentage points increase in the equity ratio will be calculated and compared.

Denoting $\frac{dr_e}{d(1/e)}$ as a k, Table 5.12 summarizes the estimations of k (in monthly unit) from different methods where the cost of equity is measured by the CAPM considering low risk anomaly, the CAPM without anomaly, the ICC and the realized return.

Table 5.12: The summarized slopes of the cost of equity on leverage in monthly unit. In the first two columns, the cost of equity is measured by the CAPM considering low risk anomaly and by the CAPM without considering the anomaly, respectively. The results are obtained in Section 5.2.2. In the third column, the cost of equity is measured by the ICC, and the result is obtained in Section 5.4.2 where the annual slope is 3.2 bps. Here we roughly transform it into a monthly unit through dividing by 12. In the last column, the cost of equity is measured by the realized return of equity. The result is obtained from Section 5.6.

	CAPM considering the anomaly	CAPM without the anomaly	ICC	Realized return of equity (IV method)
$k = \frac{dr_e}{d(1/e)}$	0.27 bps	3.81 bps	0.27 bps	6.69 bps

Rewriting $k = \frac{dr_e}{d(1/e)}$ as

$$dr_e = k \times d(\frac{1}{e}) \tag{5.7}$$

Take integral in both sides with the equity ratio from e to e^*.

$$\int_{r_e}^{r_e^*} dr_e = k \int_{e}^{e^*} (-\frac{1}{e^2})de = k\frac{1}{e}\Big|_e^{e^*} = k(\frac{1}{e^*} - \frac{1}{e}) \tag{5.8}$$

With the definition of the change in cost of equity (Δr_e):

$$\Delta r_e \equiv r_e^* - r_e = \int_{r_e}^{r_e^*} dr_e = k(\frac{1}{e^*} - \frac{1}{e}) \tag{5.9}$$

From Equation 5.9, the value of Δr_e for given value of equity ratio changes from e to e^* can be then simulated. Here, the case of ten percentage points increase in the equity ratio is examined, which means $e^* - e = 0.1$. The simulation is shown in Figure 5.5.

Supposing the current equity ratio is 10%, when the cost of equity is measured by CAPM considering low risk anomaly or by the ICC, the ten percentage points of increase in the capital ratio will lead to a very small decrease (approximately -2 bps) of cost of equity per month. It might not be strong enough to balance out the impact of ten percentage points increase in the capital ratio. The other two methods predict much larger decreases in the cost of equity. The IV model predicts the largest monthly decrease, about -33 bps per month, followed by the CAPM without anomaly method (-19 bps).

As mentioned in Section 5.4.2, we can now compare the original DGT method and the modified DGT method since we have calculated the direct effect of the capital ratio on the cost of equity. In Table 5.7 (Panel A), the linear regression of the original DGT method predicts when the equity ratio increase ten percentage points, the annual cost of equity will decrease 71 bps. However, the simulation with the modified DGT method predicts that when the equity ratio increase ten percentage points, the annual cost of equity will only decrease 24 bps[*]. The comparison indicates that the change of total cost of capital (Δr_a) predicted by the original DGT method is too small compared to the modified DGT method, because the cost of equity does not decline by a sufficient amount to balance the effect of the increase in equity ratio. The comparison also indicates that the different assumptions of linear relationships in the regressions could produce very different conclusions when using the same data.

It can be observed that the magnitude of the change in the cost of equity (Δr_e) is decreasing as the equity ratio grows for all models. When the current equity ratio is large (especially when more than 35%), all the four models predict very small magnitude of Δr_e. It indicates when the leverage is already relatively low, an additional reduction in leverage will only lead to a tiny decrease in the cost of equity. Then the decrease in the cost of equity might be insufficient to balance out the effect of the increase in the equity ratio. This means when the capital ratio in banks is already high, the stricter capital requirements will then significantly increase the total cost of funding.

[*]The monthly decrease is 2 bps obtained from Figure 5.5, so the yearly rate is obtained by multiplying by 12 months.

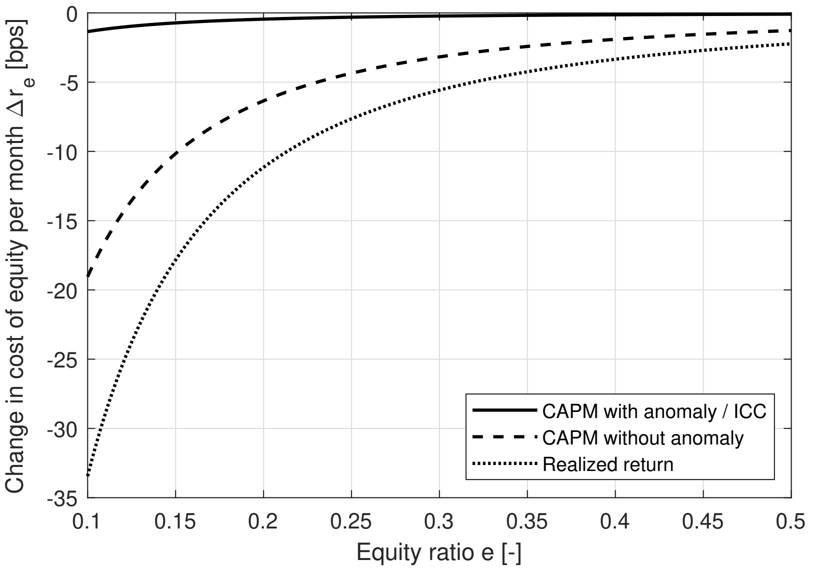

Figure 5.5: The change in cost of equity when the equity ratio increases by ten percentage points for different values of current equity ratio. The results when the cost of equity is measured by CAPM with low risk anomaly and by ICC are the same and plotted together. The results correspond to monthly rate.

Chapter 6

Conclusion

This thesis examines the impacts of increased capital requirement on the cost of capital in banks. According to the MM theorem, the reduced leverage will reduce the risk and thus reduce the cost of equity. These effects will finally balance out and the capital structure is irrelevant with the total cost of capital in a frictionless world. However, depending on how the frictions are modeled, the capital structure might be relevant.

We revisit the work by Baker and Wurgler [2015] and Dick-Nielsen et al. [2019] that utilize different models to measure the cost of capital and then investigate the impacts of the capital requirement in banks. In the work by Baker and Wurgler [2015], the cost of equity is measured by the CAPM which is adjusted by a low risk anomaly. Meanwhile, the debt is assumed to be riskless. Using this modeling framework, we reproduce the estimations and tests. We find the reduced leverage will reduce the equity beta, but the reduced equity beta does not lead to a sufficiently large decline in the cost of equity due to the low risk anomaly, the total cost of capital will then rise significantly. We estimate that a ten percentage points increase in the capital ratio will lead to a 62.4 basis points (bps) increase in the annual total cost of capital which is significant.

Dick-Nielsen et al. [2019] measure the cost of equity by the implied cost of capital (ICC) and calculate the cost of debt through the interest expenses of banks. The impacts of capital ratio on the cost of equity, the cost of debt and the total cost of capital are modeled separately. We also reproduce these regressions but with a shorter time coverage due to the limited data availability. We estimate that in the low-interest-rate environment after 2011, a ten percentage points increase in the capital ratio will lead to an 11 bps increase in the annual total cost of capital which is small. We also infer that if sufficient data covering the time before 2011 is available, the estimated increase in the capital ratio could be even lower which indicates the irrelevance of capital structure.

In addition, some extensions are proposed based on the framework of the above two studies. Firstly, we relax the riskless debt assumption made by Baker and Wurgler [2015]. We instead apply the option pricing theory to include the risk of debt in the modeling framework. According to this modification, we conclude that their final estimation of the increase in the total cost of capital is too large. In our estimation, starting from the current level of capital ratio, the increase in the annual total cost of capital corresponding to a ten percentage points increase in the capital ratio is 39.3 bps, which is moderate.

The estimation using the proposed method has dynamic characteristics instead of being static. From the analytical arguments in the proposed method, we infer that when the capital ratio of banks is much higher than the current level, the additional term due to risk of debt will approach zero. Then, under this condition, the further stricter capital requirement will lead to a significant increase in the total cost of capital which converges to the conclusion by Baker and Wurgler [2015].

The above findings and conclusions focus on the impacts of the capital requirement on the total cost of capital of banks. Since the change in the cost of equity capital accounts for a large fraction of the change of total funding costs, we also investigate the impacts of capital ratio on the cost of equity separately. In the second extension, we perform the regression of the ICC on the multiplicative inverse of capital ratio, instead of on the capital ratio as in the original work by Dick-Nielsen et al. [2019]. This modification is based on the derivation in Baker and Wurgler's framework that the cost of equity is linearly correlated with the inverse of capital ratio. We discover that different model equations will produce very different conclusions. When the independent variable is the capital ratio as in the original work of Dick-Nielsen et al. [2019], a ten percentage points increase in the capital ratio will lead to 71 bps decrease in the annual cost of equity. But when the independent variable is the inverse of capital ratio proposed in this thesis, the estimated decrease is only 24 bps, which might be insufficient to balance out a ten percentage points increase in the capital ratio. Hence, we infer this proposed method will predict a moderate increase in the total cost of capital.

The third extension is also based on the linear correlation between the cost of equity and the inverse of capital ratio. Instead of utilizing a model to measure the cost of equity, we propose a data-based method of instrumental variable (IV) by directly regressing the realized return of equity on the inverse of capital ratio, with a time dummy as IV. It predicts a very large decline when the capital ratio increases. The main limitation of this method is the noise in the dependent variable of the realized cost of equity.

In conclusion, the thesis tries to empirically answer the research question to what extent does the increased capital requirement affect the cost of capital in banks utilizing several different methods. From the proposed modification based on Baker and Wurgler [2015] with the risk of debt considered, we find their estimated increase of the total cost of capital due to stricter capital requirements is too large. In the proposed method based on Dick-Nielsen et al. [2019] with the capital ratio replaced by the inverse of capital ratio, we infer their estimated impacts of stricter capital requirement on the total cost of capital might be underestimated. Both of these proposed methods in this thesis predict a moderate increase in the total cost of capital due to stricter regulations for the banks with the current level of leverage.

Through the investigation process we have realized that there are still many factors not considered but could be important, such as the deposit insurance, the tax shields and the interest rates. In addition, apart from the cost of capital, the stricter bank regulation might have other impacts on banks. Further investigations could be insightful if more important factors are considered.

Bibliography

Anat Admati and Martin Hellwig. *The Bankers' New Clothes: What's Wrong with Banking and What to Do about It-Updated Edition*. Princeton University Press, 2014.

Gregor Andrade and Steven N Kaplan. How costly is financial (not economic) distress? evidence from highly leveraged transactions that became distressed. *The Journal of Finance*, 53(5): 1443–1493, 1998.

Malcolm Baker and Jeffrey Wurgler. Do strict capital requirements raise the cost of capital? bank regulation, capital structure, and the low-risk anomaly. *American Economic Review*, 105(5):315–20, 2015.

Malcolm Baker, Brendan Bradley, and Jeffrey Wurgler. Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. *Financial Analysts Journal*, 67(1):40–54, 2011.

Jonathan B Berk and Peter M DeMarzo. *Corporate finance*. Pearson Education, 2007.

BIS. The Basel Framework, 2020. `https://www.bis.org/basel_framework/`, last accessed on 02/04/2020.

Fischer Black and Myron Scholes. The pricing of options and corporate liabilities. *Journal of political economy*, 81(3):637–654, 1973.

Fischer Black, Michael C Jensen, Myron Scholes, et al. The capital asset pricing model: Some empirical tests. *Studies in the theory of capital markets*, 81(3):79–121, 1972.

John C Cox, Stephen A Ross, and Mark Rubinstein. Option pricing: A simplified approach. *Journal of financial Economics*, 7(3):229–263, 1979.

Jens Dick-Nielsen, Jacob Gyntelberg, and Christoffer Thimsen. The cost of capital for banks. `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3360923#references-widget/`, 2019.

Peter D Easton. Pe ratios, peg ratios, and estimating the implied expected rate of return on equity capital. *The accounting review*, 79(1):73–95, 2004.

Edwin J Elton. Presidential address: expected return, realized return, and asset pricing tests. *The Journal of Finance*, 54(4):1199–1220, 1999.

Eugene F Fama and Kenneth R French. The capital asset pricing model: Theory and evidence. *Journal of economic perspectives*, 18(3):25–46, 2004.

Eugene F Fama and James D MacBeth. Risk, return, and equilibrium: Empirical tests. *Journal of political economy*, 81(3):607–636, 1973.

Mark J Flannery and Kasturi P Rangan. What caused the bank capital build-up of the 1990s? *Review of Finance*, 12(2):391–429, 2008.

Andrea Frazzini and Lasse Heje Pedersen. Betting against beta. *Journal of Financial Economics*, 111(1):1–25, 2014.

Dan Gode and Partha Mohanram. Inferring the cost of capital using the ohlson–juettner model. *Review of accounting studies*, 8(4):399–431, 2003.

Joseph R Gordon and Myron J Gordon. The finite horizon expected return model. *Financial Analysts Journal*, 53(3):52–61, 1997.

John R Graham. How big are the tax benefits of debt? *The Journal of Finance*, 55(5):1901–1941, 2000.

Kewei Hou, Mathijs A Van Dijk, and Yinglei Zhang. The implied cost of capital: A new approach. *Journal of Accounting and Economics*, 53(3):504–526, 2012.

John C Hull. *Risk management and financial institutions.* John Wiley & Sons, Hoboken, N.J, 5. ed. edition, 2018. ISBN 9781119448112.

Michael C Jensen. The performance of mutual funds in the period 1945–1964. *The Journal of finance*, 23(2):389–416, 1968.

Anil K Kashyap, Jeremy C Stein, and Samuel Hanson. An analysis of the impact of 'substantially heightened'capital requirements on large financial institutions. *Booth School of Business, University of Chicago, mimeo*, 2, 2010.

Alan Kraus and Robert H Litzenberger. A state-preference model of optimal financial leverage. *The journal of finance*, 28(4):911–922, 1973.

John Lintner. Security prices, risk, and maximal gains from diversification. *The journal of finance*, 20(4):587–615, 1965.

Robert C Merton. On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance*, 29(2):449–470, 1974.

David Miles, Jing Yang, and Gilberto Marcheggiano. Optimal bank capital. *The Economic Journal*, 123(567):1–37, 2013.

Merton H Miller. Do the m & m propositions apply to banks? *Journal of Banking & Finance*, 19(3-4):483–489, 1995.

Frederic S Mishkin. *The economics of money, banking, and financial markets*. Pearson Education Limited, Harlow, 10. ed., global ed. edition, 2013. ISBN 0273765736.

Franco Modigliani and Merton H Miller. The cost of capital, corporation finance and the theory of investment. *The American*, 1:3, 1958.

Partha Mohanram and Dan Gode. Removing predictable analyst forecast errors to improve implied cost of equity estimates. *Review of Accounting Studies*, 18(2):443–478, 2013.

Stewart C Myers and Nicholas S Majluf. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of financial economics*, 13(2): 187–221, 1984.

James A Ohlson and Beate E Juettner-Nauroth. Expected eps and eps growth as determinantsof value. *Review of accounting studies*, 10(2-3):349–365, 2005.

Stephen A Ross. The determination of financial structure: the incentive-signalling approach. *The bell journal of economics*, pages 23–40, 1977.

William F Sharpe. Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, 19(3):425–442, 1964.

Appendix A

Additional tables and figures

Table A.1: The source and description of relevant variables.

Description	Source	Symbol
Company unique identifier in CRSP	CRSP	PERMNO
Monthly stock return	CRSP	RET
Closing price or bid/ask average	CRSP	PRC
Number of shares outstanding (thousand)	CRSP	SHROUT
Ten-year bond returns	CRSP	B10RET
Excess return on the market	Kenneth R. French Data Library	MKTRF
Risk-free rate (one-month Treasury Bill rate)	Kenneth R. French Data Library	RF
Total interest and related expenses	Compustat	XINT
Common equity	Compustat	CEQ
Total liabilities	Compustat	LT
Income before extrordinary items	Compustat	IB
Dividends on common equity	Compustat	DVC
Total deposits	Compustat	DPTC
Total asset	Compustat	AT
Risk adjusted Tier 1 ratio	Compustat	CAPR1
Risk adjusted Tier 2 ratio	Compustat	CAPR2
Tier 1 capital	Bank regulatory	RCFD/BHCK 8274
Risk weighted assets	Bank regulatory	RCFD/BHCK A223
Median value of one-year-ahead forecasts of dps	I/B/E/S	DPS1MD
Median value of one-year-ahead forecasts of eps	I/B/E/S	EPS1MD
Median value of two-year-ahead forecasts of eps	I/B/E/S	EPS2MD
Long term growth	I/B/E/S	LTG
Current price	I/B/E/S	IBP

Note: The data from the database of CRSP, Compustat and Bank regulatory is accessed through the Wharton Research Data Services.

Table A.2: The SIC code of different categories of banks. Banks are defined in the Kenneth R. French Data Library (48 industry portfolios) with the SIC code from 6000 to 6199. Concerning the research question, not all of the banks are included. For example, the foreign banks and the Federal reserve banks are excluded. In addition, the bank holding company can engage in activities related to banking and are included in the data samples.

SIC code	Industry	1970-1979	1980-1989	1990-1999	2000-2009	2010-2019	Total
6000-6000	Depository institutions	1	0	1	1	1	3
6010-6019	Federal reserve banks	N.I.	N.I.	N.I.	N.I.	N.I.	N.I.
6020-6020	Commercial banks	17	254	449	274	112	505
6021-6021	National commercial banks	33	59	92	143	108	172
6022-6022	State commercial banks - Fed Res System	28	62	109	205	148	263
6023-6024	State commercial banks-not FedResSystem	21	24	5	0	0	27
6025-6025	National commercial banks-Fed Res System	65	73	29	3	1	94
6026-6026	National commercial banks-not FedResSys.	0	2	2	0	0	2
6027-6027	National commercial banks-not FDIC	0	0	0	0	0	0
6028-6029	Misc commercial banks	2	6	27	38	31	46
6030-6036	Savings institutions	6	194	529	418	158	651
6040-6059	Other Banks	0	1	0	0	0	1
6060-6062	Credit unions	0	1	5	1	0	5
6080-6082	Foreign banks	N.I.	N.I.	N.I.	N.I.	N.I.	N.I.
6090-6099	Functions related to depository banking	N.I.	N.I.	N.I.	N.I.	N.I.	N.I.
6100-6100	Non-depository credit institutions	N.I.	N.I.	N.I.	N.I.	N.I.	N.I.
6110-6111	Federal credit agencies	N.I.	N.I.	N.I.	N.I.	N.I.	N.I.
6112-6113	FNMA	N.I.	N.I.	N.I.	N.I.	N.I.	N.I.
6120-6129	S&Ls	39	63	9	0	0	77
6130-6139	Agricultural credit institutions	0	0	0	0	0	0
6140-6149	Personal credit institutions (Beneficial)	24	21	49	31	24	90
6150-6159	Business credit institutions	21	38	64	45	23	105
6160-6169	Mortgage bankers and brokers	26	31	67	37	17	113
6170-6179	Finance lessors	0	0	1	0	0	1
6190-6199	Financial services	0	0	2	1	1	3
6710-6719	Bank Holding offices	417	692	561	93	63	1054
	Total	703	1524	2001	1290	687	3212

Note: N.I. are those banks not included in this thesis work, following the selection by Baker and Wurgler [2015].

Table A.3: The descriptive statistics of return and capital structure data of banks.

	Obs.	Mean	Median	Min	Max
Return	392123	0.0114	0.0049	-0.9308	5.4000
Price ($)	392123	20.5354	16.5000	0.0156	559.00
Shares (Million)	392123	45.2390	5.1330	0.0000	29206.40
Market excess return	600	0.0056	0.0098	-0.2324	0.1610
Risk-free rate	600	0.0038	0.0040	0.0000	0.0135
Common Equity ($Million)	24847	1964.59	98.67	0.01	244823.00
Liability ($Million)	24847	30056.35	1077.09	12.99	3589783.24
Deposit ($Million)	24847	18054.08	925.67	0.06	1974374.53
Asset ($Million)	24847	32189.98	1184.15	16.80	3771199.85
Book leverage ratio (%)	24847	90.71	91.26	51.03	99.93
Common equity ratio (%)	24847	9.05	8.54	0.00	48.97
Deposit liability ratio (%)	24847	83.95	86.58	0.26	99.88
Tier 1 ratio (%)	18967	11.98	11.44	0.00	93.63

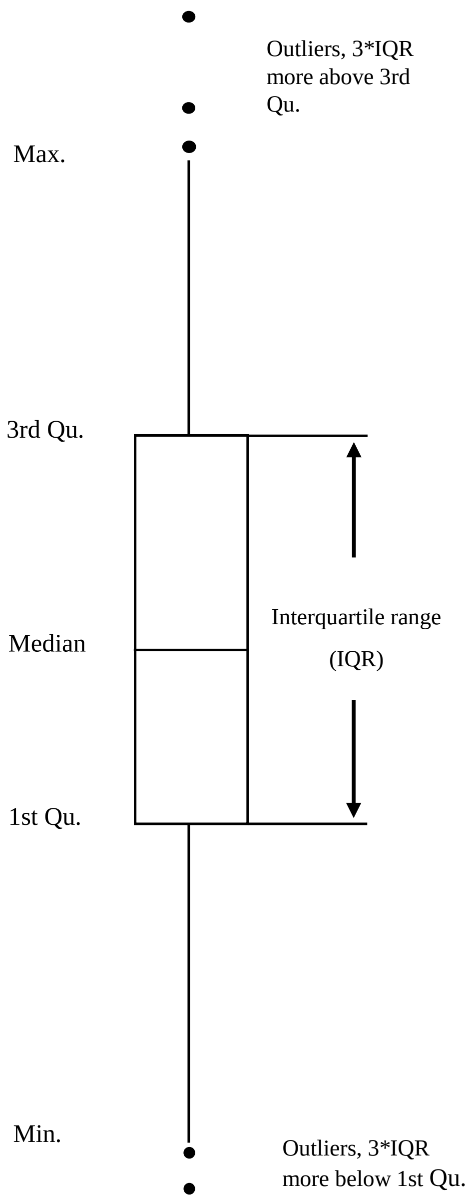

Figure A.1: The description of the box plot. This type of plot can illustrate several important statistics at the same time, such as the median, the minimum and the maximum value.

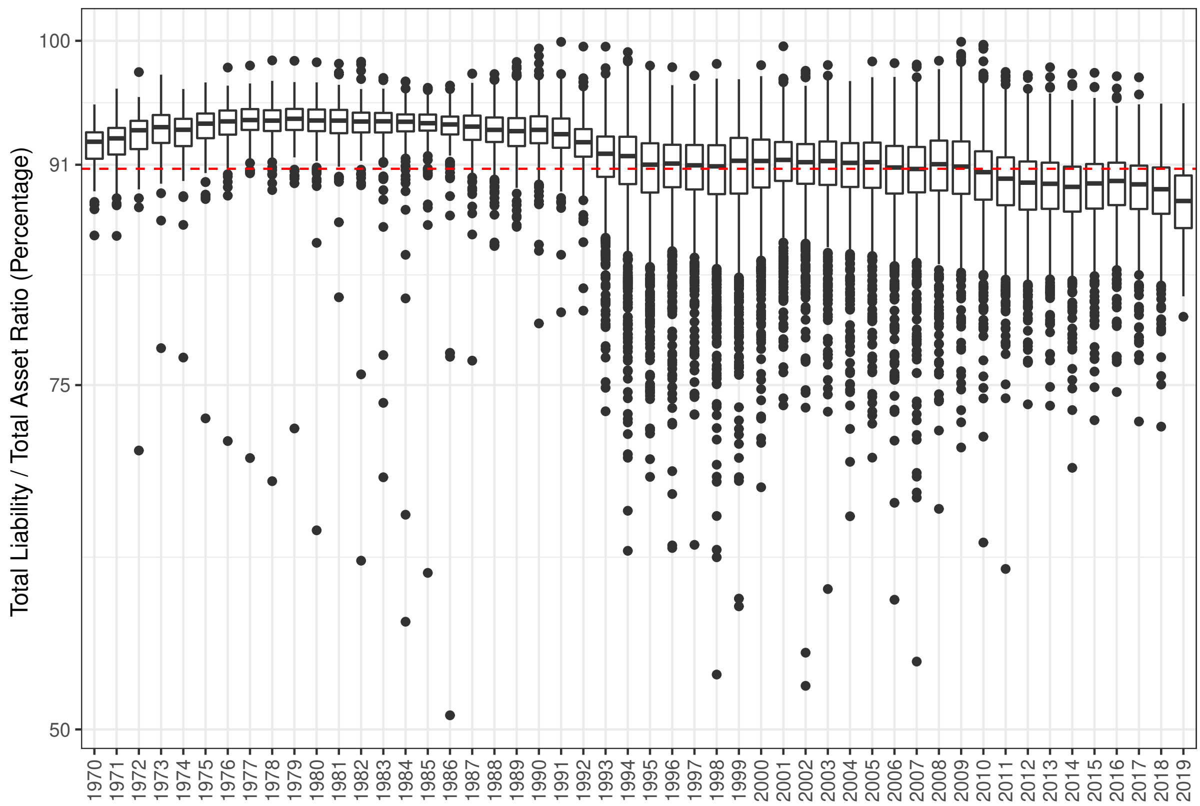

Figure A.2: The yearly distribution of book leverage ratio (Total liability / Total asset), 1970-2019. The figure takes the form of a box plot. The red dashed line is the whole sample average of the ratio, which is 90.7%.

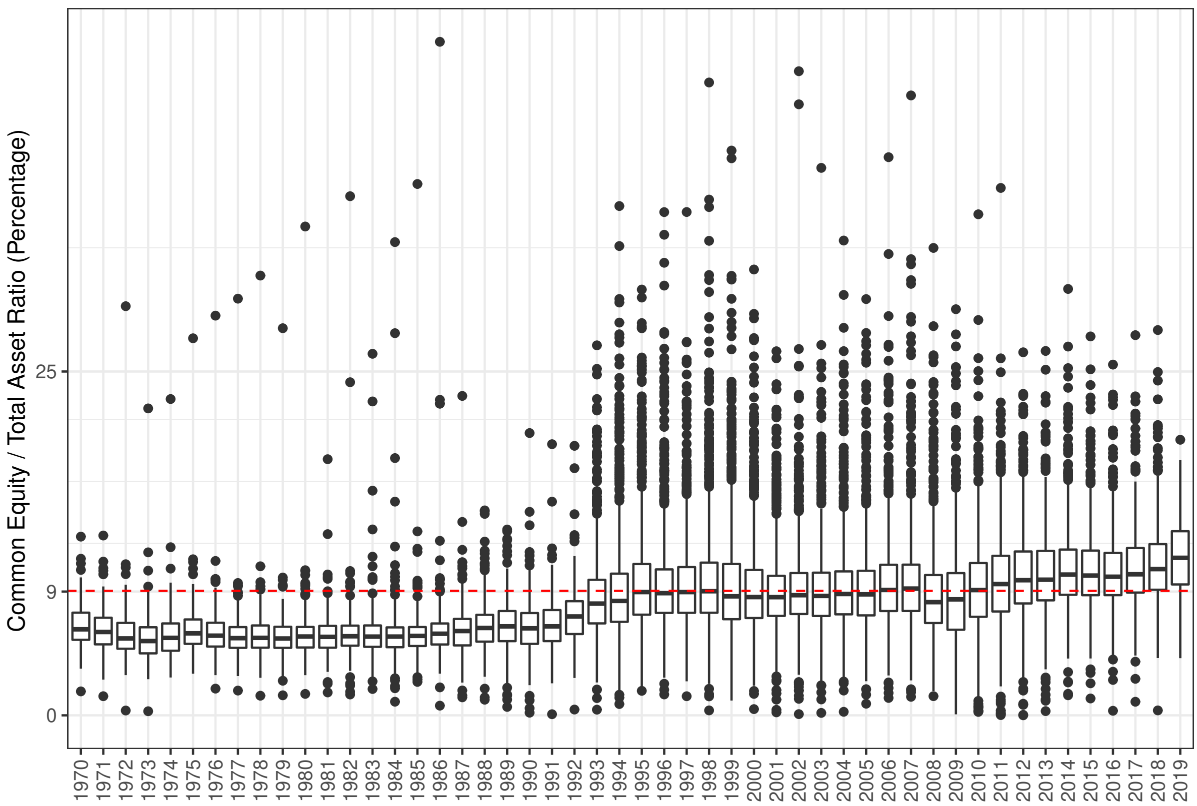

Figure A.3: The yearly distribution of common equity ratio (Common equity / Total asset), 1970-2019. The figure takes the form of a box plot. The red dashed line is the whole sample average of the ratio, which is 9.1%.

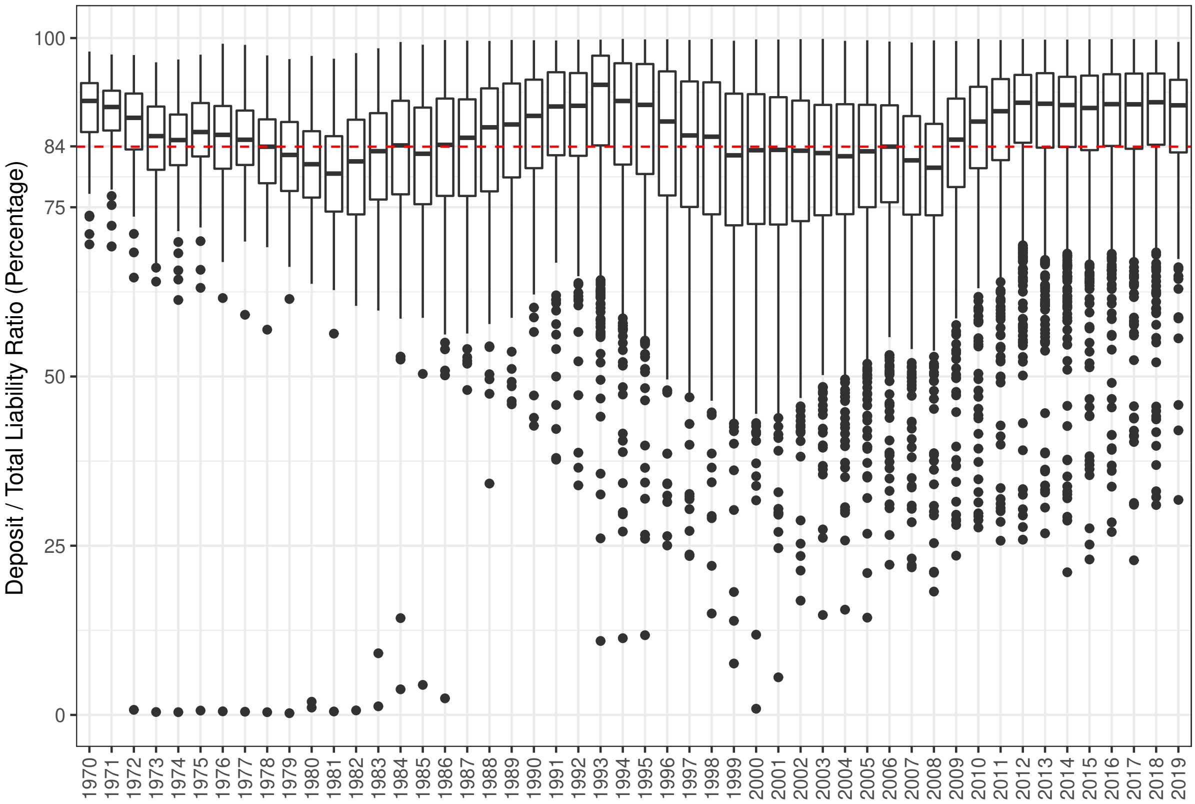

Figure A.4: The yearly distribution of deposit liability ratio (Deposit / Total liability), 1970-2019. The figure takes the form of a box plot. The red dashed line is the whole sample average of the ratio, which is 84%.

Appendix B

Applying Black-Scholes-Merton model

In valuing the options, a replicating portfolio is a portfolio consisted of other securities that has exactly the same value as the option. Thus, the objective in creating such a portfolio is to use a combination of risk-free borrowing or lending and the underlying asset to create the same cash flows with the option.

In Section 3, we used the notation of equity (E) and underlying asset of (A) to express the property of equity. In this section, we will follow the general notations used in the option pricing theories. The call option C is underlying on a non-dividend stock (S), and this option is replicated by Δ shares of stock and one share of bond B.

$$C = S\Delta + B \tag{B.1}$$

The dynamics of the call option is same with the replicating portfolio,

$$dC = \Delta dS + dB \tag{B.2}$$

Assuming the price of the stock is an Ito process,

$$dS_t = \mu(S_t, t)dt + \sigma(S_t, t)dz_t \tag{B.3}$$

Where $\mu(S_t, t)d_t$ is the drift term, and $\sigma(S_t, t)dz_t$ is the volatility term.

In addition, the riskless bond B has the mean equal to r (risk-free rate), and volatility equal to zero. Thus,

$$dB = rBdt \tag{B.4}$$

Combining Equation B.3 and B.4, Equation B.2 becomes:

$$\begin{aligned} dC &= \Delta(\mu(S_t,t)dt + \sigma(S_t,t)dz_t) + rBdt \\ &= (\Delta\mu(S_t,t) + rB)dt + \Delta\sigma(S_t,t)dz_t \end{aligned} \tag{B.5}$$

Since the call option is also a derivative underlying on the stock, we can find the dynamics of it by applying Ito's Lemma,

$$\begin{aligned} dC &= C_t dt + C_S dS_t + \frac{1}{2}C_{SS}(dS_t)^2 \\ &= (C_t + \mu(S_t,t)C_S + \frac{1}{2}\sigma^2(S_t,t)C_{SS})dt + \sigma(S_t,t)C_S dz_t \end{aligned} \tag{B.6}$$

Where the short-hand notations are used with $C_t = \frac{\partial C(S_t,t)}{\partial t}$, $C_S = \frac{\partial C(S_t,t)}{\partial S_t}$, $C_{SS} = \frac{\partial^2 C(S_t,t)}{\partial S_t \partial t}$.

Comparing Equation B.5 and B.6, the last term in Equation B.5 should be equal to the last term in Equation B.6:

$$\Delta\sigma(S_t,t)dz_t = \sigma(S_t,t)C_S dz_t \tag{B.7}$$

From the above equation, we can solve the Δ:

$$\Delta = C_S \tag{B.8}$$

From the Black-Scholes-Merton model:

$$C = S\Phi(d_1) - \mathrm{PV}(K)\Phi(d_2) \tag{B.9}$$

where

$$\begin{aligned} d_1 &= \frac{ln(S/\mathrm{PV}(K))}{\sigma\sqrt{T}} + \frac{\sigma\sqrt{T}}{2} \\ d_2 &= d_1 - \sigma\sqrt{T} \end{aligned}$$

The value of Δ is given by:

$$\Delta = C_S = \Phi(d_1) \tag{B.10}$$

Appendix C

Details in deriving ICC

The OJ model is derived by relaxing and changing some assumptions of the GGM model. It still assumes that price is the present value of future dividends, but there is no restriction on the payout policy. In addition, the perpetual growth rate g can be different from a short-term growth rate. The details of deriving OJ models are as follows.

Similar with Equation 3.24 but without assuming the constant growth rate of dividends in every future period, the OJ model starts with:

$$P_0 = \text{PV}(\sum_{t=1}^{\infty} dps_t) = \sum_{t=1}^{\infty} dps_t R^{-t} \tag{C.1}$$

In order to relate the Equation C.1 with the expected earnings, an additional sequence $\{y_t\}_{t=0}^{\infty}$ is introduced. It can be any sequence as if it can satisfy: $R^{-T} y_T \to 0$ as $T \to \infty$ (y_T will not explode). As if this condition is satisfied, it is shown that:

$$y_0 + \sum_{t=1}^{T} R^{-t}(y_t - Ry_{t-1}) = 0 \text{ when } T \to \infty \tag{C.2}$$

Proving $y_0 + \sum_{t=1}^{T} R^{-t}(y_t - Ry_{t-1}) = 0$ when $T \to \infty$

$$\begin{aligned} R^{-T} y_T &= y_0 + R^{-1}y_1 - y_0 + R^{-2}y_2 - R^{-1}y_1 + ... + R^{-T}y_T - R^{-T+1}y_{T-1} \\ &= y_0 + R^{-1}(y_1 - Ry_0) + R^{-2}(y_2 - Ry_1) + ... + R^{-T}(y_T - Ry_{T-1}) \\ &= y_0 + \sum_{t=1}^{T} R^{-t}(y_t - Ry_{t-1}) \\ &= 0 \text{ when T} \to \infty \end{aligned} \tag{C.3}$$

Combining Equation C.1 and C.2 together:

$$\begin{aligned} P_0 &= y_0 + \sum_{t=1}^{\infty} dps_t R^{-t} + \sum_{t=1}^{\infty} R^{-t}(y_t - Ry_{t-1}) \\ &= y_0 + \sum_{t=1}^{\infty} R^{-t}(dps_t + y_t - Ry_{t-1}) \end{aligned} \tag{C.4}$$

Now that y_t can be any sequence as long as it will not explode, it is appealing to use an *eps* related sequence. The term $\frac{eps_{t+1}}{r}$ is chosen here, it is considered as a measure of expected cost to invest in a share as mentioned in GGM. So, it satisfies the non-exploding condition. The initial value $y_0 = \frac{eps_1}{r}$, and $y_t = \frac{eps_{t+1}}{r}$. Insert y_t in Equation C.4, it becomes:

$$P_0 = \frac{eps_1}{r} + \sum_{t=1}^{\infty} R^{-t}(dps_t + \frac{eps_{t+1}}{r} - R\frac{eps_t}{r}) \tag{C.5}$$

Denoting the terms in the brackets as $z_t = \frac{1}{r}(rdps_t + eps_{t+1} - Reps_t)$, it becomes:

$$P_0 = \frac{eps_1}{r} + \sum_{t=1}^{\infty} R^{-t} z_t \tag{C.6}$$

Taking a closer look at z_t or rz_t:

$$rz_t = rdps_t + eps_{t+1} - Reps_t = eps_{t+1} - (Reps_t - rdps_t) \tag{C.7}$$

The second term $Reps_t - rdps_t = eps_t + r(eps_t - dps_t)$ serves as a benchmark of expected *eps* of time $t+1$, this is because $eps_t - dps_t$ is the expected retained earnings of time t, firms use the retained earnings to run business and the return of them in time t+1 is $r(eps_t - dps_t)$. Thus, in this benchmark case, the expected *eps* in time $t+1$ is the expected *eps* in time t plus a investment return: $eps_t + r(eps_t - dps_t)$. However, the earnings might be generated from other sources, or there might exist other growth potentials, the final expected *eps* of time $t+1$ is eps_{t+1}. Thus, the term of rz_t or z_t measures the growth potential of *eps* in period $(t, t+1)$.

An important assumption regarding z_t is made that: z_t grows at rate $\gamma - 1$, i.e., $z_{t+1} = \gamma z_t$, where $1 \leq \gamma < R$. The condition that γ is equal or larger than 1 means the *eps* has a growing growth potential. $\gamma < R$ is consistent with the non-exploding condition. Applying this assumption and the sum of Proportional series, equation C.6 becomes:

$$P_0 = \frac{eps_1}{r} + \frac{z_1}{R - \gamma}, \text{with } z_1 = \frac{1}{r}(rdps_1 + eps_2 - Reps_1) \tag{C.8}$$

Rearranging it will produce a unary quadratic function of r, solving the function gives the

ICC of equity:

$$r = \frac{1}{2}(\gamma - 1 + \frac{dps_1}{P_0}) + \sqrt{(\frac{1}{2}(\gamma - 1 + \frac{dps_1}{P_0}))^2 + \frac{eps_1}{P_0}[\frac{eps_2 - eps_1}{eps_1} - (\gamma - 1)]} \tag{C.9}$$

Solving the unary quadratic function of ICC

From Equation C.8:

$$P_0 = \frac{eps_1}{r} + \frac{z_1}{R - \gamma}, \text{with } z_1 = \frac{1}{r}(rdps_1 + eps_2 - Reps_1) \tag{C.10}$$

Inserting z_1 and rearranging it:

$$\begin{aligned}
&rP_0 = eps_1 + \frac{rdps_1 + eps_2 - Reps_1}{R - \gamma} \\
&rP_0 = eps_1 + \frac{rdps_1 + eps_2 - (1 + r)eps_1}{1 + r - \gamma} \\
&(1 + r - \gamma)rP_0 = (1 + r - \gamma)eps_1 + rdps_1 + eps_2 - eps_1 - reps_1 \\
&P_0r^2 + P_0r - \gamma P_0r = (1 - \gamma)eps_1 + rdps_1 + \Delta eps_2 \\
&P_0r^2 + (P_0 - \gamma P_0 - dps_1)r - (1 - \gamma)eps_1 - \Delta eps_2 = 0
\end{aligned} \tag{C.11}$$

The above equation can be considered as a unary quadratic function on r, solve it:

$$\begin{aligned}
r &= \frac{-(P_0 - \gamma P_0 - dps_1) + \sqrt{(P_0 - \gamma P_0 - dps_1)^2 + 4P_0((1 - \gamma)eps_1 + \Delta eps_2)}}{2P_0} \\
&= \frac{\gamma - 1 + \frac{dps_1}{P_0}}{2} + \sqrt{\frac{1}{4}(\gamma - 1 + \frac{dps_1}{P_0})^2 + \frac{\Delta eps_2 - (\gamma - 1)eps_1}{P_0}}
\end{aligned} \tag{C.12}$$

Denoting $A = \frac{1}{2}(\gamma - 1 + \frac{dps_1}{P_0})$, it becomes:

$$\begin{aligned}
r &= A + \sqrt{A^2 + \frac{eps_1}{P_0}(\frac{\Delta eps_2}{eps_1} - (\gamma - 1))} \\
&= A + \sqrt{A^2 + \frac{eps_1}{P_0}(\frac{eps_2 - eps_1}{eps_1} - (\gamma - 1))}
\end{aligned} \tag{C.13}$$

It is the expression in Equation C.9.

The short term growth in Equation C.9 is a two-year ahead forecasting growth rate ($\frac{eps_2 - eps_1}{eps_1}$), it is modified by Dick-Nielsen et al. [2019] to be the average of the two-year ahead forecasting growth rate and a five-year ahead forecasting growth rate (LTG):

$$STG = \sqrt{\frac{eps_2 - eps_1}{eps_1} * LTG} \tag{C.14}$$

Carefully rearranging equation C.9 and with the above adjustment, the final equation of ICC shown in equation 3.22 is obtained.

PEG model

The PEG model suggested by Easton [2004] and Mohanram and Gode [2013] is a simplified version of OJ model. By ignoring the dividends and setting $\gamma = 1$, the OJ model equation becomes the simplified PEG model equation as shown in Equation 3.23.

Appendix D

Code availability

The computer scripts used in the empirical tests in this thesis work are written in R language. In the scripts, there are WRDS database access, data processing, empirical tests with various models and codes for plotting the results. The scripts are available under the license of Creative Commons Zero v1.0 Universal, and are hosted on GitHub.com.

`https://github.com/zhuolugao/Master_Thesis_Code`