Essays on Implied Cost of Capital Estimation and Implementation for Corporates and Banks: In Association with Customer Satisfaction, Equity Market Discipline and an Estimation Approach

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List of Abbreviations

ACSI American Customer Satisfaction Index

AEG Abnormal Earnings Growth

AR Accuracy Ratio

BHC Bank Holding Company

BPS Book Value per Share

CAP Cumulative Accuracy Profile

CD Certificates of Deposits

CDS Credit Default Swaps

CF Cash Flow Changes

DD Distance to Default

DR Cost of Equity (Discount Rate) Changes

EPS Earnings per Share

FOC First Order Condition

GDP Gross Domestic Product

HAC Heteroscedasticity and Autocorrelation Consistent

ICC Implied Cost of (Equity) Capital

IRP Implied (Equity) Risk Premium

RIM Residual Income Model

ROI Return on Investments

SIC Standard Industrial Classification

VIF Variance Inflation Factor

WRDS Wharton Research Data Services

1 Introduction

1.1 Motivation and Contribution

In this dissertation I use accounting based valuation models to primarily estimate the corresponding cost of equity (capital) and use the estimated values in empirical research and in the framework of an estimation approach. The methodological aspect of my dissertation falls under the literature branch of implied cost of capital (ICC) which is well established in finance and accounting. The economic aspect of my dissertation addresses capital market relevant issues, stemming from research in marketing and monetary economics. After a short introduction including a methodological review of the ICC models I use, I present two working papers in the second and third chapter and end my dissertation with a fourth chapter on a new estimation approach.

The second chapter is based on a working paper I wrote with Martin Artz (Frankfurt School of Finance and Management). In it we investigate the association between customer satisfaction and the firm's cost of equity using ICC as a forward-looking, ex-ante measurement approach. We further use ICC to decompose firm value into cash and cost of equity effects of customer satisfaction changes. Doing so, this is the first study, up to my knowledge, quantifying cost of equity effects of customer satisfaction and estimating the relative importance of these cost of equity effects in relation to pure cash effects of customer satisfaction changes.

Customer satisfaction has been established as a central non-financial performance measure in academic research and corporate practice. The growing interest in this construct has emerged due to its effect on firm's future cash flows via the customers' resulting buying behavior (Banker and Mashruwala, 2007; Bonacchi et al.; Hauser et al., 1994; Ittner and Larcker, 1998). Starting from a discussion whether customer satisfaction provides information for financial markets beyond what is reflected in current accounting metrics (Ittner and Larcker, 1998; Ittner et al., 2009; Jacobson and Mizik, 2009), a large body of work has found a positive association between customer satisfaction and the firm's market value of equity (Anderson et al., 2004; Ittner and Larcker, 1998; Mittal et al., 2005), making customer satisfaction metrics also a useful indicator for stock market participants in predicting the firm's level and variability of future cash flows. Given this evidence, an emerging interest has developed not only in whether customer satisfaction is associated with firm value, but also in how exactly it is related to firm value. Analyzing this precise link requires both, considering cash (or growth) effects in the numerator and cost of equity effects in the denominator as usually suggested in discounted cash flow models of firm valuation. The relation between customer satisfaction and net cash effects has been a major element in empirical research so far and seems to have persisting effects over time. Thus, current customer satisfaction changes affect future customer behavior and therefore future cash flows of the firm. Consequently, much work has shown a positive association of customer satisfaction with future revenues (Ittner and Larcker, 1998; Ittner et al., 2009), future cash flows (Gruca and Rego, 2005), and future earnings (Ittner et al., 2009; Mittal et al., 2005). Empirical research, however, is rather limited on the risk side, particularly in the matter of cost of equity. Anderson and Mansi (2009) show a negative association with the cost of debt but do not (intend to) give insights regarding the cost of equity. Closest evidence in this regard is provided by Tuli and Bharadwaj (2009) who show that customer satisfaction is negatively associated with both, firm's systematic and firm's unsystematic risk. However, their study does not address the question whether customer satisfaction is associated with lower cost of equity. This missing link makes it difficult to form an opinion about the importance of the influence of customer satisfaction on the risk profile of the firm in relation to pure cash flow effects. Identifying an association allows estimating an economic impact in terms of basis points and to identify the relative importance of cash and risk effects of customer satisfaction for firm value.

The contribution of the second chapter is threefold. First, we investigate the association between customer satisfaction and the cost of equity. In contrast to prior empirical studies in the customer satisfaction literature, we analyze ex-ante measures of the firm's cost of equity to estimate the precise economic effects of customer satisfaction. Estimates based on historical-information are contaminated by firm-specific cash flow related changes and firm-specific discount factor related changes (Elton, 1999) and are claimed to be "unavoidably imprecise" (Fama and French, 1997, p. 153). Our approach instead exploits changes in future earnings to identify changes in the cost of equity. The appeal of such a measure lies in the nature of its derivation, both being forward-looking and combining current market and book values with growth forecasts of the firm's future cash flows (e.g., Gebhardt et al. (2001); Easton (2004); Pástor et al. (2008)). Rather than relying on estimates based on realized returns or dividend yields, this approach explicitly attempts to account for revisions in cash flow changes due to customer satisfaction when estimating the cost of equity effects. In our analyses, we find a robust negative association between customer satisfaction as measured by the American Customer Satisfaction Index (ACSI) and the cost of equity. These findings contribute to the literature linking immaterial asset management of firms with the cost of equity such as corporate reputation (Cao et al., 2015) or corporate social responsibility initiatives (Ghoul et al., 2011). Second, following the literature on return decomposition, we break down firm value in form of returns into its cash flow and cost of equity effects (Chen et al., 2013). We attempt to contribute to the question whether customer satisfaction contributes to firm value primarily due to changes in growth expectations regarding future cash flows or due to changes in the firm's cost of equity. Similar to Hail and Leuz (2009), we decompose realized returns by varying cash flows but holding the cost of equity constant (and vice versa). We use several different investment horizons representing the period over which changes in customer satisfaction and firm value are measured. Once we increase the investment horizon, we find a positive, consistent and growing association between customer satisfaction and the cash effect for the longer horizons on the one hand and between customer satisfaction and the cost of equity effect for shorter horizons on the other hand. Hence, the cash flow effect starts weaker than the cost of equity effect but overtakes the latter for all investment horizons beyond three years. This result is surprising and stands in contrast to the large body of literature dealing with the cash flow implications for customer satisfaction: first, this literature merely neglects the importance of cost of equity effects and second, this literature usually (at least implicitly) assumes immediate effects on future cash flows. Beyond these findings, our approach on linking customer satisfaction to firm value might be useful in the context of other intangible assets of the firm. Third, we split our sample into two subsamples having a low and a high state of sales uncertainty respectively. We rerun the above analyses for both subsamples and find that the effects of customer satisfaction on cost of equity are highly significant and higher in magnitude in a state of high sales uncertainty, while these effects are non-significant in a state of low sales uncertainty. We also find that the results distinguishing between the cash flow effect and the cost of equity effect are more pronounced in a state of high sales uncertainty. The results in a state of low sales uncertainty seem to be similar for the cash flow effect and the cost of equity effect.

The third chapter is based on a working paper I wrote with Ferdinand Elfers (University of Mannheim). In it we use the ICC to estimate the rate of return required by the stockholders of U.S. bank holding companies (BHCs). We use the implied risk premium (IRP), calculated as ICC minus the risk-free rate, to investigate directly whether stock prices are adjusted to information about the business risk of a BHC as suggested by the concept of market discipline. Market discipline requires that investors have incentives and the ability to monitor the risk position of banks, and that they translate their knowledge into economic transactions ("market monitoring", e.g., requiring higher returns or withdrawing funds when perceiving high risk). Managers in turn are expected to adapt their risk behavior accordingly in order to avoid funding problems or excessive cost of capital ("market influencing", see Flannery, 2001). A further distinction can be made between *direct* market discipline, where the disciplining mechanism takes place directly between banks and the market, and *indirect* market discipline, where supervisors use market based signals to trigger regulatory action.

While the monitoring incentives of debt holders (e.g., Hannan and Hanweck (1988); Flannery and Sorescu (1996); Billett et al. (1998); Park and Peristiani (1998); DeYoung et al. (2001); Jagtiani et al. (2002); Sironi (2003); Demirgüc-Kunt and Huizinga (2004); Hadad et al. (2011)) might be weakened as they are protected by the regulatory capital buffer and institutional safety nets such as deposit insurance or (implicit) government bail-out guarantees, no such mechanisms exist for stockholders. In addition, stock market data is in general readily observable and more easily comparable than information on various debt instruments. It therefore seems promising to investigate whether market monitoring takes place in stock markets. There has not been any prior work using ICC (or IRP) in the context of market discipline. Using IRP makes it possible to test for *direct* market discipline in stock markets. This allows us to address a gap in the literature on market monitoring.

Thus the first contribution of the third chapter is that estimating the IRP allows us to isolate the risk discount factor and therefore provides a clearer understanding of direct stock market discipline than could be achieved so far, but without needing to resort to stock volatility or specific negative information events. As a second contribution, we further examine whether the IRP captures (distress) risk information that goes beyond current observable accounting risk indicators and thus might serve as a useful signal for *indirect* market discipline. In particular, we gauge the informational content of IRP in a prediction model of severe rating downgrades, partially through explicitly comparing it to other market based information (similar to variables used by e.g., Jordan et al. (2000); Distinguin et al. (2006); Stiroh (2006); Curry et al. (2008); Auvray and Brossard (2012)) to analyze whether the IRP provides any additional value in predicting bank distress. Our third and final contribution is the relation of our first two contributions to the question whether distress risk is priced in equity returns which is ultimately empirical and has become an important point of contention in the literature on cost of equity (e.g., (Dichev, 1998; Griffin and Lemmon, 2002; Vassalou and Xing, 2004; Campbell et al., 2008; Chava and Purnanandam, 2010; George and Hwang, 2010; Kapadia, 2011; Conrad et al., 2012)). By providing a detailed risk analysis of the financial sector, which has been excluded by other studies so far, we contribute to this ongoing discussion.

In the fourth and last chapter I introduce a new approach aimed at simultaneously estimating all drivers (input variables) of an accounting valuation model. My estimation approach extends the models from Easton (2004) and Nekrasov and Ogneva (2011). Stated differently, it aims at a methodological equilibrium between the components of the accounting valuation model, the (implied) cost of capital, expected future earnings, expected earnings growth and expected future dividends. All previous research, up to my knowledge, assume a constant dividend payout ratio or a deterministic function for it and rely on analyst consensus earnings forecasts (e.g. from I/B/E/S) in order to proxy for expected future earnings and dividend payout ratio respectively. Aside from the unrealistic assumption of a constant dividend payout ratio for future years, analyst earning forecasts have been shown to be biased differently among firms with different characteristics, leading to false estimates of ICC as shown in Easton and Sommers (2007). Hence, it is important that ICC estimates are in balance (equilibrium) with estimates of earning forecasts and other input variables.

The contribution of my approach is twofold. The first contribution is estimating ICC, being in a steady state with all other input variables (while estimating the change in earnings growth, similar to Nekrasov and Ogneva (2011)). All the other approaches, including the one by Nekrasov and Ogneva (2011), have concentrated only on estimating or determining a subset of the input variables, ICC (and earnings growth). The second contribution is that it allows simultaneous estimation of expected future earnings and expected future dividends if estimates of ICC and earnings growth were given. Up to my knowledge the literature so far estimates earnings and dividends using separate models, i.e. they are not linked together through an accounting based valuation model. Hence my approach extends the literature on earnings and dividends estimation.

1.2 Implied Cost of Capital Models

Throughout the first two chapters I compute ICC using as the main model the one by Pástor et al. (2008) (and Lee et al. (2009)) and for robustness purposes the models by Gebhardt et al. (2001) and Easton (2004). In the third chapter I derive an estimation approach which is based on the valuation model by Easton (2004). These three established models cover the three main kinds of net present value models used in accounting and finance research as I elaborate on them below. Using these models to estimate ICC I minimize the quadratic difference between the left hand-side, stock price, and the right-hand side, valuation model, until it is less than or equal to a specific predetermined bound, set to 10^{-10}.

Pástor et al. (2008) estimate ICC using a valuation model which discounts earnings distributed to equity shareholders. It extends alternative models by introducing estimation functions for earnings forecasts and plowback (equity reinvestment) rates and elongating the valuation time horizon T from 2, 5 or 12 years to 15 years.

$$p_t = \sum_{s=1}^{T} \frac{FE_{t+s}(1-b_{t+s})}{(1+r_e)^s} + \frac{FE_{t+s+1}}{r_e(1+r_e)^T} \tag{1.1}$$

where FE_{t+s} are earnings forecasts, b_{t+s} is the plowback rate (one minus the payback ratio), r_e is the cost of equity and T is the horizon after which the terminal value of the model starts. FE_{t+1} and FE_{t+2} are assigned starting values. For periods $t+3$ to $t+T+1$ the growth FE_{t+s} is defined through the following sequence.

$$FE_{t+s} = FE_{t+s-1}(1+g_{t+s}) \tag{1.2}$$

$$g_{t+s} = g_{t+s-1} \exp\left(\frac{\log(g/g_{t+3})}{T-1}\right) \tag{1.3}$$

The plowback rate is derived from financial statements for periods $t+1$ and $t+2$ as one minus the payout ratio. For periods $t+3$ to $t+T$ the plowback rate is defined through the following sequence.

$$b_{t+s} = b_{t+s-1} - \frac{b_{t+2} - b}{T-1} \tag{1.4}$$

Following Pástor et al. (2008), in order to derive the steady-state rates for earnings growth and plowback, I assume that the steady-state growth rate g equals the gross domestic product (GDP) growth rate and assume sustainable growth to determine b from $g = ROI \times b$, where ROI is the steady-state return on investments. I then set $ROI = r_e$ such that b becomes $b = g/r_e$.

Gebhardt et al. (2001) estimate ICC using a residual income model which anchors on contemporaneous equity book value and adds the residual income with respect to expected income in future years. The time horizon T is set to 12 years.

$$p_t = bv_t + \sum_{s=1}^{T-1} \frac{FROE_{t+s} - r_e}{(1+r_e)^s} bv_{t+s-1} + \frac{FROE_{t+T} - r_e}{r_e(1+r_e)^{T-1}} bv_{t+T-1} \tag{1.5}$$

where bv_{t+s} are equity book values imputed using the clean surplus relation, $bv_{t+s} = bv_{t+s-1}(1+FROE_{t+s} * b_{t+1})$.[1] $FROE_{t+s}$ are return on equity forecasts, defined as $FROE_{t+s} = FE_{t+s}/bv_{t+s-1}$. I use the same input values for FE_{t+1}, FE_{t+2}, g_{t+3} and b_{t+1} as for model (1.1).

$$\begin{aligned} FROE_{t+3} &= \frac{FE_{t+2}(1+g_{t+3})}{bv_{t+1}} \\ FROE_{t+s} &= FROE_{t+s-1} - \frac{FROE_{t+3} - ROE_{median}}{T-3} \end{aligned}$$

where the second equation is used for $s > 3$. ROE_{median} is the 10-year ROE median for each industry according to Fama & French (1997).

Easton (2004) estimates ICC using an abnormal earnings growth (AEG) model which anchors on capitalized earnings and adds the AEG component with respect to expected earnings growth. After some modifications the following model is derived.

$$p_t = \frac{FE_{t+2} + r_e(1-b_{t+1})FE_{t+1} - FE_{t+1}}{r_e^2} \tag{1.6}$$

[1] Gebhardt et al. (2001) assume a constant payout ratio for all future periods.

where FE_{t+1}, FE_{t+2} and b_{t+1} are defined as for model (1.1).

All three kinds of models with theoretically infinite time horizon are equivalent if the clean surplus relation holds, i.e. book value of equity of a specific year of reference equals book value of equity of the previous year plus earnings of the year of reference less paid dividends of the year of reference.[2] In their implementation they differ however as demonstrated above.

[2]Intuitively put, no items may bypass the income statement. Hence equity will only be affected by the income statement.

2 Customer Satisfaction, Cost of Equity and Firm Value Decomposition

This chapter is based on a working paper I wrote with
Martin Artz (Frankfurt School of Finance and Management).

2.1 Introduction

In this paper, we investigate the association between customer satisfaction and the firm's cost of equity using a forward-looking, ex-ante measurement approach. We use this cost of equity measure to decompose firm value into cash flow and cost of equity effects of customer satisfaction changes. Doing so, this is the first study quantifying cost of equity effects of customer satisfaction and estimating the relative importance of these cost of equity effects in relation to pure cash effects of customer satisfaction changes.

Customer satisfaction has been established as a central non-financial performance measure in academic research and corporate practice. The growing interest in this construct has emerged due to its effect on firm's future cash flows via the customers' resulting buying behavior (Banker and Mashruwala, 2007; Bonacchi et al.; Hauser et al., 1994; Ittner and Larcker, 1998). Starting from a discussion whether customer satisfaction provides information for financial markets beyond what is reflected in current accounting metrics (Ittner and Larcker, 1998; Ittner et al., 2009; Jacobson and Mizik, 2009), a large body of work has found a positive association between customer satisfaction and the firm's market value of equity (Anderson et al., 2004; Ittner and Larcker, 1998; Mittal et al., 2005), making customer satisfaction metrics also a useful indicator for stock market participants in predicting the firm's level and variability of future cash flows.

Given this evidence, an emerging interest has developed not only in whether customer satisfaction is associated with firm value, but also in how exactly it is related to firm value. Analyzing this precise link requires both, considering cash (or growth) effects and cost of equity effects as usually suggested in discounted cash flow models of firm valuation. The relation between customer satisfaction and net cash effects has been a major element in empirical research so far. Satisfied customers show higher retention rates, word-of-mouth, willingness to pay, and cross-selling, and, on the other hand, are more efficient to handle with regard to complaints, pay defaults, and search. Most importantly, these effects seem to persist over time and thus, current customer satisfaction changes affect future customer behavior and therefore future cash flows for the firm. Consequently, much work has shown a positive association of customer satisfaction with future revenues (Ittner and Larcker, 1998; Ittner et al., 2009), future cash flows (Gruca and Rego, 2005), and future earnings (Ittner et al., 2009; Mittal et al., 2005). Empirical research, however, is rather limited on the risk side, particularly in the matter of cost of equity. Anderson and Mansi (2009) show a negative association with the cost of debt but do not (intend to) give insights regarding the cost of equity. Studying the implications of customer satisfaction on cost of equity is important beyond its influence on the cost of debt. In particular, multiple conflicts of interest between debt holders and equity holders exist and whether customer satisfaction is value increasing due to lower cost of financing might be differently perceived by those parties with opposing interests (Cao et al., 2015). Closest evidence in this regard is provided by Tuli and Bharadwaj (2009) who show that customer satisfaction is negatively associated with both, firm's systematic and firm's unsystematic risk. However, their study does not address the question whether customer satisfaction is associated with lower cost of equity. This missing link makes it difficult to form an opinion about the importance of the influence of customer satisfaction on the risk profile of the firm in relation to pure cash flow effects. Identifying an association between customer satisfaction on the one hand and cost of equity and firm value components on the other hand allows us to estimate an economic impact in terms of interest rates basis points and to identify the relative importance of cash and risk effects of customer satisfaction for firm value.

The contribution of this study is threefold. First, we investigate the association between customer satisfaction and the cost of equity. In contrast to prior empirical studies in the customer satisfaction literature, we analyze ex-ante measures of the firm's cost of equity to estimate the precise economic effects of customer satisfaction. Historical estimates capture information which is not fully available to market participants at the time new customer satisfaction figures are provided. Stated differently, these returns are contaminated by firm-specific cash flow related changes and firm-specific discount factor related changes (Elton, 1999) and are claimed to be “unavoidably imprecise” (Fama and French, 1997, p. 153). Our approach instead exploits changes in future earnings to identify changes in the cost of equity. The appeal of such a measure lies in the nature of its derivation, both being forward-looking and combining current market and book values with growth forecasts of the firm’s future cash flows. Rather than relying on estimates based on realized returns or dividend yields, this approach explicitly attempts to account for revisions in cash flow changes due to customer satisfaction when estimating the cost of equity effects. We use an approach developed by Pástor et al. (2008) (and Lee et al. (2009)) which is especially applicable in our context since it is based on a valuation model which discounts all earnings assigned to equity holders. Several robustness checks using alternative accounting-based valuation models (Gebhardt et al., 2001; Easton, 2004) deliver similar results. All approaches allow us to explicitly capture potentially unobserved heterogeneity on the firm- and time-level beyond additional determinants of the cost of equity. In our analyses, we find a robust negative association between customer satisfaction as measured by the American Customer Satisfaction Index (ACSI) and the cost of equity. In economic terms, an increase in 10 points in the ACSI results in a decrease of 40 to 65 basis points in cost of equity which is economically significant and meaningful, but not too large to be implausible. These findings contribute to the literature linking immaterial asset management of firms with the cost of equity such as corporate reputation (Cao et al., 2015), corporate social responsibility initiatives (Ghoul et al., 2011) or customer concentration (Dhaliwal et al., 2015). Comparing the magnitude of our results on cost of equity to the results from Dhaliwal et al. (2015) on cost of equity, we find that an increase of one standard deviation of customer satisfaction decreases cost of equity by 24.88 to 40.43 basis points while an increase of one standard deviation of customer concentration increases the cost of equity by 3.997 to 9.828 basis points.[3]

Second, we take full advantage of the cost of equity measure we derive as the internal rate of return using a valuation model. Following the literature on return decomposition, we break down firm value in form of returns into its cash flow and cost of equity effects (Chen et al., 2013). We attempt to contribute to the question whether customer satisfaction contributes to firm value primarily due to changes in growth expectations regarding future cash flows or due to changes in the firm's cost of equity. Similar to Hail and Leuz (2009), we decompose realized returns by varying cash flows but holding the cost of equity constant (and vice versa). We use several different investment horizons representing the period over which changes in customer satisfaction and firm value are measured. Once we increase the investment horizon, we find a positive, consistent and growing association between customer satisfaction and the cash effect for the longer horizons on the one hand and between customer satisfaction and the cost of equity effect for shorter horizons on the other hand. Hence, the cash flow effect starts weaker than the cost of equity effect but overtakes the latter for all investment horizons beyond three years. This result is surprising and stands in contrast to the large body of literature dealing with the cash flow implications for customer satisfaction: first, this literature merely neglects the importance of cost of equity effects and second, this literature usually (at least implicitly) assumes immediate effects on future cash flows. Beyond these findings, our approach on linking customer satisfaction to firm value might be useful in the context of other intangible assets of the firm.

Third, we split our sample into two subsamples having a low and high state of sales uncertainty respectively. We rerun the analyses on cost of equity for both subsamples and find that the effects are highly significant and higher in magnitude in a state of high sales uncertainty, while these effects are non-significant in a state of low sales uncertainty. Further, we rerun the analyses on the two components of firm value decomposition and find that the results distinguishing between the cash flow effect and the cost of equity effect are more pronounced

[3] The comparison to Cao et al. (2015) and Ghoul et al. (2011) is not possible because the standard deviation of their respective measure is not reported for the corresponding full sample.

in a state of high sales uncertainty. The results in a state of low sales uncertainty seem to be similar for the cash flow effect and the cost of equity effect, i.e. the importance of one effect over the other is indifferent to increasing the investment horizon.

The remainder of the paper is organized as follows. In Section 2.2 we review related literature streams and develop our hypotheses. Section 2.3 describes the methodology and the data sources we use for testing our hypotheses including sample description and the construction of the dependent and independent variables. Section 2.4 presents the main results with regard to cost of equity effects. In Section 2.5 we show the results for the decomposition of firm value into cash and cost of equity effects. Section 2.6 reruns the above analyses under states of low and high sales uncertainty. Section 2.7 concludes.

2.2 Literature Review and Hypotheses Development

Investors face uncertainty when predicting the expected rate of return, and value relevant information can, to some extent, reduce this estimation risk (Clarkson et al., 1996). We argue that customer satisfaction contains incremental information with regard to customers' future buying behavior and therefore to the firm's future cash flows. In this regard, it has been shown that satisfied customers do not only influence the level but also the variability of future cash flows (Gruca and Rego, 2005). First, customers show more regular buying cycles and less variance in buying behavior (Noordewier et al., 1990; Tuli et al., 2007). Second, variance in customer treatment and service costs are reduced (Tuli and Bharadwaj, 2009). Third, customer satisfaction servers as a switching barrier and customers less likely react to competitor actions such as price promotions or advertising campaigns (Banker and Mashruwala, 2007; Narayandas, 1998).

Although customer satisfaction is considered as a critical asset to firm value, this information is usually difficult to observe. Prior research shows that intangibles such as R&D or employee satisfaction are likely to be incorrectly valued by investors (Chan et al., 2001; Edmans, 2011; Hirshleifer et al., 2013). Research using the ACSI shows that analysts in particular and the stock market in general perceive this information as value relevant beyond financial accounting metrics (Ngobo et al., 2012; Jacobson and Mizik, 2009; Ittner et al., 2009). We therefore expect that customer satisfaction reduces information asymmetry for stock market participants with regard to customers' future buying behavior and the variability of the firm's cash flows.

A second argument stems from customer satisfaction being related to corporate reputation (Cao et al., 2015). Firms with higher customer satisfaction ratings are likely to attract more public media and investor attention which in turn is supposed to increase stock liquidity. Empirical research has found highly recognized stocks being more liquid (Lehavy and Sloan, 2008).

We therefore expect customer satisfaction to be negatively associated with the cost of equity. Vice versa, our study is also an empirical test whether customer satisfaction information provided by the ACSI matters beyond other types of firm-specific information. Annual reports, conference calls, or earnings forecasts might already explicitly or implicitly include information about the firm's future cash flow patterns.

Establishing an empirical relation between customer satisfaction and cost of equity in the first place, it remains an empirical question whether customer satisfaction contributes to firm value primarily due to changes in growth expectations regarding future cash flows or due to changes in the firm's cost of equity. We exploit the fact that financial analysts explicitly provide forecasts for firm growth. This allows us to decompose firm value changes due to changes in customer satisfaction into two components: those attributable to changes in the cost of equity and those attributable to changes in future cash flows. In line with prior findings with regard to stock returns (e.g., Jacobson and Mizik (2009)), future cash flows (e.g., Gruca and Rego (2005)), and systematic firm risk (Tuli and Bharadwaj, 2009) we expect an effect on both. However, it remains an empirical question whether the risk-reduction effect or the cash flow growth effect of customer satisfaction impacts firm value in the short and long-run and what the relative contribution of both effects is, depending on the respective time horizon of firm value changes.

2.3 Methodology and Data

2.3.1 Customer Satisfaction

For measuring customer satisfaction, we use data obtained from the American Customer Satisfaction Index (ACSI). The ACSI was developed in 1994 by the University of Michigan Business School's National Quality Research Center. In the ACSI measurement system, customer satisfaction is a latent variable calculated from survey responses (see Fornell, 1992; Fornell et al., 1996, for a complete description of the methodology).[4] The resulting satisfaction score ranges from 0 to 100, with 100 representing the highest level of satisfaction. The satisfaction measure used in the data is the average of the mean annual rating for each firm obtained from ACSI. ACSI data is released yearly in different months depending on the industry of the firm.

An important and nontrivial issue when dealing with ACSI data is how to match scores with GVKEY identifiers from COMPUSTAT to merge ACSI information with the other databases we use. Challenges occur for firms where both, the parent and its divisions are represented in the index, where the parent is not, but a single division is, or where mergers and acquisitions took place. Besides the study by Ittner et al. (2009), we are not aware of any study transparently describing how to deal with these circumstances which can (although do not necessarily have to) have significant implications for our empirical results. Although, the matching procedure of Ittner et al. (2009) is very supportive, we still found cases not covered by them. We therefore explain in Appendix A.1.1 our choice of all potential cases we faced which are naturally at the researchers' subjective choice.

[4] A key advantage of this customer satisfaction measure is the methodological consistency across all the firms. That is, exactly the same survey instrument, interviewing methodology, and statistical techniques are applied to create the satisfaction index, which ensures that variation in observed satisfaction scores cannot be attributed to methodological differences.

2.3.2 The Cost of Equity

Our measure of the cost of equity is a forward-looking measure of expected return, denoted implied cost of capital (ICC).[5] We use "forward-looking" to indicate using only current values and future estimates in the derivation of ICC (compared to using current and/or historical values in other models).

In this paper we use the model from Pástor et al. (2008) as described below. ICC is the internal rate of return that is implied by equating the price on the left hand side to the valuation formula on the right hand side of the valuation model. All variables below are seen from the point of view of time t (conditioned on the information available at time t). The time index resembles the time at which the variable realized its value.

Out of the various models found in the literature to estimate ICC we deliberately choose the model by Pástor et al. (2008) for two reasons.[6] The first reason is that it extends the alternative models by introducing estimation functions for earnings forecasts and plowback rates and elongating the valuation period from 2, 5 or 12 years to 15 years. The second reason is that it discounts earnings distributed to equity shareholders (comparable to cash flows) and not residual earnings (Claus and Thomas, 2001; Gebhardt et al., 2001) or abnormal earnings growth (Easton, 2004; Ohlson and Juettner-Nauroth, 2005). Stated differently, we estimate the cost of equity which is directly related to the share of earnings assigned to shareholders. Hence, this estimate is suitable to measure the association between customer satisfaction and the cost of equity.

$$p_t = \sum_{s=1}^{T} \frac{FE_{t+s}(1-b_{t+s})}{(1+r_e)^s} + \frac{FE_{t+s+1}}{r_e(1+r_e)^T}, \tag{2.1}$$

[5] Cost of capital can be regarded as a discount rate, expected return or systematic risk interchangeably. See Cochrane (2005) for details on that matter.

[6] We also compute ICC based on the models by Gebhardt et al. (2001) and Easton (2004) and get similar results as described in Subsection 2.4.4.

where FE_{t+s} are earnings forecasts, b_{t+s} is the plowback rate (retention of earnings, i.e. one minus the payback ratio), r_e is the cost of equity and T is the horizon after which the terminal value of the model starts. FE_{t+1} and FE_{t+2} are assigned starting values. For periods $t+3$ to $t+T+1$ the growth rate g_{t+s} of FE_{t+s} is defined such that the logarithm of the ratio g_{t+s}/g_{t+s-1} equals the logarithm of the ratio g/g_{t+3} divided by $T-1$, g being the value this function converges to. Since we take the logarithm of both ratios and divide the second ratio by the number of periods, this function evolves exponentially from the growth rate at $t+3$ to the steady-state growth rate g which sets in by $t+T+2$.

$$\begin{aligned} FE_{t+s} &= FE_{t+s-1}(1+g_{t+s}) \\ \log(g_{t+s}/g_{t+s-1}) &= \frac{\log(g/g_{t+3})}{(t+T+2)-(t+3)} \Leftrightarrow g_{t+s} = g_{t+s-1}\exp\left(\frac{\log(g/g_{t+3})}{T-1}\right) \end{aligned}$$

The plowback rate is derived from financial statements for periods $t+1$ and $t+2$ as one minus the payout ratio. For periods $t+3$ to $t+T$ the plowback rate is linearly mean-reverted to a steady-state plowback rate b which sets in by $t+T+1$.

$$b_{t+s} - b_{t+s-1} = \frac{b - b_{t+2}}{(t+T+1)-(t+2)} \Leftrightarrow b_{t+s} = b_{t+s-1} - \frac{b_{t+2} - b}{T-1}$$

Following Pástor et al. (2008) we assume a linear decline in the plowback rates because they appear to mean-revert slower than earnings growth rates, where there is empirical evidence that the latter mean-revert rapidly, hence the exponentially declining rate. In order to derive the steady-state rates for earnings growth and plowback, we assume that the steady-state growth rate g equals the gross domestic product (GDP) growth rate. Furthermore we assume sustainable growth, i.e. the current plowback rate affects succeeding earnings growth as $g = ROI \times b$, where ROI is the steady-state return on investments. We then set $ROI = r_e$, assuming that competition drives ROI down to the cost of equity (capital). The steady-state plowback rate b becomes $b = g/r_e$.

As the valuation Model (2.1) typically does not yield a closed-form solution, we use a heuristic to minimize the distance between the price p_t on the left hand side and the valuation formula on the right hand side of Equation 2.1 according the the unknown cost of equity r_e. We use the quadratic difference as the distance between both sides of the equation in order to have a differentiable target function with a theoretical minimum of zero, hence when the valuation formula prices the asset perfectly. The minimization problem is executed under the conditions with which FE_{t+s}, g_{t+s}, b_{t+s} and $b = g/r_e$ are computed, as explained above. Note that the last equation is a function of the unknown r_e. The optimization is said to converge when the quadratic difference between the left hand side and right hand side of Equation (2.1) is less than or equal to a specific predetermined bound, set to 10^{-10}.[7]

2.3.3 Firm Value Decomposition

We decompose returns following the approach by Chen et al. (2013) which uses analyst forecasts of cash flows by using the valuation model by Pástor et al. (2008) described above. In the last two decades another approach based on predictability along the lines of Campbell (1991) and Vuolteenaho (2002) has been used which decomposes unexpected returns in (usually long period) a sum of predicted cash flows as the cash flow component and a sum of unexpected returns as a cost of equity component. Chen et al. (2013) argue that the predictability approach is sensitive to the sample period, predictive variables and measure of cash flows. The approach by Chen et al. (2013), on the other hand, does not predict any of its input variables and defines the cash flow component (cost of equity component), henceforth denoted by cash flow changes (cost of equity changes) as change in the stock returns through varying cash flows while holding everything else constant (varying cost of equity while holding everything else constant). Chen et al. (2013) use ICC as the basis for their approach and point out that ICC is forward-looking and uses earnings forecasts based on how the market perceives

[7] We use the SAS procedure `proc optmodel` to run the optimization problem as described above.

future earnings, i.e. it does not need the prediction of long series of variables. They use these properties of ICC and its use of current and forecasted data to explain price changes. By the above reasoning we choose to use the newer and more "robust" model introduced by Chen et al. (2013) than to resort to the older and partially flawed predictability models.

Following Chen et al. (2013), we start by the definition of the return without dividends at point in time t over the period or investment horizon j, denoted by $ret_{t,j}$. We exclude the dividends from the definition of the return as they do not play an important role regarding the volatility of returns over different time periods. We then split the return into two components reflecting the change only in cash flows and cost of equity respectively, cash flow changes and cost of equity changes. In order to be able to vary cash flows (cost of equity) while holding everything else constant, we first define the price for year $t+j$, P_{t+j}, as a function $f(c_{t+j}, q_{t+j})$ of cash flows as seen from the perspective of year $t+j$, c_{t+j}, and the cost of equity for year $t+j$, q_{t+j} (ICC in this model). Varying cash flows over j time periods while holding the cost of equity constant is either (a) $f(c_{t+j}, q_{t+j}) - f(c_t, q_{t+j})$ if we hold the cost of equity constant at $t+j$ or (b) $f(c_{t+j}, q_t) - f(c_t, q_t)$ if we hold the cost of equity constant at t. Analogous reasoning follows for varying the cost of equity while holding cash flows constant.

As becomes clear, the two components stem from the definition of the return and from defining price as a function of cash flows and the cost of equity. Since the cash flows (cost of equity) change can be defined in two different ways ((a) and (b) from above), cash flow changes (cost of equity changes) are defined as their average.

$$ret_{t,j} = \frac{P_{t+j} - P_t}{P_t} = \frac{f(c_{t+j}, q_{t+j}) - f(c_t, q_t)}{P_t} = CF_{t,j} + DR_{t,j} \tag{2.2}$$

$$CF_{t,j} = \frac{1}{2}\left(\frac{f(c_{t+j}, q_{t+j}) - f(c_t, q_{t+j})}{P_t} + \frac{f(c_{t+j}, q_t) - f(c_t, q_t)}{P_t}\right) \tag{2.3}$$

$$DR_{t,j} = \frac{1}{2}\left(\frac{f(c_t, q_{t+j}) - f(c_t, q_t)}{P_t} + \frac{f(c_{t+j}, q_{t+j}) - f(c_{t+j}, q_t)}{P_t}\right), \tag{2.4}$$

where

$$CF_{t,j} = \text{ cash flow changes}$$
$$DR_{t,j} = \text{ cost of equity changes}$$

In our understanding, $CF_{t,j}$ and $DR_{t,j}$ are "as-if" price changes, following the notation from Hail and Leuz (2009), who apply a similar approach using log returns. Their approach is however only an approximation, such that their $CF_{t,j}$ and $DR_{t,j}$ do not add up to $ret_{t,j}$.[8] We borrow however their intuition behind "as-if" price changes, the price change (or return), if we vary only some components of the price while holding the other components constant. This is just like computing the price change in some components *as if* the other components stayed constant. We use DR (discount rate) for cost of equity changes to be consistent with the notation used in Chen et al. (2013).

2.3.4 Data and Descriptives

Our final sample results from merging customer satisfaction values with mainly three different databases. The customer satisfaction data comes from the American Customer Satisfaction Index website[9]. We obtained ACSI-specific industry affiliations from the ACSI website and email conversations with ACSI representatives. We retrieve yearly accounting data on financial statements from COMPUSTAT North America. We obtain monthly data on stock prices, returns and number of shares outstanding from CRSP and analyst forecasts for earnings per

[8] In the following we use the notation from Hail and Leuz (2009).

$$\Delta P = \log(P_0/P_{-3}) = \Delta P_{CF} + \Delta P_{COC} = \log(P_{CF,0}/P_{-3}) + \log(P_{COC,0}/P_{-3})$$

P_t is the price in year t, ΔP_{CF} is the "as-if" change in cash flows, ΔP_{COC} is the "as-if" change in the cost of equity, $P_{CF,0}$ is the price computed using cash flows as seen in $t = 0$ and the cost of equity from $t = -3$ and $P_{COC,0}$ is the price computed using the cost of equity from $t = 0$ and the cash flows as seen in $t = -3$. However their definition of both "as-if" changes does not add up to ΔP.

$$\log(P_{CF,0}/P_{-3}) + \log(P_{COC,0}/P_{-3}) = \log \frac{P_{CF,0}P_{COC,0}}{P_{-3}^2} \neq \log \frac{P_{CF,0} + P_{COC,0}}{P_{-3}} = \Delta P$$

[9] See `http://www.theacsi.org/the-american-customer-satisfaction-index`

share (EPS) from I/B/E/S. We merge COMPUSTAT, CRSP and I/B/E/S using the algorithm proposed by Wharton Research Data Services (WRDS).

Going back to the process of computing ACSI values for a specific firm, it takes some time until surveys have been completed and numbers have been aggregated together into one value, i.e. ACSI values should reflect the perception and satisfaction of the market some time before the release of these values. We therefore merge the ACSI values with the computed ICC values 3 month before their release. Based on Pástor et al. (2008), we obtain monthly data on prices, returns and number of shares outstanding from CRSP and require that the following COMPUSTAT items are available: common dividends, net income (defined as Income Before Extraordinary Items), book value of common equity and fiscal year-end date. CRSP and I/B/E/S data come from the same month in which ICC is computed, whereas COMPUSTAT data comes from the most recent fiscal year beginning at most 15 month and ending at least 3 month prior to that month.[10] Following the below formula to calculate the net payout ratio, and hence the plowback rate, we obtain data on share repurchases and new stock issuance from COMPUSTAT. We obtain further accounting items from COMPUSTAT and use them to construct control variables in the regressions in Section 2.4.3. Figure 2.1 demonstrates how our sample is merged together.

From I/B/E/S we use the one-year-ahead EPS forecast and nonnegative two-year-ahead EPS forecast[11] for FE_{t+1} and FE_{t+2} respectively and the forecasted long-term earnings growth rate (Ltg) for the earnings growth rate at $t+3$. We require the availability of at least the one-year-ahead EPS forecast[12], adjust earnings forecast for dilution and use the mean of analyst forecasts whereas we use the median estimate for the long-term growth rate instead as

[10] Since I/B/E/S data estimates figures for the following fiscal year end, we multiply the right hand side of the valuation Model (2.1) by $(1+r_e)^{m/12}$, where m is the number of month until the fiscal year end.

[11] Negative two-year-ahead EPS lead to negative FE_{t+s} for $s > 3$ which results in meaningless ICC. In unreported results we relax this condition and get very similar results.

[12] If Ltg is missing while FE_{t+1} and FE_{t+2} are not, it is set equal to $Ltg = FE_{t+2}/FE_{t+1} - 1$. If Ltg and FE_{t+2} are both missing, they are set equal to $Ltg = FE_{t+1}/E_t - 1$ and (even if Ltg is not missing) $FE_{t+2} = FE_{t+1}(1 + Ltg)$, where E_t is the most recent realized earnings. Ltg is winsorized from below and above at the 2% and 100% levels.

Figure 2.1: Graphical Overview of the Merging Procedure

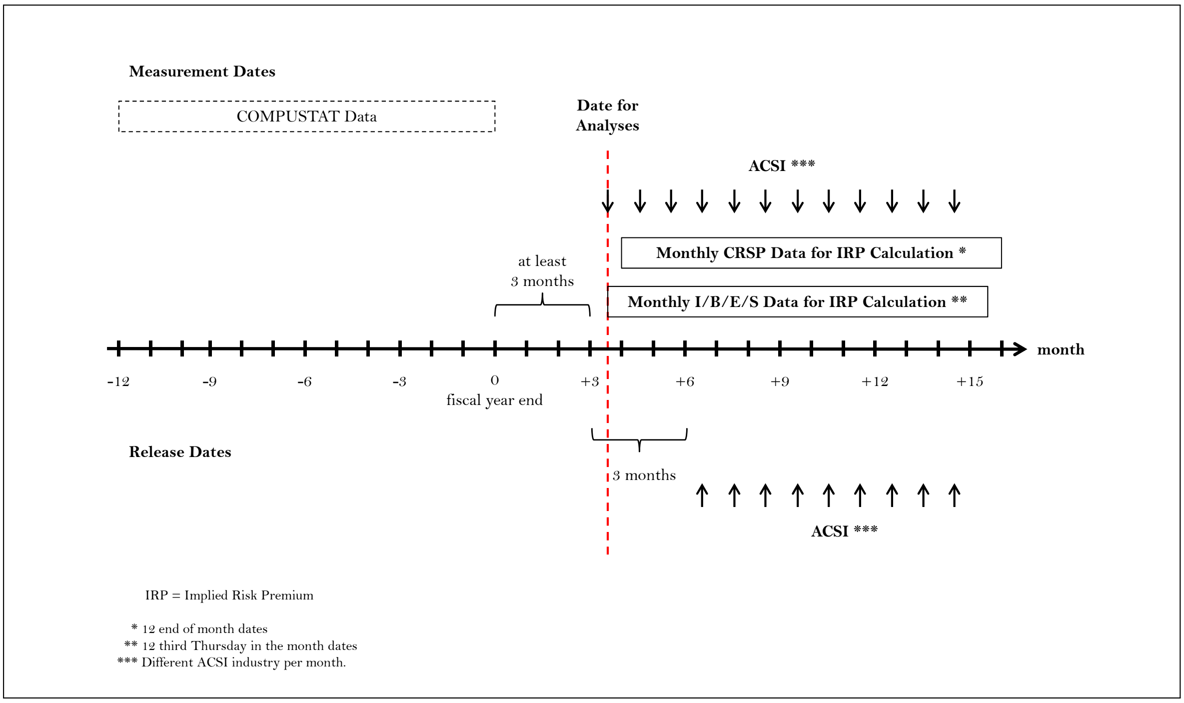

Figure 2.1 illustrates the merging procedure of the data we use throughout our analyses. The ICC is computed in the fourth month after the firm-specific fiscal year end when I/B/E/S data is released (typically on the third Thursday) which constitutes the date for each observation in our analyses. Where we need CRSP data on stock returns, we use historical data up to the end of the same month. We use accounting data from the preceding fiscal year end to allow for a publication lag of at least three months. Customer satisfaction is obtained from ACSI values released 3 month after the date of the corresponding observation as explained in Section 2.3. Stated inversely, we merge ACSI values with computed ICC values 3 month before their release.

explicitly recommended by Thomson Financial on WRDS.[13]

The payout ratio is calculated as net payout in year t (NP_t), i.e. dividends plus share repurchases minus new stock issuances, divided by net income in year t (NI_t). Dividends are the common dividends paid by the firm in year t, the share repurchases are the common and preferred stocks repurchased by the firm in year t and new stock issuances are the common

[13] See `http://wrds-web.wharton.upenn.edu/wrds/support/Data/_001Manuals%20and%20Overviews/_003I-B-E-S/_001Data%20Manuals/_015TF%20Estimates%20Glossary%20-%20February%202008.pdf.cfm`

and preferred stocks sold by the firm in year t.[14]

In order to match our data to the 48 Fama-French industries[15] and compute industry-size portfolio medians of payout ratios, we need Standard Industrial Classification (SIC) codes for each firm-year of COMPUSTAT data. Since SIC codes are missing for some dates per firm, we infer missing values by filling in the most recent known SIC code for each firm-year.

Following Pástor et al. (2008), we obtain data on nominal GDP growth rates from the Bureau of Economic Analysis.[16] We use GDP percent changes based on current dollars. We compute for each year the steady-state GDP growth rate g as the average of past annual GDP growth rates up to that year.

Table 2.2 reports descriptive summary statistics of the variables we use in the tests in the first part of the paper and Table 2.3 shows their pairwise Pearson correlations. For interpretive reasons, we report ICC multiplied by 100 and interpret the coefficients as percentages. We drop all observations negative ICC values since negative cost of equity is conceptually meaningless (Easton, 2004). To remove outliers, we truncate the top 0.5% and bottom 0.5% of ICC[17] and winsorize other ACSI and other regressors at the respective top 0.5% and bottom 0.5%.

We start with 270 firms with ACSI values, which is reduced to 225 firms after merging the ACSI values with ICC and control variables. Table 2.1 provides a breakdown of our sample for each year in the sample period whereas in Table 2.2 we report summary descriptive statistics. As for the control variables the following are based on Gebhardt et al. (2001): total assets (SIZE) is taken from COMPUSTAT, market leverage (LEV) is long-term debt from COMPUSTAT divided by market value computed from the monthly prices, the book-to-market ratio (BTM)

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[14] If the payout ratio is above 1 or below -0.5, it is set equal to the median payout ratio of the corresponding industry-size portfolio, where the firms are sorted into the 48 Fama & French industries and then into three equal numbered portfolios based on market capitalization per industry. The medians of the payout ratio industry-size portfolio are winsorized at -0.5 from below.

[15] See the website of Kenneth R. French `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html`

[16] See `http://www.bea.gov/national/index.htm#gdp`

[17] Since the computation of ICC results in a wide range of results, winsorizing it would still keep a lot of weight on the tails which might significantly deform its distribution.

is book value of equity from COMPUSTAT divided by the market value, the mean absolute error of forecasts (ERROR) is calculated as the mean absolute forecast error (EPS forecast minus actual EPS) divided by the mean EPS over the past 60 months (requiring a minimum of 24 months), all taken from I/B/E/S, and forecasted long-term earnings growth (GROWTH) is taken from /I/B/E/S. Based on Tuli and Bharadwaj (2009) we define return on assets (ROA) as operating income before depreciation from COMPUSTAT divided from total assets of the previous period and R&D investments (RD) as research and development expense from COMPUSTAT divided by total assets. We define the Fama & French beta (FF_BETA) and standard deviation of the corresponding residuals (FF_RES_VOL) by running Fama & French regressions (see Fama and French, 1993a) using daily returns from CRSP and daily data from the website of Kenneth R. French. [18] The betas of the market risk premium and the standard deviation of the residuals of these regressions are estimated for each end of month based on the past year of daily data starting with the date itself (at least 3 month of daily data are required, i.e. $255/4 \approx 64$ days). The Kaplan & Zingales index (KAZI) is based on the variables and regression coefficient taken from Lamont et al. (2001).

[18] See `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research`

Table 2.1: Sample Descriptives per Year

Year	Firms
1993	19
1994	102
1995	105
1996	97
1997	93
1998	91
1999	91
2000	90
2001	105
2002	108
2003	107
2004	115
2005	119
2006	133
2007	135
2008	130
2009	129
2010	133
2011	126
2012	94
Total	225

The table provides an overview of the number of firms by year. The sample comprises an unbalanced panel of a maximum of 225 publicly listed firms with the required ICC data available over the period from 1994 (1993 after dating ACSI values 3 month backwards) to 2012.

(Continued . . .)

Var	N	Mean	Std Dev	p5	p50	p95

Table 2.2: Summary Statistics

Var	N	Mean	Std Dev	p5	p50	p95
ICC	2,122	9.65	3.23	5.43	9.28	15.11
ACSI	2,122	76.30	6.22	66.00	76.33	86.00
SIZE	2,122	64.15	209.08	1.68	15.58	261.50
LEV	2,115	2.96	26.62	0.01	0.33	4.55
BTM	2,122	3.89	33.81	0.04	0.41	3.63
ROA	2,039	0.16	0.10	0.03	0.14	0.31
RD	2,122	0.01	0.02	0.00	0.00	0.05
ERROR	2,076	0.09	0.82	-0.12	0.06	0.43
GROWTH	2,122	0.11	0.08	0.03	0.10	0.22
FF_BETA	2,115	0.95	0.40	0.41	0.90	1.65
FF_RES_VOL	2,115	4.30	2.31	1.92	3.74	8.39
KAZI	1,760	-2.51	22.31	-9.28	-0.93	1.57

The table presents descriptive statistics for the variables used in the analyses in sections 2.4 and 2.5. ICC is reported as a percentage. Total assets are denominated in billion dollars. The reported variables are defined as follows: implied cost of capital (ICC), customer satisfaction (ACSI), total assets (SIZE), market leverage (LEV), the book-to-market ratio (BTM), return on assets (ROA), R&D expenses to total assets (RD), the mean absolute error of forecasts (ERROR), forecasted long-term earnings growth (GROWTH), the Fama & French beta (FF_BETA), the standard deviation of the Fama & French residuals (FF_RES_VOL) and the Kaplan & Zingales index (KAZI). We collect financial data from COMPUSTAT, stock market data from CRSP and analyst data from I/B/E/S.

Table 2.3 reports Pearson correlations. The correlations of all regressors with ICC (to be found in the first column) are mostly significant and most of them show the expected sign. Particularly, ICC is significantly negatively correlated with ACSI. Furthermore ICC (as a measure of expected return) is significantly negatively correlated with KAZI. This finding relates to (Lamont et al., 2001) who find constrained firms have lower returns.

Table 2.3: Correlations

	ICC	ACSI	SIZE	LEV	BTM	ROA	RD	FF_BETA	FF_RES_VOL	ERROR	LTG
ACSI	-0.12										
	0.00										
SIZE	0.14	-0.12									
	0.00	*0.00*									
LEV	-0.09	0.05	0.01								
	0.00	*0.02*	*0.70*								
BTM	-0.10	0.08	0.00	0.85							
	0.00	*0.00*	*0.91*	*0.00*							
ROA	-0.03	0.19	-0.24	-0.08	-0.08						
	0.24	*0.00*	*0.00*	*0.00*	*0.00*						
RD	-0.07	0.18	-0.04	0.03	0.06	0.11					
	0.00	*0.00*	*0.07*	*0.17*	*0.00*	*0.00*					
ERROR	0.00	0.01	0.05	-0.01	-0.01	-0.00	0.00				
	0.99	*0.67*	*0.03*	*0.71*	*0.58*	*0.92*	*0.84*				
GROWTH	0.23	0.04	-0.05	-0.02	0.01	0.13	0.27	0.03			
	0.00	*0.04*	*0.03*	*0.44*	*0.62*	*0.00*	*0.00*	*0.18*			
KAZI	-0.05	0.02	-0.05	0.01	0.01	0.00	-0.04	-0.00	-0.05		
	0.03	*0.48*	*0.03*	*0.71*	*0.68*	*0.85*	*0.11*	*0.97*	*0.04*		
FF_BETA	0.11	-0.22	0.14	-0.04	-0.07	-0.22	0.10	-0.01	0.18	-0.03	
	0.00	*0.00*	*0.00*	*0.07*	*0.00*	*0.00*	*0.00*	*0.60*	*0.00*	*0.25*	
FF_RES_VOL	0.09	-0.14	-0.03	0.06	0.04	-0.04	0.21	-0.01	0.33	-0.00	0.42
	0.00	*0.00*	*0.14*	*0.01*	*0.09*	*0.05*	*0.00*	*0.72*	*0.00*	*0.92*	*0.00*

The table reports Pearson correlations. Two-tailed *p*-values in italic.

2.4 Customer Satisfaction and Cost of Equity

2.4.1 ACSI Stickiness

ACSI values vary minimally over time, i.e. they are sticky. We construct the following histogram in Figure 2.2 of the percentage of sticky changes from year to the next for a specific firm. We define a change from year $t-1$ to year t as sticky if the ACSI value in year t is up to 2.5% below or up to 2.5% above the ACSI value in year $t-1$. It becomes evident from 2.2 that the range of percentages of changes in ACSI values ranges over the whole line from 0% to 100%. The vertical red line resembles the mean of the percentage of sticky changes, 45.96%. The vertical blue line resembles the median of the percentage of sticky changes, 50%, i.e. at least half of the firms have 50% or higher sticky ACSI changes from year to the next.

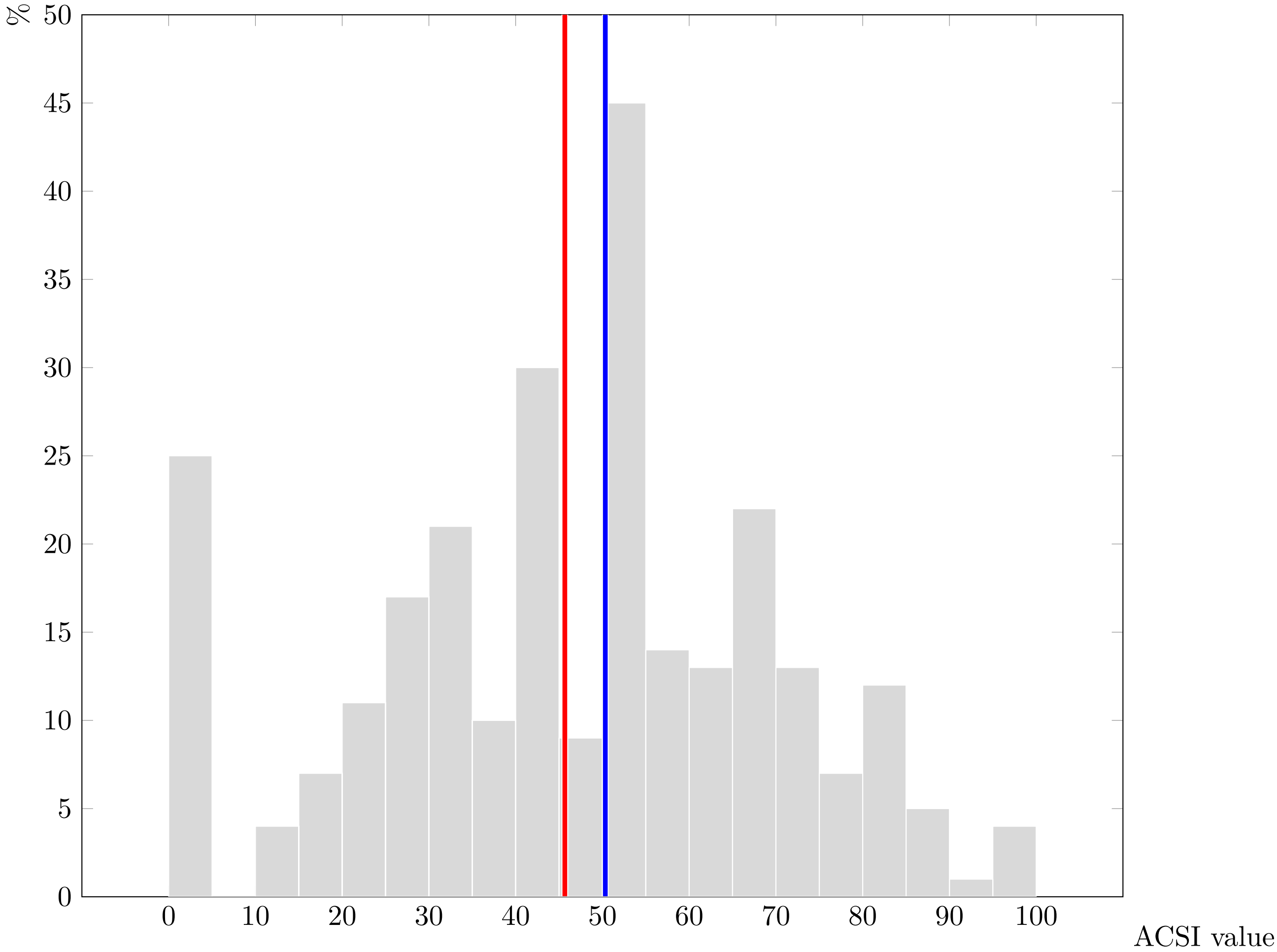
To empirically test stickiness we compute the changes of ACSI values between each two consecutive years and test the mean of this series of changes for significantly being different from zero (with robust heteroscedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors having a bandwidth of 2). The p-value is 0.791, i.e. we can not reject the null hypothesis that the difference between ACSI values between two consecutive years is zero. Thus this stickiness likely reduces the power in our analyses which will have an affect on the regressions in Section 2.5.

2.4.2 Univariate Tests

Following Gebhardt et al. (2001), we start in this section with univariate tests to pin down the nature of the association between customer satisfaction and cost of equity and report the results in Table 2.4. We run our univariate analyses (and all further regressions) using Newey and West (1987) standard errors (having a bandwidth of 2).[19]

[19] These are heteroskedasticity and autocorrelation consistent (HAC) standard errors. The bandwidth (L) is determined according to a rule of thumb, currently practiced as mentioned in Greene (2011). $L \approx T^{1/4}$, where T is the number of time periods.

Figure 2.2: Stickiness Histogram



The histogram shows the percentage of sticky changes from year to the next for a specific firm. A change from year $t-1$ to year t is defined as sticky if the ACSI value in year t is 2.5% below or 2.5% above the ACSI value in year $t-1$. The vertical red line resembles the mean of the percentage of sticky changes, 45.96%. The vertical blue line resembles the median of the percentage of sticky changes, 50%.

We divide our sample each year into 5 equal portfolios according to customer satisfaction, $Q1$ having the lowest and $Q5$ having the highest values. We then test the significance of the difference between $Q5$ and $Q1$ the means and medians of ICC. As we see in Table 2.4 the results have a negative sign and are highly significant which confirms the negative correlation between ICC and ACSI and hence the negative association between customer satisfaction and cost of equity.

Table 2.4: Analysis of ICC Sensitivity to ACSI (Univariate Tests)

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	p-Value
Ranked by **ACSI**							
acsi_mean	67.38	73.38	76.60	79.99	84.21	16.83	
icc_mean	10.41	9.62	9.76	9.61	9.10	-1.31	0.000***
icc_median	9.90	9.30	9.60	9.08	8.81	-1.09	0.000***

The table reports univariate tests on the difference in the ICC between firms with low and high values for ACSI. For each year, we divide the sample into five portfolios according to ACSI. We then compute the mean and median ICC per portfolio and test the difference between the portfolios in the highest (Q5) and lowest quintile (Q1) using Newey and West (1987) standard errors with a bandwidth of 2 Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

2.4.3 Mulitvariate Tests

To test the incremental effect of customer satisfaction on cost of equity, we regress ACSI and further covariates (controls) on ICC (we do not report the intercept coefficients in our regressions).

$$ICC_{it} = \alpha + \beta ACSI_{it} + \sum_{k} \gamma_k Control_{itk} + \epsilon_{it} \tag{2.5}$$

In the first regression we use as controls total assets (SIZE), market leverage (LEV), the book-to-market ratio (BTM), return on assets (ROA), R&D expenses to total assets (RD), the mean average absolute error of forecasts (ERROR) and forecasted earnings long-term growth (GROWTH). We include ERROR to control for forecast bias, as shown by Easton and Sommers (2007). Hail and Leuz (2009) explain that if earnings forecasts are overestimated but the market adjusts its price accordingly downwards, then ICC will be overestimated as well. By including ERROR as defined in 2.3.4, we apply a similar approach as done by Hail and Leuz (2009). We include GROWTH to control for growth versus mature firms. If $T = 15$

in this case is too short (long) for growth (mature) firms, we might underestimate ICC for growth firms and overestimate ICC for mature firms. Gebhardt et al. (2001) state that if a firm characteristic, customer satisfaction in our case, is correlated with growth, not controlling for that might lead to spurious results.

With the further regressions we control for further measures of systematic and unsystematic risk. In the second regression we add the Fama & French beta (FF_BETA) which is an established measure for systematic risk. We substitute in the third regression FF_BETA with the standard deviation of Fama & French residuals (FF_RES_VOL), an established measure for unsystematic risk. We conclude with a fourth regression where we include all the previous control variables and both measures of systematic and unsystematic risk. The intuition behind these regressions is to test the effect of customer satisfaction on ICC while controlling for usual accounting, capital market and marketing controls together with established measures of systematic and unsystematic risk. We check with our regression if ACSI still has an association with ICC after controlling for the usual controls and measures of systematic and unsystematic risk, i.e. we check if ACSI has an incremental effect on ICC over the control variables and risk measures from previous literature (e.g., Gebhardt et al. (2001); Tuli and Bharadwaj (2009)).

Endogeneity in our research design might arise from financial constraints. If a firm has financial constraints it will have difficulties acquiring new equity capital and financing customer satisfaction initiatives such as investments in product quality. So we need to control for firms endogenously choosing to influence the relation between cost of equity and customer satisfaction. We do that through introducing the above defined Kaplan & Zingales index (KAZI) as a control into our regressions. Higher values of KAZI indicate more financially constrained firms.

Table 2.5 reports the results of the four multivariate regressions of ACSI and various controls on ICC. Panel A reports regressions with year-fixed effects while panel B reports the same regressions with year-fixed and firm-fixed effects. Although our focus and main results are the ones found in panel B, we report panel A to show that firm-fixed effects take out much of the variance and hence could reduce the significance. Yet our results with firm-fixed effects are highly significant, confirming that customer satisfaction is negatively associated with cost of equity of the firm, independent of the panel specification we use. [20] We run the same regressions with year-fixed and firm-random effects and get equivalent results as reported in Appendix A.1.3 in Table A2.

ACSI has a negative sign in all four regression, whether we use only year-fixed effects or year-fixed and firm-fixed effects. The p-values indicate high significance and range from 0.002 to 0.005 in the case of only year-fixed effects and from 0.012 to 0.015 in the case of year-fixed and firm-fixed effects. This confirms that an increase in customer satisfaction reduces cost of equity. This finding is independent of the econometric panel specification and combination of control variables we use. As explained in 2.3.4 ICC is multiplied by 100, such that we can interpret its estimated coefficients as percentages. Customer satisfaction decreases ICC by 0.040% - 0.042% in the case of using only year-fixed effects and 0.062% - 0.065% in the case of year- and firm-fixed effects, i.e. a 10 point increase in ACSI decreases ICC by 40 - 65 basis points. The signs and p-values of the usual control variables and risk measures do not vary much between regressions and panel specification. RD has a significant negative sign in regressions (1) - (4) in panel A and regressions (1) and (2) in panel B while it is negative and barely insignificant regressions (3) and (4) in panel B. Furthermore FF_BETA is positive but insignificant in panel A, as one would expect a measure of systematic risk to influence another measure of systematic risk positively however it shows negative and still insignificant results in panel B. As for FF_RES_VOL it has negative and insignificant estimates throughout all regression in both panels. These partially mixed and insignificant results do not change the tenor of our results, since we include the covariates only as controls, i.e. in order to make sure we do not omit any variables. KAZI has a negative sign and is highly significant in panel A,

[20] Although none of the established studies before on customer satisfaction use firm-fixed effects, probably because of the low within variance in customer satisfaction, we are able to show significance throughout all four specifications. Tuli and Bharadwaj (2009) use first differences which is however not equivalent to using firm-fixed effects. We do not have a reason to believe that there is serious serial correlation in the error term and hence abstain from using first differences. To control for possible autocorrelation we use Newey and West (1987) standard errors as explained above.

Table 2.5: Analysis of ICC Sensitivity to ACSI

Panel A: Year-Fixed Effects

	(1)	(2)	(3)	(4)
ACSI	-0.041***	-0.040***	-0.042***	-0.041***
	0.003	*0.005*	*0.002*	*0.003*
SIZE	0.008***	0.008***	0.008***	0.007***
	0.000	*0.000*	*0.000*	*0.000*
LEV	0.012*	0.012*	0.013**	0.012*
	0.053	*0.057*	*0.048*	*0.051*
BTM	-0.029***	-0.028***	-0.029***	-0.028***
	0.000	*0.000*	*0.000*	*0.000*
ROA	0.190	0.295	0.114	0.249
	0.848	*0.771*	*0.906*	*0.804*
RD	-10.77***	-11.00***	-10.36**	-10.46***
	0.008	*0.007*	*0.011*	*0.010*
ERROR	-0.056	-0.055	-0.057	-0.055
	0.386	*0.401*	*0.380*	*0.393*
GROWTH	13.874***	13.726***	14.062***	13.944***
	0.000	*0.000*	*0.000*	*0.000*
FF_BETA		0.119		0.223
		0.665		*0.479*
FF_RES_VOL			-0.026	-0.048
			0.652	*0.467*
KAZI	-0.005***	-0.005***	-0.005***	-0.005***
	0.009	*0.009*	*0.009*	*0.009*
N	1738	1738	1738	1738
adj_R2	*0.181*	*0.181*	*0.181*	*0.181*

Panel B: Year-Fixed and Firm-Fixed Effects

	(1)	(2)	(3)	(4)
ACSI	-0.062**	-0.063**	-0.064**	-0.065**
	0.015	*0.014*	*0.012*	*0.012*
SIZE	0.006**	0.006**	0.006**	0.006**
	0.014	*0.015*	*0.012*	*0.013*
LEV	0.003	0.003	0.003	0.003
	0.746	*0.711*	*0.708*	*0.691*
BTM	-0.014	-0.015	-0.014	-0.015
	0.161	*0.141*	*0.160*	*0.143*
ROA	7.773***	7.657***	7.623***	7.572***
	0.000	*0.000*	*0.000*	*0.000*
RD	-10.85*	-10.76*	-9.286	-9.678
	0.052	*0.054*	*0.130*	*0.115*
ERROR	-0.174**	-0.176**	-0.175**	-0.176**
	0.046	*0.048*	*0.042*	*0.045*
GROWTH	19.613***	19.652***	19.663***	19.680***
	0.000	*0.000*	*0.000*	*0.000*
FF_BETA		-0.286		-0.235
		0.263		*0.386*
FF_RES_VOL			-0.053	-0.037
			0.442	*0.613*
KAZI	0.000	0.000	0.000	0.000
	0.924	*0.906*	*0.840*	*0.851*
N	1738	1738	1738	1738
adj_R2	*0.496*	*0.496*	*0.496*	*0.496*

The table reports OLS coefficient estimates based on robust heteroscedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors (having a bandwidth of 2). The base sample comprises 1,714 yearly observations from 185 firms (we loose firms because of missing values) over the time period from 1994 (1993 after dating ACSI values 3 month backwards) to 2012. The dependent variable is the ICC and the variable of interest is ACSI as presented in section 2.3.2 and 2.3.4 respectively. We include year-fixed effects in the regressions of panel A whereas we include year-fixed and firm-fixed effects in panel B, but do not report their results. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

but has a magnitude of zero and is insignificant in panel B. The negative sign of KAZI agrees with the correlations in Table 2.3 and poses a similar result as in Lamont et al. (2001).

The adjusted R^2 of our regressions is 18.1% throughout all regressions in panel A and 49.6% throughout the regressions in panel B. Adjusted R^2 is higher when firm-fixed effects are introduced, since part of the variance is eliminated, the variance between firms, and we control for more firm characteristics. Although not usual, our regressions show for each combination of control variables with fixed effects the same adjusted R^2. Keeping in mind that we are using linear regression models without any dynamic structure (i.e. without any further lagged control variables), these values of adjusted R^2 indicate a very good fit.

2.4.4 Robustness Checks

In this subsection we discuss several robustness checks to test the sensitivity of our main results. As seen in the above subsection we use ICC based on the model from Pástor et al. (2008) which might give rise to two issues. First, we should assure that a different model used to compute ICC shows similar results, i.e. our results should not be sensitive to the model itself. Second, since the risk-free rate varies over the month of the release of ACSI figures, we should look at the firm-specific systematic risk profile excluding the risk-free rate, i.e. the implied risk premium (IRP) which captures the systematic risk not shared by the market.[21] We run the regressions of panel B from Table 2.5 with the ICC model from Gebhardt et al. (2001), a simpler but still established residual income model (RIM) in the accounting and finance literature, and get equivalent results as reported in Appendix A.1.3 in Table A3. Further, we report the same regressions in Appendix A.1.3 in Table A4 with the ICC model from Easton (2004), another established abnormal earnings growth (AEG) model in the accounting and

[21] Risk-free rates are taken from the database of the federal reserve (see `http://www.federalreserve.gov/releases/h15/data.htm`) and defined as the market yield on U.S. Treasury securities at 10-year constant maturity, following Pástor et al. (2008)

finance literature, and also get similar results with higher p-values though.[22] [23] We also run these regressions with the IRP and get similar results as well. Hence we claim that our results are sensitive neither to the model nor to whether we use the whole cost of equity or just the risk premium.

Another assumption is the time horizon used before the period of the terminal value starts, hence T from Subsection 2.3.2. We run our main regressions with two different time horizons, 10 years and 20 years respectively and arrive at similar results.

2.5 Customer Satisfaction and Firm Value Decomposition

In this part of the paper we decompose firm value into a cash flow component and a cost of equity component and test the effect of customer satisfaction on both of them. Taking the stock return of the firm as the driver of its shareholder value and equating it to a valuation model, cash flows constitute its numerator and the cost of equity serves as the discount factor in its denominator, as seen in Equation (2.1).

We are interested in the change in value of the firm if we change only cash flows or the cost of equity respectively. For that purpose we use the superior measure from the first part of the paper, the ICC.

We test the effect of the change in customer satisfaction (Δ acsi) on cash flow changes (CF) and cost of equity changes (DR) for the years $j \in \{1 \dots 5\}$. j is the investment horizon, i.e. the period over which we compute the stock returns and the corresponding "as-if" changes, cash flow changes and cost of equity changes. If for example $j = 3$ DR and CF are computed according to Equations (2.3) and (2.4).

[22] The RIM and AEG model are variations of net present value models such as the discounted earnings model of the model by Pástor et al. (2008) we use.

[23] We use the main models from Gebhardt et al. (2001) and Easton (2004) respectively, but the input variables from Pástor et al. (2008), i.e. EPS forecasts, forecasted long-term earnings growth and the plowback rate (or payout ratio). We do this in order to keep the models and their related ICCs comparable.

$$
\begin{aligned}
CF_{t,3} &= \frac{1}{2}\frac{f(eps_{t+3},\ldots,eps_{t+18+1},b_{t+3},\ldots,b_{t+18},ICC_{t+3}) - f(eps_t,\ldots,eps_{t+15+1},b_t,\ldots,b_{t+15},ICC_{t+3})}{P_t} \\
&+ \frac{1}{2}\frac{f(eps_{t+3},\ldots,eps_{t+18+1},b_{t+3},\ldots,b_{t+18},ICC_t) - f(eps_t,\ldots,eps_{t+15+1},b_t,\ldots,b_{t+15},ICC_t)}{P_t} \\
DR_{t,3} &= \frac{1}{2}\frac{f(eps_t,\ldots,eps_{t+15+1},b_t,\ldots,b_{t+15},ICC_{t+3}) - f(eps_t,\ldots,eps_{t+15+1},b_t,\ldots,b_{t+15},ICC_t)}{P_t} \\
&+ \frac{1}{2}\frac{f(eps_{t+3},\ldots,eps_{t+18+1},b_{t+3},\ldots,b_{t+18},ICC_{t+3}) - f(eps_{t+3},\ldots,eps_{t+18+1},b_{t+3},\ldots,b_{t+18},ICC_t)}{P_t}
\end{aligned}
$$

We regress changes in ACSI (Δ ACSI) and changes in controls on $CF_{t,j}$ and $DR_{t,j}$ to capture the effect of customer satisfaction changes on cash flow changes and cost of equity changes respectively (we do not report the intercept coefficients in our regressions).

$$CF_{it,j} = \alpha_j^c + \beta_j^c \Delta_j ACSI_{it} + \sum_k \gamma_{k,j}^c \Delta_j Control_{itk} + \epsilon_{it,j}^c \tag{2.6}$$

$$DR_{t,j} = \alpha_j^d + \beta_j^d \Delta_j ACSI_{it} + \sum_k \gamma_{k,j}^d \Delta_j Control_{itk} + \epsilon_{it,j}^d, \tag{2.7}$$

where j is the investment horizon and Δ_j is the difference over j years, i.e. $\Delta_j X_t = X_t - X_{t-j}$. We include changes in the following variables as controls: total assets (Δ SIZE), return on assets (Δ ROA) and the book-to-market ratio (Δ BTM). Table 2.6 reports the results of the multivariate regressions of the change in customer satisfaction on CF and DR for each of the 5 years as investment horizons with the above listed control variables. The number above each column is j, the investment horizon in years.

The absence of significance for Δ ACSI in most of the regressions could be traced back to the lack of power of the model due to the stickiness of ACSI values as shown in 2.4.1. We tackle this problem by making use of the monthly data we have and hence use up the whole sample size and all the variance we have in our sample in order to boost up the power of the regressions. Table 2.7 reports the results of monthly multivariate regressions of the change in customer satisfaction on each of CF and DR for each of the 5 years. We assume the same customer satisfaction (M_ACSI) and accounting data for the whole year and use monthly

Table 2.6: Analysis of the Sensitivity of Firm Value Decompostion to ACSI

Panel A: Cash Flow Changes

	(1)	(2)	(3)	(4)	(5)
Δ ACSI	-0.006	-0.006	-0.001	0.006	0.017
	0.405	*0.532*	*0.951*	*0.582*	*0.129*
Δ SIZE	0.000	0.000	0.000*	-0.001***	-0.001***
	0.868	*0.174*	*0.080*	*0.005*	*0.001*
Δ BTM	-0.020	-0.020	-0.009	0.023	0.010
	0.373	*0.304*	*0.874*	*0.390*	*0.586*
Δ ROA	1.328**	2.396**	4.517***	5.900***	6.330***
	0.013	*0.025*	*0.000*	*0.000*	*0.000*
N	820	820	820	820	820
adj_R2	*0.072*	*0.084*	*0.125*	*0.142*	*0.138*

Panel B: Cost of Equity Changes

	(1)	(2)	(3)	(4)	(5)
Δ ACSI	0.014**	0.017***	0.014*	0.014	0.010
	0.043	*0.007*	*0.087*	*0.163*	*0.292*
Δ SIZE	0.000	0.000	0.000	0.000	0.000*
	0.252	*0.580*	*0.934*	*0.314*	*0.058*
Δ BTM	-0.034**	-0.008	-0.017	-0.032	-0.014
	0.043	*0.586*	*0.681*	*0.227*	*0.556*
Δ ROA	-0.829	-0.643	-1.504***	-1.365**	-0.738
	0.166	*0.351*	*0.003*	*0.011*	*0.384*
N	820	820	820	820	820
adj_R2	*0.068*	*0.057*	*0.067*	*0.084*	*0.039*

The table reports OLS coefficient estimates based on robust heteroscedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors (having a bandwidth of 2). The base sample comprises 770 yearly observations from 117 firms (we loose firms because of missing values and lagged variables in the calculation of changes) over the time period from 1998 to 2011. The dependent variable is cash flow changes ($CF_{it,j}$) in panel A and cost of equity changes ($DR_{t,j}$) in Panel B whereas the variable of interest is the change in ACSI ($\Delta_j ACSI_{it}$), all presented in sections 2.3.3 and 2.5. j represents the investment horizon, going from 1 to 5 (see column headers). We include year-fixed effects, but do not report their results. Two-tailed p-values in italic. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

ICC, CRSP and I/B/E/S values.[24] [25] The idea here is to increase the power of the regressions by increasing the sample size and the resulting variation in capital market expectations. The increased variation comes from the monthly ICC, CRSP and I/B/E/S data which we use now compared to using only one out of twelve values per variable in yearly regressions. We show that the effect of Δ M_ACSI on CF starts with insignificant results but persists and increases

[24] We run the same regression as in Table 2.7, where we interpolate customer satisfaction values (S_ACSI) between their release dates of every two consecutive years to get different values for each month when the value of ACSI changes from one year to the other. We get similar results as reported in Appendix A.1.3 in Table A5.

[25] In unreported results we also run the regressions from Subsection 2.4.3 in the same monthly manner. We get more significance but also lower coefficient estimates.

afterwards with the number of years (length of the investment horizon). The effect of Δ M_ACSI on DR is highly significant over lower investment horizons. The effect of Δ M_ACSI on CF starts being insignificant up to year three, becomes highly significant in year four with 0.016 and increases to a highly significant 0.025 in year five. The effect of Δ M_ACSI on DR starts with 0.003 in year one, increases to 0.011 in year three and decreases back to 0.001 in year five, being highly significant in years two and three. The effect of Δ M_ACSI on CF becomes larger than the effect of Δ M_ACSI on DR starting in year four and persists in that manner. Note that the magnitude of the coefficients should be compared between DR and CF for the same investment horizon. As in Subsection 2.4.4 we run also the regressions with a valuation time horizon of 10 years and 20 years respectively and get equivalent results.

Our results are compatible with the results from Chen et al. (2013), who find that CF increases in importance with the investment horizon compared to DR in explaining returns. Note that CF becomes higher than DR starting in year (investment horizon) four and does not revert. As for the interpretation of the results, we start by quoting Chen et al. (2013): "... the impact of cost of equity changes is temporary and attenuated with time. In the long-run limit, all stock return changes must be cash flow changes ... This is a fundamental property that holds irrespective of economic models." Basically they are saying that returns and hence the cost of equity are mean reverting, such that if returns increase today, they will have to decrease at some future point in time. This explains the results that we get only in that the effect on CF persists and increases over the various investment horizon j while the effect on DR decreases after year three. Furthermore Chen et al. (2013) state that "... analyst sluggishness can be mitigated at longer horizons. This suggests that the model might explain price variations better at longer horizons ...". This explains the increasing highly significant CF magnitude we observe as the investment horizon j increases.

This confirms the results that Chen et al. (2013) show, in that cash flow changes outweighs cost of equity changes in explaining stock returns. Remember that stock returns are a value driver and are positively associated with customer satisfaction according to the literature listed in Sections 2.1 and 2.2. By decomposing stock returns into CF and DR and showing that the

Table 2.7: Analysis of the Sensitivity of Monthly Firm Value Decompostion to Constant ACSI Values

Panel A: Cash Flow Changes

	(1)	(2)	(3)	(4)	(5)
Δ M_ACSI	0.002	0.002	0.005	0.016***	0.025***
	0.253	*0.459*	*0.116*	*0.000*	*0.000*
Δ SIZE	0.000	0.000***	0.000***	0.000***	-0.001***
	0.353	*0.001*	*0.000*	*0.000*	*0.000*
Δ BTM	-0.033***	-0.034***	-0.031***	0.016*	0.025***
	0.000	*0.000*	*0.002*	*0.054*	*0.000*
Δ ROA	1.319***	3.296***	4.628***	5.581***	7.157***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
N	9840	9840	9840	9840	9840
adj_R2	*0.083*	*0.158*	*0.166*	*0.162*	*0.165*

Panel B: Cost of Equity Changes

	(1)	(2)	(3)	(4)	(5)
Δ M_ACSI	0.003	0.008***	0.011***	0.003	0.001
	0.156	*0.000*	*0.000*	*0.200*	*0.705*
Δ SIZE	0.000	0.000	0.000	0.000**	0.000***
	0.114	*0.231*	*0.297*	*0.029*	*0.000*
Δ BTM	-0.033***	-0.004	0.004	-0.028***	-0.030***
	0.000	*0.394*	*0.612*	*0.000*	*0.000*
Δ ROA	-0.563***	-0.989***	-1.138***	-0.922***	-1.242***
	0.001	*0.000*	*0.000*	*0.000*	*0.000*
N	9840	9840	9840	9840	9840
adj_R2	*0.057*	*0.081*	*0.08*	*0.086*	*0.077*

The table reports OLS coefficient estimates based on robust heteroscedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors (having a bandwidth of 2), similar to the regressions of table 2.6 but with monthly data as described in section 2.5. The base sample comprises 8,873 monthly observations from 122 firms (we loose firms because of missing values and lagged variables in the calculation of changes) over the time period from 1998 to 2012. The dependent variable is cash flow changes ($CF_{it,j}$) in panel A and cost of equity changes ($DR_{t,j}$) in Panel B whereas the variable of interest is the change in ACSI ($\Delta_j ACSI_{it}$), all presented in sections 2.3.3 and 2.5. j represents the investment horizon, going from 1 to 5 (see column headers). We include year-fixed effects, but do not report their results. Two-tailed *p*-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

association between CF and ACSI persists and increases compared to the association between DR and ACSI, we establish that ACSI increases the value of the firm through increasing cash flows on the long run and decreasing cost of equity short-term.

2.6 Customer Satisfaction under Varying Sales Uncertainty

We investigate the effect of customer satisfaction on cost of equity and firm value decomposition in states of low and high sales uncertainty. We divide our sample into two subsamples, the first having the pre 10 years standard deviation of sales (STDDEV_SALES) below its whole sample median (LOW) and the second having STDDEV_SALES above or equal to its whole sample median (HIGH).

2.6.1 The Effect on Cost of Equity

To test the incremental effect of customer satisfaction on cost of equity in states of low and high sales uncertainty, we run the same regressions as in Table 2.5. We report our results in Table 2.8 with year-fixed effects split into panel A for low sales uncertainty and panel B for high sales uncertainty. As becomes clear from both panels, the negative effect of customer satisfaction on cost of equity is higher for high sales uncertainty and highly significant only in this state.

Table 2.8: Analysis of ICC Sensitivity to ACSI Conditional on Sales Uncertainty

Panel A: Low Sales Uncertainty

	(1)	(2)	(3)	(4)
ACSI	-0.016	-0.010	-0.018	-0.012
	0.436	*0.615*	*0.373*	*0.537*
N	931	931	931	931
adj_R2	*0.207*	*0.209*	*0.207*	*0.212*

Panel B: Low Sales Uncertainty

	(1)	(2)	(3)	(4)
ACSI	-0.078***	-0.078***	-0.077***	-0.077***
	0.000	*0.000*	*0.000*	*0.000*
N	779	779	779	779
adj_R2	*0.161*	*0.16*	*0.16*	*0.159*

Panel C: Difference between Low and High Sales Uncertainty

	(1)	(2)	(3)	(4)
DIFF	0.062**	0.068**	0.059**	0.064**
	0.035	*0.022*	*0.046*	*0.029*

The table reports OLS coefficient estimates based on robust heteroscedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors (having a bandwidth of 2). The base sample from table 2.5 is split into two subsamples, where the pre 10 years standard deviation of sales is low (below the median) in panel A and high (above or equal to the median) in panel B. The dependent variable is the ICC and the variable of interest is ACSI as presented in section 2.3.2 and 2.3.4 respectively. Panel C reports the tests of the significance of the absolute value of the difference between the respective ACSI coefficients in panels A and B. We include control variables and year-fixed effects, but do not report their results. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

ACSI does not have any significant effect on ICC under low sales uncertainty while it decreases ICC by 0.077% - 0.078% under high sales uncertainty, i.e. a 10 point increase in ACSI decreases ICC by 77 - 78 basis points. These magnitudes are higher than the magnitudes in Table 2.5 where we use the whole sample, i.e. where we test the average effect for states of low and high sales uncertainty. In panel C we test the absolute value of the difference between the coefficients of ACSI in panel A and panel B respectively.[26] In a state of high sales uncertainty ACSI reduces ICC by 0.059% - 0.068% more than it does in a state of low sales uncertainty, all results being highly significant.

2.6.2 The Effect on Firm Value Decomposition

We decompose firm value into a cash flow component and a cost of equity component under states of low and high sales uncertainty to check how the effect of customer satisfaction changes on both components varies in these different states. We run the same regressions as in Table 2.7 and report our results in Table 2.9, split into panel A for cash flow changes (CF) and panel B for cost of equity changes (DR). Each panel is further split in results on the effect of ACSI changes (Δ ACSI) on the respective firm value decomposition component a in state of low sales uncertainty in the first part and results for a state of high sales uncertainty in the second part. The third part of both panels tests the absolute value of the difference between the coefficients of Δ ACSI in states of low and high sales uncertainty respectively. Our findings hint at less variation or rather more stability in a state of low sales uncertainty regarding the effects of customer satisfaction changes on cash flow changes and cost of equity changes respectively. However, in a state of high sales uncertainty, these effects become more distinct between the dominant effect on CF for high investment horizons and the dominant effect of DR for low investment horizons.

In a state of low sales uncertainty Δ ACSI has a persistent and highly significant effect on both CF and DR starting in year two. In a state of high sales uncertainty Δ ACSI has a

[26] This difference is tested in Tables 2.8 and 2.9 using Student's t-distribution with degrees of freedom according to Satterthwaite (1946) and Welch (1947).

Table 2.9: Analysis of the Sensitivity of Monthly Firm Value Decomposition to Constant ACSI Values Conditional on Sales Uncertainty

Panel A: Cash Flow Changes with Low and High Sales Uncertainty

	(1)	(2)	(3)	(4)	(5)
Δ M_ACSI (Low)	0.003	0.014***	0.015***	0.014***	0.017***
	0.213	*0.000*	*0.000*	*0.000*	*0.000*
Δ M_ACSI (High)	0.002	-0.002	-0.001	0.021***	0.039***
	0.379	*0.567*	*0.836*	*0.000*	*0.000*
DIFF_CF	0.001	0.016***	0.016***	0.006	0.023***
	0.744	*0.000*	*0.003*	*0.334*	*0.000*

Panel B: Cost of Equity Changes with Low and High Sales Uncertainty

	(1)	(2)	(3)	(4)	(5)
Δ M_ACSI (Low)	0.002	0.006**	0.010***	0.012***	0.014***
	0.547	*0.018*	*0.002*	*0.001*	*0.000*
Δ M_ACSI (High)	0.004	0.009***	0.011***	-0.002	-0.008**
	0.100	*0.000*	*0.000*	*0.614*	*0.012*
DIFF_R	0.002	0.003	0.001	0.014***	0.022***
	0.554	*0.425*	*0.841*	*0.009*	*0.000*

The table reports OLS coefficient estimates based on robust heteroscedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors (having a bandwidth of 2). The base sample from table 2.7 is split into two subsamples, where the pre 10 years standard deviation of sales is low (below the median) in the first parts of panels A and B and high (above or equal to the median) in the second parts of panels A and B. The dependent variable is cash flow changes ($CF_{it,j}$) in panel A and cost of equity changes ($DR_{t,j}$) in panel B whereas the variable of interest is the change in ACSI ($\Delta_j ACSI_{it}$), all presented in sections 2.3.3 and 2.5. j represents the investment horizon, going from 1 to 5 (see column headers). The third part of each panel reports the tests of significance of the absolute value of the difference between the respective ACSI coefficients. We include control variables and year-fixed effects, but do not report their results. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

strong and highly significant effect on CF for years four and five, while its effect on DR is strong and highly significant for years two and three (the negative and significant coefficient in year five is counter-intuitive and strengthens our argument). These results show that in a state of low sales uncertainty the effects of Δ ACSI on both components of firm value are similar and persistent over the investment horizon, whereas in a state of high sales uncertainty the effect on DR dominates for low investment horizons while the effect on CF dominates for high investment horizons. The magnitudes of the significant effects in a state of high sales uncertainty are mostly higher than the corresponding magnitudes in the analysis of the whole sample in Table 2.7. Note that the third part of panel A mostly shows significant absolute differences for low investment horizons and the third part of panel B shows significant absolute differences for high investment horizons, i.e. these results are the counterpart of the investment horizons where the two components, CF and DR, dominate. For low investment horizons and in a state of low sales uncertainty Δ ACSI increases CF by 0.016% more than it does in a state of high sales uncertainty. For high investment horizons and in a state of low sales uncertainty Δ ACSI increases DR by 0.014% - 0.022% more than it does in a state of high sales uncertainty.

2.7 Conclusion

In this paper, we examine the cost of equity (capital) effects of customer satisfaction changes. Prior research put much emphasis on overall firm valuation effects and on cash effects of customer satisfaction. One important and unresolved question is whether these effects stem from reductions in the cost of equity, from increases in future cash flow, or both. Furthermore, the relative importance of both drivers of firm value in unclear. However, customer satisfaction plays a major role in a firm's resource allocation decisions and as a non-financial performance measure in executive compensation contracts (Chen et al., 2015). Thus, understanding the precise relationship of how customer satisfaction is related to firm value is of great interest to both, academic research and practice.

We first investigate the association between customer satisfaction and the cost of equity. In contrast to prior empirical research in the customer satisfaction literature, we analyze ex-ante estimates of the firm's cost of equity instead of using ex-post measures of firm risk. In our analyses, we find a robust negative association between customer satisfaction as measured by the American Customer Satisfaction Index (ACSI) and the cost of equity, controlling for a large set of covariates with year-fixed and firm-fixed effects. In economic terms, an increase in 10 points in the ACSI results in a decrease of 40 to 65 basis points which is economically significant and meaningful, but not too large to be implausible.

Second, we decompose firm value into its two main components, namely cash flows and cost of equity. In this way, we contribute to the open question whether customer satisfaction contributes to firm value primarily due to changes in growth expectations regarding future cash flows or due to changes in the firm's cost of equity. We find a positive, consistent and growing association between customer satisfaction and both effects, the cash effect and the cost of equity effect, for different investment horizons. The cash flow effect starts weaker than the cost of equity effect but overtakes the latter for all investment horizons beyond three years. Thus, we find that the effect of customer satisfaction in the short-run is contributing to a reduction in firm risk which is observed and priced by capital markets. The cash effect, which has been the major element in the theoretical and empirical literature on customer satisfaction and valuation is manifesting later and outperforms the cost of equity effect after a certain point in time. Stated differently, we find that changes in customer satisfaction contribute to firm value in the short-run by cost of equity and in the long-run by cash growth effects. As with customer satisfaction in this paper, our methodological approach and empirical estimation can easily be transferred to other intangible assets of the firm such as corporate reputation (Cao et al., 2015), corporate social responsibility initiatives (Ghoul et al., 2011), brand equity, or employee satisfaction (Edmans, 2011).

Third, we rerun our analyses for two subsamples being in a state of low and high sales uncertainty respectively. We find that the effects are highly significant and higher in magnitude in a state of high sales uncertainty, while these effects are non-significant in a state of low sales uncertainty. Further, we find that the results distinguishing between the cash flow effect and the cost of equity effect are more pronounced in a state of high sales uncertainty.

Finally, our paper has several limitations and provides avenues for further research. First, although we control for fixed effects in both the firm and time dimensions and control for the set of covariates which is supposed to affect a firm's cost of equity level, it is possible that we did not incorporate all possible influences over time. Furthermore, we cannot exclude that causality runs the other way, i.e. lower cost of equity levels allow a firm to invest in customer satisfaction initiatives. Given that we include firm's research and development expenditures and the extent to which firms are financially constrained, we think that this concern is reasonably addressed. Finally, as any study relying on data from the ACSI, we rely on the sample of firms being represented in that index. Although these firms do not suffer from self-selection, the findings shown have to be interpreted cautiously.

3 Is the Cost of Equity Higher for Risky Banks? Evidence of Stock Market Discipline Using the Implied Cost of Capital

This chapter is based on a working paper I wrote with Ferdinand Elfers (University of Mannheim).

3.1 Introduction

3.1.1 Overview

In this paper we use the implied cost of capital (ICC) to estimate the rate of return required by the stockholders of U.S. bank holding companies (BHCs). The required rate of return reflects the risk discount stockholders apply to expected cash flows. We then use the implied risk premium (IRP), calculated as ICC minus the risk-free rate, to investigate directly whether stock prices are adjusted to information about the business risk of a BHC as suggested by the concept of market discipline.

Market discipline requires that investors have incentives and the ability to monitor the risk position of banks, and that they translate their knowledge into economic transactions ("market monitoring", e.g., requiring higher returns or withdrawing funds when perceiving high risk). Managers in turn are expected to adapt their risk behavior accordingly in order to avoid funding problems or excessive cost of capital ("market influencing", see Flannery (2001)). A further distinction can be made between *direct* market discipline, where the disciplining mechanism takes place directly between banks and the market, and *indirect* market discipline, where supervisors use market based signals to trigger regulatory action. With increasing complexity of financial markets, rising costs of banking supervision and fear of regulatory capture (Stigler, 1971; Kane, 1989), the concept has been discussed for many years (Lane, 1993; Berger, 1991). Lately it has received additional attention as a complement or alternative to traditional government oversight (e.g., Meyer (1999)). A prominent example is the introduction of the third pillar of Basel II in 2006, which requires detailed risk disclosures to foster market discipline.

Numerous empirical studies have investigated the market's "monitoring" ability to assess bank risk and react accordingly (for overviews see e.g., Flannery and Nikolova, 2004; Flannery, 1998; Gilbert, 1990).[27] Most of these papers focus on debt securities such as bonds, credit default swaps (CDS) or deposits and certificates of deposits (CD). Intuitively, debt holders should be highly averse towards bank risk, because it is potentially only detrimental to their position. For stockholders, the incentive structure is not as clear, as they could also profit from the upward potential of risky behavior. If the increase in expected payoffs dominates that of the risk discount, bank managers can increase the value of equity through higher risk taking. As Merton (1977) shows, this holds in particular under deposit insurance, where equity payoffs correspond to a put option, the value of which increases in asset risk (see e.g., Laeven and Levine, 2009; Park, 1997; Ritchken et al., 1993; Keeley, 1990). Furthermore, the risk conception relevant for a diversified equity investor is *systematic* risk, and it is not a priori clear whether systematic risk is necessarily aligned with the risk of financial distress relevant for debt investors and bank supervisors.

The monitoring incentives of debt holders might however be weakened as they are protected by the regulatory capital buffer and institutional safety nets such as deposit insurance or (implicit) government bail-out guarantees. No such mechanisms exist for stockholders, and in addition, stock market data is in general readily observable and more easily comparable than information on many debt instruments. Also, the notion that equity capital is "expensive" and that the cost of equity capital is not risk sensitive is an argument brought forward regularly by practitioners [28] and remains a point of contention among academics (see Baker and Wurgler, 2015). It therefore seems promising and relevant to investigate whether market monitoring takes place in stock markets. Yet, as outlined above, a proper analysis of this relation will

[27] It has proven much more difficult to find evidence of actual market influencing (Baele et al., 2011; Ashcraft, 2008; Bliss and Flannery, 2001; Rajan, 2001).

[28] "The bank aims to apply all capital levers at its disposal before considering raising equity from investors" (Deutsche Bank CEO Anshu Jain in 2012, `http://www.wsj.com/articles/SB10001424127887323528404578452892111767284`)

require to disentangle the risk discount from expected cash flows. To address this problem, we use the ICC as a forward-looking discount factor. To our best knowledge, there has not been any prior work using ICC in the context of market discipline. The basic idea of ICC computation is to set the observed stock price equal to a valuation model based on current book and market values and analyst forecasts of future earnings/cash flows. The ICC is then determined as the internal rate of return that solves this equation (e.g., Claus and Thomas, 2001; Gebhardt et al., 2001; Easton, 2004; Ohlson and Juettner-Nauroth, 2005; Pástor et al., 2008), from which we calculate IRP as ICC minus the risk-free rate of return. In contrast to e.g., beta from the CAPM or Fama & French 3-factor model, IRP thus is a forward looking measure of firm-specific systematic risk implied only by current and forecasted information and does not depend on noisy (average) realized returns (see e.g., Elton, 1999; Lundblad, 2007).

We compute the IRP for a large sample of U.S. BHCs for the period from 1986 to 2012 using the methodology proposed by Pástor et al. (2008). We choose the model by Pástor et al. (2008) as a recent and sophisticated ICC model that does not impose restrictive data requirements or severe assumptions like clean surplus accounting.[29] Nevertheless, we also employ other approaches in our robustness checks in Section 3.4.3. In the first step, we analyze IRP from the perspective of *direct* market discipline. More specifically, we investigate whether IRP varies with numerous well-established risk indicators based on accounting numbers (e.g., capitalization strength, asset quality, liquidity, etc.). We find a robust and significant relation between IRP and most of these variables, indicating that stockholders do indeed monitor banks' risk taking and adjust prices accordingly. To our best knowledge, we are the first to directly capture this baseline mechanism of market discipline through the cost of equity empirically.

In the second step, we examine the ex-ante usefulness of our measure in predicting actual bank distress, i.e. we examine the IRP as a risk signal from the viewpoint of *indirect* market

[29]See e.g., Chen et al. (2013) or Li et al. (2013).

discipline. We find that, in particular in the long run, the IRP adds significantly to the informative value of prediction models based on accounting and other market based indicators. However, as the IRP apparently does not capture the idiosyncratic portion of distress risk, it should be complemented with other appropriate measures.

3.1.2 Prior Literature and Contribution

Using IRP makes it possible to test for *direct* market discipline in stock markets. This allows us to address a gap in the literature on market monitoring. Most studies in this field of research are concerned with market disciplining by debt holders.[30] Classical examples for such studies are Pettway (1976) (capital notes), Avery et al. (1988) (subordinated notes and debentures) and Hannan and Hanweck (1988) (CDs), while the more recent work includes e.g., Dinger and Von Hagen (2009) (interbank borrowing), Sironi (2003) (subordinated notes and debentures), Hall et al. (2003) (CDs), Jagtiani et al. (2002) (bond yields), DeYoung et al. (2001) (subordinated debentures), Goldberg and Hudgins (2002); Park and Peristiani (1998) (deposits) and Flannery and Sorescu (1996) (subordinated debentures). Other studies are more concerned with the institutional background (deposit insurance, etc.) that shape debt-related monitoring incentives, most notably Karas et al. (2013), Hadad et al. (2011), Demirgüc-Kunt and Huizinga (2004), Goldberg and Hudgins (2002), Martinez Peria and Schmukler (2001) and Billett et al. (1998).

Stock prices have been examined as a source of market discipline only to a much lesser extent. Also, the larger part of this literature concentrates on price volatility as a risk signal from the perspective of indirect market discipline. Auvray and Brossard (2012) analyze the effects of ownership dispersion on the accuracy of a Merton-KMV-style distance-to-default indicator based on stock prices in predicting rating downgrades. Trutwein and Schiereck (2011) compare stock returns and CDS spreads for a small sample of failed U.S. banks during 2008 and find that stock returns even precede CDS as risk indicators. Curry et al. (2008) examine whether

[30] There is also substantial analytical literature on this relationship (see e.g., Chen and Hasan, 2011; Evanoff and Wall, 2000; Calomiris and Kahn, 1991).

stock market information (volatility, abnormal returns, share turnover) adds predictive power to accounting based forecasting models of BOPEC ratings. Stiroh (2006) uses stock price volatility to identify risk factors in banks' business models. Distinguin et al. (2006) investigate the predictive power of several stock market indicators (returns, Z-Score, distance-to-default measure) to forecast rating downgrades for European banks. Jordan et al. (2000) find that the strength of stock market reactions to announcements of formal supervisory actions depends strongly on the prior transparency of banks' disclosures (a similar point is made by Penas and Tümer-Alkan (2010)). Billett et al. (1998) show how stock returns around rating downgrades depend on the share of insured liabilities. Berger et al. (2000) compare information implied by stock returns (and ownership composition) with private and regulatory ratings to predict future bank performance and find that, while generally not much related to the rating assessments, stock returns perform well particularly with respect to performance measures not directly focused on default risk. Park and Peristiani (2007) choose a different approach that explicitly addresses the issue of moral hazard associated with bank shareholders ,i.e. a possible proclivity for inappropriate risk-taking. They establish that the relationship between Tobin's q and failure probabilities (based on accounting ratios or a distance-to-default model) depends on the relative value of the bank's option and charter value.

As our first contribution, estimating the IRP allows us to isolate the risk discount factor and therefore provides a clearer understanding of direct stock market discipline than could be achieved so far, without needing to resort to stock volatility or specific negative information events. Besides that, establishing the value relevance of risk information also speaks to the discussion on bank transparency and mandated risk disclosures outside the U.S.

As a second contribution, we further examine whether the IRP captures (distress) risk information that goes beyond current observable accounting risk indicators and thus might serve as a useful signal for *indirect* market discipline. In particular, we gauge the informational content of IRP in a prediction model of severe rating downgrades. We explicitly compare IRP to other market based information (distance-to-default, standard deviation of returns, etc.) to analyze whether IRP provides any additional value in predicting bank distress.

As our third and final contribution, both these questions relate our study to the broader general literature on the cost of equity. Conceptually, well-diversified stockholders should only price systematic risk in terms of asset volatility. From the viewpoint of market discipline, overall asset volatility is however less relevant than the prevention of bank distress. Intuitively, it is plausible that systematic risk is higher for banks with a high probability of distress. Yet the question whether distress risk is priced in equity returns is ultimately empirical and has become an important point of contention in the literature on cost of equity. It has been a common assumption that distress risk is the underlying factor that explains the size and value effect in the Fama-French three factor model (Chan and Chen, 1991; Fama and French, 1996). Depending on the default risk indicator, this has been partly confirmed (Vassalou and Xing, 2004; Kapadia, 2011), whereas other studies found evidence that firms with high implied default risk actually earn lower realized returns (Dichev, 1998; Griffin and Lemmon, 2002; Campbell et al., 2008; Da and Gao, 2010), which has been discussed as the “distress risk puzzle”. Some recent studies attempt to find an explanation for this counterintuitive result beyond simple mispricing. George and Hwang (2010) suggest that the systematic component of default risk stems from high distress costs, but that affected firms endogeneously choose low leverage and therefore have low risk of default. Anginer and Yildizhan (2014) contend that prior studies based on accounting ratios and the Merton model fail to distinguish between the diversifiable and the non-diversifiable component of distress risk. They propose a method to calculate the non-diversifiable distress risk from credit spreads and find a positive association with equity returns. Conrad et al. (2012) however argue that firms with high implied distress risk also have the highest potential for extremely high subsequent returns. Assuming an investor preference for assets with lottery-like positively skewed payout distributions as suggested by Barberis and Huang (2008), this might be the reason for low average returns in equilibrium. Ogneva et al. (2014) calculate the conditional probability of a recession given a firm’s failure to distinguish between systematic and unsystematic distress risk. They find that firms with the highest systematic distress risk earn a significant risk premium. Finally, Chava and Purnanandam (2010) emphasize that realized returns are only a noisy estimate of ex-ante required cost of equity, as has been established by prior literature (Elton, 1999; Lundblad, 2007). Similar to our approach, they instead compute the ICC and find a positive association with default risk. By providing a detailed risk analysis of the financial sector, which has been excluded by other studies so far, we contribute to this ongoing discussion.

The remainder of the paper proceeds as follows. In Section 3.2, we derive and present the methodology to compute the implied cost of capital. In Section 3.3, we outline the research design, describe our sample and provide descriptive statistics. Section 3.4 contains the results for our tests both on direct and indirect market discipline. Section 3.5 concludes.

3.2 Computing the Implied Risk Premium

The implied risk premium (IRP) is the implied cost of (equity) capital (ICC), which is a forward-looking measure of expected returns, minus the risk-free rate of return. We use "forward-looking" to indicate that only current values and future estimates are used in the derivation of the ICC (compared to using current and/or historical values in other models). In this section, we provide detailed information on the valuation model we use to compute the implied cost of capital in this paper.

Under the familiar discounted cash flow model, the stock price is calculated as

$$p_t = \sum_{s=1}^{T} \frac{1}{(1+r_e)^s} \mathbb{E}_t(x_{t+s}), \tag{3.1}$$

where p_t is the price and x_{t+s} is the asset payoff (in this case dividends, stock repurchases etc.). $\mathbb{E}_t(\cdot)$ stands for expected values conditioned on the information up to time t. This risk correction is directly made in the discount factor r_e, which represents the cost of (equity) capital and can be denoted as a discount rate or the expected return. Assuming rational behavior and sufficient portfolio diversification, r_e corrects only for systematic risk, whereas idiosyncratic or unsystematic risk is not reflected in the asset price.

Following the literature, in this paper we follow the methodology from Pástor et al. (2008) to empirically back out the implied cost of (equity) capital. ICC is the internal rate of return that is implied by equating the price on the left hand side to the valuation formula on the right hand side.

$$p_t = \sum_{s=1}^{T} \frac{FE_{t+s}(1 - b_{t+s})}{(1 + r_e)^s} + \frac{FE_{t+T+1}}{r_e(1 + r_e)^T} \tag{3.2}$$

All variables in Equation (3.2) are seen from the point of view of time t, i.e. conditioned on the information available up to time t. The index resembles the time at which the variable is to realize its value. FE_{t+s} are forecasts of yearly earnings, b_{t+s} is the plowback rate (one minus the payback ratio), r_e is the cost of (equity) capital and T is the horizon after which we begin to compute the terminal value of the stock. FE_{t+1} and FE_{t+2} are assigned starting values. For periods $t + 3$ to $t + T + 1$ an exponentially declining growth rate g_{t+s} is defined, which mean-reverts the growth rate at $t + 3$ to a steady-state growth rate g setting in by $t + T + 2$ (see below and Section 3.3.2).

$$\begin{aligned} FE_{t+s} &= FE_{t+s-1}(1 + g_{t+s}) \\ g_{t+s} &= g_{t+s-1} \exp\left(\frac{\log(g/g_{t+3})}{T - 1}\right) \end{aligned}$$

The plowback rate b_{t+s} is derived from financial statements for periods $t + 1$ and $t + 2$ as one minus the payout ratio. For periods $t + 3$ to $t + T$, the plowback rate is linearly mean-reverted to a steady-state plowback rate b.

$$b_{t+s} = b_{t+s-1} - \frac{b_{t+2} - b}{T - 1},$$

In contrast to earnings growth rates, where empirical evidence suggests rapid mean-reversion (hence the exponentially declining rate), Pástor et al. (2008) assume a linear decline in the plowback rates to reflect them reverting typically rather slower than the former. For the steady-state growth rate, g is set equal to the gross domestic product (GDP) growth rate. Furthermore we presume sustainable growth, i.e. the current plowback rate affects subsequent earnings growth as $g = ROI \times b$, where ROI is the steady-state return on investments. ROI

is set equal to r_e, assuming that competition drives ROI down to the cost of equity. The steady-state plowback rate b then becomes $b = g/r_e$.

The valuation Model (3.2) typically does not yield a closed-form solution. We therefore use a heuristic to minimize the distance between the price p_t on the left hand side and the valuation formula on the right hand side according to the unknown cost of equity r_e. We employ the quadratic difference as the distance between both sides of the equation in order to have a differentiable target function with a theoretical minimum of zero (when the valuation formula prices the asset perfectly). The minimization problem is executed under the conditions used to compute FE_{t+s}, g_{t+s}, b_{t+s} and $b = g/r_e$ (note that the last equation is a function of the unknown r_e itself). The optimization is said to converge when the quadratic difference between the left-hand side and right-hand side of (3.2) is less than or equal to a specific predetermined bound, which we set to 10^{-10}.[31]

3.3 Research Design and Data

3.3.1 Research Design

Our analysis is divided in two parts to cover both direct and indirect market discipline. First, we examine the association between the IRP and various publicly available indicators of bank risk. The question here is whether stockholders "punish" banks with a greater risk of getting into financial distress through higher cost of funding. Direct market discipline suggests that this alone should deter banks from excessive risk taking. This is a plausible point as (a) banks, in particular in periods of crisis, might face the need to recapitalize through capital increases, and (b) bank managers aim to maximize equity value, which is ceteris paribus reduced by a high cost of equity (the discount effect might however be dominated by higher expected cash flows on a net basis). Second, we analyze whether the IRP is useful as an ex-ante indicator of

[31] We use the SAS procedure `proc optmodel` to run the above described optimization problem. The starting value for r_e is set to 12%, which is used in other established papers on ICC. Where the heuristic does not converge, the starting value is set to 10%.

distress risk for indirect market discipline, i.e., whether supervisors can profit from considering the IRP to distinguish between banks more or less likely to default in the future.

For the first part, we abstain from explicitly quantifying the risk of default (e.g., through a logit model), as our mostly accounting based risk variables (leverage, loan losses, liquidity, funding etc.) are all well-established measures of bank stability in the literature (see Altman et al., 2014, for a discussion). Furthermore, as market discipline ultimately aims at influencing banks' risk taking behavior, these variables directly correspond to the different dimensions of risk management that stockholders would ideally want to scrutinize. Our results therefore implicitly also speak to the relevance of disclosing such information for non-U.S. banks.

Similar to Gebhardt et al. (2001), we begin our analysis with an array of univariate tests. At each quarter, we divide our sample into five portfolios according to each risk variable. We then compute the mean and median IRP per portfolio and test the difference between the portfolio in the highest (Q5) and lowest quintile (Q1). After establishing the univariate relations, we examine the impact of risk information on the cost of equity by estimating the following regression model for our panel of BHCs over the entire sample period.

$$IRP_{it} = \alpha + \sum \beta_j \ RiskIndicator_{ijt} + \sum \gamma_j \ Control_{ijt} + \epsilon_{it} \tag{3.3}$$

The IRP is a forward-looking measure of expected returns reflecting investors' expectations in relation to future payouts. Assuming that stockholders aggregate all available information into plausible estimates of future developments, IRP should not only reflect contemporaneous, but as well future business risk. To substantiate this reasoning, in the next step, we re-estimate Equation (3.3) with the vector of future accounting risk indicators.

$$IRP_{it} = \alpha + \sum \beta_j \ RiskIndicator_{ijt+\tau} + \sum \gamma_j \ Control_{ijt+\tau} + \epsilon_{it}, \tag{3.4}$$

where τ indicates the lead, ranging of one to twelve quarters ahead.

Having established that the IRP reflects a BHC's risk position, in the second part we aim to investigate whether it contains information that is useful to predict bank distress even beyond the other publicly available risk indicators such as in Equation (3.3). We are now also interested in the predictive performance of the IRP relative to other (historical) market based risk indicators such as beta, return variability or the estimated distance to default. However, an empirical analysis of this question is challenging as BHCs formally default only rarely. We therefore follow Distinguin et al. (2006) and Auvray and Brossard (2012) and use rating downgrades instead of actual defaults. In particular, we code a downgrade from an S&P rating of BBB- or higher to BB+ or lower (i.e., junk bond status) as a distress event and an upgrade from BB+ or lower to BBB- or higher as a recovery.[32]

For the subsample of BHCs with available rating data, we begin our analysis with computing the cumulative accuracy ratio for predicting rating downgrades over the next year for the IRP and other market based risk indicators. We also depict the temporal development of the IRP compared to other variables before the distress event. For a more rigorous examination, in the next step, we estimate a complementary log-log regression model[33] to predict such rating downgrades over several prediction horizons.

$$\begin{aligned} Prob(Downgrade_{it+\tau}) =& 1 - \exp(-\exp(\alpha + \beta\ IRP_{it} + \sum \gamma_j\ RiskIndicator_{ijt} \\ & + \sum \delta_j\ Control_{ijt} + \epsilon_{it})) \end{aligned} \tag{3.5}$$

We include the other market based risk indicators and estimate the model in Equation (3.5) both with and without the IRP to gauge its incremental informative value. Finally, we also estimate a (Cox proportional hazard) duration model.

[32]Using this rating-based proxy for financial distress seems plausible as many of the banks classified as distressed were taken over by competitors soon after the downgrade.

[33] We use the complementary log-log model because it better fits the extremely asymmetrical distribution of downgrades and non-downgrades compared to classical logit or probit models. However, estimating a logit or probit model yields qualitatively and quantitatively similar results.

$$h_{it} = h_{0t} \exp(\beta \; IRP_i + \sum \gamma_j \; RiskIndicator_{ij} + \sum \delta_j \; Control_{ij} + \epsilon_{it}), \tag{3.6}$$

where the hazard rate h_{it} is defined as the probability of BHC i being downgraded at time t conditional on having survived until that point in time.

$$h_{it} = Prob(T_i = t | T_i \geq t; X_i) \tag{3.7}$$

Here, T_i is a random variable measuring the time until the severe downgrade of BHC i and X_i is the same vector of firm specific explanatory variables as in Equation (3.5). However, these covariates are measured only at the time when the BHC enters the sample and are held fixed for the rest of the sample period, thus providing a flexible way of capturing the long-term nature of IRP.

3.3.2 Sample Data

Our sample data is obtained by merging four databases. Accounting data needed for the IRP computation and as accounting risk indicators are taken from BHCs' financial statements filed with the Federal Reserve Bank (FR Y-9C reports). Stock prices, returns and analyst forecasts are downloaded from CRSP and I/B/E/S, respectively. Finally, S&P credit ratings are taken from COMPUSTAT. All of the data are accessed using the Wharton Research Data Services (WRDS) interface. CRSP plays a central role for data mapping. We merge BHCs' financial statements with CRSP using the mapping table by the Federal Reserve Bank of New York.[34] This table maps each BHC to a PERMCO identifier from CRSP and is available from 1990. We can then merge the data with I/B/E/S and COMPUSTAT using the proposed algorithm from WRDS.

We begin the sample selection process with all BHCs having FR Y-9C reports available on

[34] http://www.newyorkfed.org/research/banking_research/datasets.html

WRDS and require that data on net income and common shares outstanding is available (thus losing all unlisted BHCs). Based on the ICC literature (e.g., Gebhardt et al. (2001), Pástor et al. (2008)), we use income before extraordinary items and other adjustments for the holding company (i.e., excluding noncontrolling minority interests). Common shares outstanding from the FR Y-9C reports are used to compute earnings per share (EPS). We then merge the data with CRSP to obtain stock prices and returns that are also needed for the computation of alternative market based risk indicators in the second part of the analysis.

After merging the dataset with I/B/E/S, we combine the data with analyst forecasts of 1-year-ahead (FE_{t+1}) and 2-year-ahead earnings per share (FE_{t+2})[35] and the long-term earnings growth rate (Ltg).[36] We require the availability of at least the one-year-ahead EPS forecast.[37] As the availability of I/B/E/S earnings forecasts for more than two years ahead is low[38], we follow Pástor et al. (2008) and use the exponential growth decline formula described in Section 3.2 directly after period $t+2$. For each earnings forecast (adjusted for dilution) we use the mean of analyst forecasts and for long-term growth we use the median of analyst forecasts as recommended by Thomson Financial.[39] We calculate the plowback rate at $t+1$ and $t+2$ as one minus the payout ratio. We estimate the payout ratio as net payout in year t (NP_t), i.e., dividends plus share repurchases minus new stock issuances, divided by net income in year t (NI_t). Dividends are the common dividends paid in year t, share repurchases are the common and preferred stocks repurchased in year t and new stock issuances are the

[35] We do not exclude negative 2-year-ahead EPS since distressed BHCs build an essential part of our sample for the analysis in Section 3.4.2. We run the same (unreported) regressions excluding BHC-quarters with negative 2-year-ahead EPS and get very similar results.

[36] Since I/B/E/S data provides estimates for the following fiscal year end, we multiply the right hand side of the valuation model in Equation (3.2) by $(1 + r_e)^{m/12}$, where m is the number of months until the fiscal year ends.

[37]If Ltg is missing while FE_{t+2} is not, it is set equal to $Ltg = FE_{t+2}/FE_{t+1} - 1$. If Ltg and FE_{t+2} are both missing, they are set equal to $Ltg = FE_{t+1}/E_t - 1$ and $FE_{t+2} = FE_{t+1}(1 + Ltg)$ (the same holds if Ltg is not missing), where E_t is the most recent realized earnings. When Ltg takes values that are larger than 100% (or smaller than 2%) we assign values of 100% (2%) instead.

[38] In our sample the availability is as follows: EPS_1 (99.6%), EPS_2 (92.7%), EPS_3 (26.3%), EPS_4 (8.9%), EPS_5 (5.7%) and Ltg (70.8%)

[39] `http://wrds-web.wharton.upenn.edu/wrds/support/Data/_001Manuals%20and%20Overviews/_003I-B-E-S/_001Data%20Manuals/_015TF%20Estimates%20Glossary%20-%20February%202008.pdf.cfm`

common and preferred stocks sold in year t. Common dividends, common and preferred stocks repurchased and common and preferred stocks sold are obtained from the FR Y-9C reports and are assumed to be zero if their values are missing.[40] GDP figures are obtained from the Bureau of Economic Analysis.[41] We use GDP percentage changes based on current dollars, and compute the steady-state GDP growth rate (g from Section 3.2) for each year as the average of past annual GDP growth rates up to that year.

We then estimate the ICC and drop all observations with negative ICC values since negative cost of equity are conceptually meaningless (Easton, 2004). We calculate the IRP from the ICC using the yield on 10-year government bonds as the risk-free rate, taken from the database of the Federal Reserve Bank.[42] To remove outliers, we truncate the top 1% and bottom 1% of IRP values[43]

For the rating data required for the second part of the analysis we use S&P Domestic Long Term Issuer Credit Ratings. These ratings fall into the following categories: AAA, AA, A, BBB, BB, B, CCC, CC, SD, and D. Categories AA to CCC can be amended with a + or − sign to signal relative standing in the corresponding category. The category D (SD) implies default (selective default). To operationalize financial distress, we use similar definitions as in Auvray and Brossard (2012), but adapted to S&P ratings: If the rating changes from BBB- or better to BB+ or worse, this downgrade is coded as a distress event. If the rating changes from BB+ or worse to BBB- or better, this is recorded as a recovery. The threshold from BBB- to BB+ is chosen as it separates non-investment grade from investment grade issuers.

Throughout the analysis, we use several accounting based risk indicators from the FR Y-9C reports to capture public information on a bank's risk position. We choose these variables from

[40] If the payout ratio is above 1 or below -0.5, it is set equal to the median payout ratio of the corresponding size portfolio, where the BHCs are sorted into three equal numbered portfolios based on market capitalization. The medians of the payout ratio size portfolios are winsorized at -0.5 from below.

[41] `http://www.bea.gov/national/index.htm#gdp`

[42] `http://www.federalreserve.gov/releases/h15/data.htm`

[43] Since the computation of IRP results in a wide range of results, winsorizing it would still keep a lot of weight on the tails which might significantly deform its distribution. Other market based risk indicators and accounting risk indicators are winsorized at the respective top 1% and bottom 1%.

Figure 3.1: Schematic Overview of the Merging Procedure

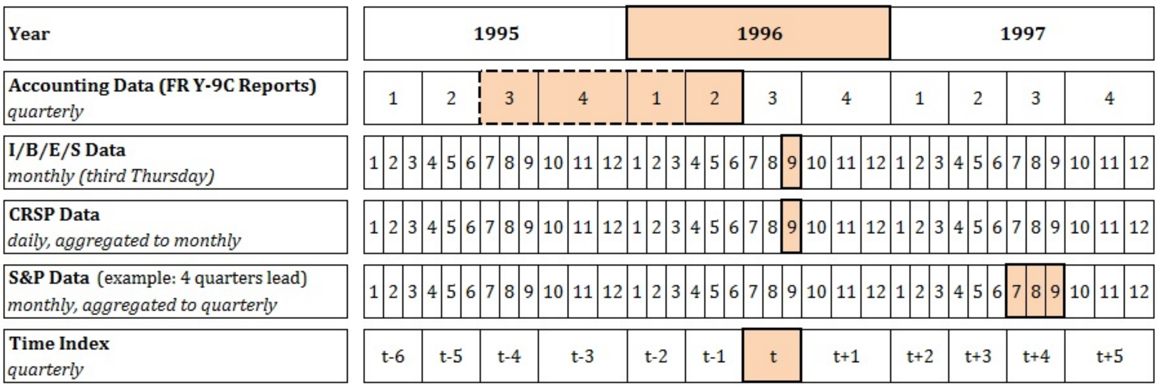


Figure 3.1 illustrates the merging procedure for an example period in the third quarter (Q3) of 1996. The IRP is computed in the last month of each quarter when I/B/E/S data is released (typically on the third Thursday). Where we need CRSP data on stock returns, we use historical data up to the end of that month. We use accounting data from the end of the preceding quarter to allow for a publication lag of at least two months (data needed in the computation of the IRP is aggregated to yearly data going back four quarters). For the distress prediction we begin with rating data in the month following the IRP computation month. If the rating changes from BBB- or higher to BB+ or lower, this is recorded as a distress event. The BHC is then dropped from the panel until it eventually recovers again. For the discrete choice regressions in Table 3.8, we look at specific quarterly prediction horizons of at least one quarter. For example, for a prediction four quarters ahead, we would only be interested in rating changes that occur from 7/1997 to 9/1997.

several well-established research papers on market discipline to represent different aspects of a BHC's capitalization strength, profitability, cost efficiency, asset quality and liquidity/funding situation.[44] Following Park and Peristiani (2007), we furthermore add statewise unemployment data from the Bureau of Labor Statistics.[45] The data from CRSP, I/B/E/S and S&P is available on a daily or monthly basis. We merge it with the quarterly FR Y-9C data using a lead of at least two months after the end of each quarter to allow for a publication lag.[46] Details on the merging procedure are illustrated in Figure 3.1.

Table 3.1 provides variable definitions, data sources and source papers for all variables. Table

[44] More precisely, we begin with a larger number of variables and iteratively eliminate the variable with the largest variance inflation factor (VIF) until the largest VIF is lower than or equal to 5 to avoid multicollinearity among the explanatory variables. VIF is defined as $1/(1 - R_k^2)$, where R_k^2 is the coefficient of determination from the regression of the $k - th$ accounting risk indicator on the other indicators. If the k-th indicator is collinear with the remaining ones R_k^2 should be close to 1, resulting in a large VIF.

[45] `http://www.bls.gov/help/hlpforma.htm#OEUS`

[46] There is a variable for the date of the report submission (BHCKF841), but it is empty throughout the entire sample period.

Table 3.1: Risk Indicators and Other Controls

Panel A: Accounting Risk Indicators

Name	Variable	Definition	Category	Paper
EQUITY	Book Equity to TA	Book Equity / Total Assets	Capitalization Strength	Park & Peristiani 2007
LLR	Loan Loss Reserves to TA	Loan Loss Reserves / Total Assets	Capitalization Strength	Park & Peristiani 2007
ROA	Return on Assets	Net Income / Total Assets	Profit Efficiency	Park & Peristiani 2007
ROA_VOL	Standard Deviation of ROA	Standard Deviation of ROA over 12 (at least 5) quarters	Profit Efficiency	Hannan & Hanweck 1998
EFFICIENCY	Noninterest Expense Ratio	Noninterest Expenses / Net Income	Cost Efficiency	Park & Persitiani 2007
PAST_DUE	90 Days Past Due to TA	90 Days or more Past Due Accruing Loans / Total Assets	Asset Quality	
CHARGEOFFS	Net Chargeoffs to TA	(Chargeoffs - Recoveries) / Total Assets	Asset Quality	Park & Peristiani 2007
LLP	Loan Loss Provisions to TA	Loan Loss Provisions / Total Assets	Asset Quality	Curry, Fissel & Hanweck 2008
LOANS	Net Loans to TA	Loans Net of Unearned Income / Total Assets	Business Model	Park & Peristiani 2007
EQU_INV	Equity Investments to TA	Investments in Unconsolidated Subsidiaries and Associated Companies / Total Assets	Business Model	Park & Peristiani 2007
COMM_LOANS	Commercial & Industrial Loans to TA	Commercial and Industrial Loans / Total Assets	Business Model	Park & Peristiani 2007
CONS_LOANS	Consumer Loans to TA	Consumer Loans / Total Assets	Business Model	Park & Peristiani 2007
LIQUIDITY	Liquid Assets to TA	Liquid (Trading) Assets / Total Assets	Liquidity	Park & Peristiani 2007
CORE_DEP	Core Deposits to TA	Core Deposits Held in Domestic Offices / Total Assets	Funding	Park & Peristiani 2007
LARGE_DEP	Time Deposits Larger 100k to TA	Time Deposits of 100k or More / Total Assets	Funding	Curry, Fissel & Hanweck 2008
DEP_COST	Interest Expenses to Total Deposits	Interest Expenses / Total Deposits	Funding	Hadad, Agusman, Monroe, Gasbarro & Zumwalt 2011
GAP	One Year Maturity Gap to Book Equity	(Earning Assets Repricable Within One Year- Liabilities Repricable Within One Year) / Book Equity	Interest Rate Sensitivity	DeYoung, Flannery, Lang & Sorescu 1998
SIZE	Total Assets	Total Assets	Size	Park & Peristiani 2007
UMEMPL	Statewise Unemployment Rate	Unemployment Rate from the Bureau of Labor Statistics (See `http://data.bls.gov/cgi-bin/srgate`)	Macroeconomic Effects	Park & Peristiani 2007

Table 3.1: Risk Indicators and Other Controls (Continued)

Panel B: ICC Controls

Name	Variable	Category	Computation / Source
ERROR	Mean Absolute Error of Forecasts	Forecast Bias	Mean absolute forecast error (EPS forecast minus actual EPS) divided by the mean EPS over the past 36 months (requiring a minimum of 24 months)
GROWTH	Long-Term Earnings Growth Rate	Growth	Downloaded from I/B/E/S

Panel C: Further Market Risk Indicators

Name	Variable	Category	Computation
DD	Distance to Default	Distress Risk	See appendix A.2.1
RET_VOL	Standard Deviation of Returns	Systematic Risk	Standard deviation of daily returns multiplied by $\sqrt{255}$
FF_BETA	Fama & French Beta	Systematic Risk	Beta (coefficient) of the market factor from Fama and French (1993b) regressions
FF_RES_VOL	Standard Deviation of Fama & French Residuals	Unsystematic (idiosyncratic) Risk	Standard deviation of the residuals from Fama and French (1993b) regressions multiplied by $\sqrt{255}$

The table provides detailed information on the variables employed throughout the analysis. Panel A explains the accounting based risk indicators we use and gives a reference paper for each variable. Panel B explains two variables we use as controls for the IRP for technical reasons as explained in section 3.4.1.2. Panel C explains further market measures based on historical stock data we use for purposes of comparison in section 3.4.2. For each variable in panel C, as time horizon we use the most recent year (255 days) with minimal availability of three months (64 days) from the corresponding date itself. RET_VOL and FF_RES_VOL are then transformed to estimated yearly standard deviations (see Fu, 2009).

3.2, Panel A summarizes the sample selection process. We start out with 365,562 BHC-quarter observations from 11,825 unique BHCs from 1990 to 2012. The sample size is reduced to 40,281 observations (1,034 unique BHCs) when requiring data on net income and common shares outstanding and after merging the Y-9C data with CRSP. In the next step, we merge the data with forecast information from I/B/E/S, reducing the sample to 24,796 BHC-quarters (844 unique BHCs) that allows the computation of the IRP. However, the computation procedure does not converge in all cases, and after the removal of outliers, our final sample of available IRP observations is 22,569 (818 unique BHCs) and 15,791 (674) after merging them with the accounting risk indicators required for the first part of the analyses.

For the second part, we require S&P rating data to be available for at least three consecutive months. This leads to a further decrease in sample size leaving 158 rated BHCs that also have IRP data available. We merge the rating data with the rest of the variables using different lag structures that lead to different observation numbers depending on the respective analysis. As an example, merging rating and IRP data with a lag of one quarter yields 5,383 quarterly observations. In our final sample, we observe 24 severe rating downgrades that qualify as a distress event and 15 recoveries.[47] Detailed information on these firms is given in Appendix A.2.2 in Table A6. Table 3.2, Panel B provides a breakdown of our sample for each year in

Table 3.2: Sample Descriptives

Panel A: Sample Selection

Sample Step Description	Quarterly Observations	BHCs
BHC data downloaded from WRDS	365562	11825
ICC calculation required variables: net income and common shares outstanding	131418	4277
Merge with CRSP data	40281	1034
Merge with I/B/E/S data and restrict to existing 1-year-ahead EPS forecasts	24796	844
Compute ICCs	22569	818
Compute further dependent and independent variables and eliminate missings	15791	674
Merge COMPUSTAT S&P ratings with IRPs (example: one quarter lag)	5383	158

[47] We observe 7 BHCs with only junk ratings throughout our sample period.

Table 3.2: Sample Descriptives (Continued)

Panel A: Sample per Year

Year	BHCs	BHC-quarters	Defaults	Recoveries
1990	218	746	5	0
1991	210	693	4	0
1992	233	789	1	1
1993	237	872	0	5
1994	259	898	0	2
1995	295	1005	0	1
1996	300	1060	0	0
1997	312	1085	0	0
1998	327	1119	0	2
1999	335	1119	0	0
2000	312	1101	1	0
2001	304	1049	0	0
2002	315	1117	0	0
2003	323	1174	1	0
2004	311	1120	0	0
2005	334	1213	2	0
2006	313	1171	0	0
2007	293	1068	0	0
2008	266	913	0	0
2009	254	818	7	0
2010	266	905	3	1
2011	240	878	0	2
2012	232	656	0	1
Total	818	22569	24	15

The table provides an overview of the sample selection process (Panel A), and indicates the number of individual BHCs, quarterly IRP observations and severe downgrades/recoveries (i.e., downgrades/upgrades from BBB- or higher to BB+ or lower and vice versa) by year (Panel B). The IRP sample comprises an unbalanced panel of a maximum of 818 publicly listed BHCs with the required data available over the period from 1990 to 2012. Of these, we find 158 BHCs with rating data available on COMPUSTAT.

the sample period.

Table 3.3 reports summary descriptive statistics for the variables of the first part of our analyses (Panel A) and for the other market based risk indicators we use in the second part of our analyses (Panel B). IRP and all ratios are reported as percentages, whereas total assets

Table 3.3: Summary Statistics

Var	N	Mean	Std Dev	p5	p50	p95
Direct Market Discipline						
IRP	15,791	5.81	4.09	1.51	5.11	11.87
EQUITY	15,791	9.12	2.39	6.07	8.77	13.25
LLR	15,791	1.03	0.48	0.47	0.94	1.92
ROA	15,791	0.25	0.23	0.01	0.27	0.46
ROA_VOL	15,791	0.12	0.20	0.02	0.06	0.49
EFFICIENCY	15,791	366.86	687.20	50.92	280.31	996.03
PAST_DUE	15,791	0.14	0.29	0.00	0.06	0.53
CHARGEOFFS	15,791	0.08	0.13	-0.00	0.04	0.31
LLP	15,791	0.10	0.14	0.00	0.06	0.34
LOANS	15,791	62.97	13.34	38.28	64.83	81.08
EQU_INV	15,791	0.06	0.14	0.00	0.00	0.33
COMM_LOANS	15,791	11.59	7.29	1.96	10.31	25.15
CONS_LOANS	15,791	6.00	5.89	0.24	4.03	17.09
LIQUIDITY	15,791	26.37	12.59	7.35	25.15	49.67
CORE_DEP	15,791	62.25	14.79	34.41	64.34	81.87
LARGE_DEP	15,791	11.17	7.22	2.61	9.65	25.43
DEP_COST	15,791	0.57	0.29	0.13	0.56	1.04
GAP	15,791	1.37	2.06	-1.99	1.28	4.93
SIZE	15,791	28.64	146.89	0.49	2.42	89.93
UNEMPL	15,791	6.23	2.07	3.60	5.80	10.50
Indirect Market Discipline						
DD	4,900	4.91	3.63	1.55	4.43	9.13
RET_VOL	5,280	5.22	2.82	2.51	4.55	10.07
FF_BETA	5,280	1.16	0.44	0.56	1.11	1.91
FF_RES_VOL	5,280	4.03	1.96	1.94	3.54	7.54

The table presents descriptive statistics for the variables used in the analyses on direct and indirect market discipline. IRP and all ratios are presented as percentages. Total assets are denominated in billion dollars. IRP is computed as presented in Section 3.2. All other variable definitions are given in Table 3.1. The sample composition is outlined in Table 3.2. We collect financial data from BHCs' FR Y-9C reports, analyst data from I/B/E/S, stock market data from CRSP and S&P rating data from COMPUSTAT.

are reported in billion dollars. The mean implied risk premium is 5.81%, which is somewhat higher than results from prior studies on non-financial firms and reasonable given BHCs' high level of leverage. With a mean market value of 28.64 billion dollars the BHCs in our final sample are fairly large, which is likely an unavoidable consequence of restricting the sample to BHCs that are listed and covered by analysts. The various risk indicators however reveal ample variation in the BHCs' business model, funding structure and risk position. Table 3.4 shows Pearson correlations.

3.4 Empirical Results

In this section, we first describe the univariate and multivariate empirical results of our analysis of direct market discipline.[48] We then go on to a series of analyses to gauge the informative value of the implied risk premium with respect to distress prediction.

3.4.1 Direct Market Discipline

3.4.1.1 Univariate Tests

In the first part of the analysis, we investigate whether the cost of equity varies in accordance with observable accounting risk indicators. We begin with exploring the relationship for each risk indicator separately. Table 3.5 shows the results for testing the difference in IRP between the portfolios of BHCs in the highest quintile (Q5) and and the ones in the lowest quintile (Q1) of each risk indicator. [49] These univariate results are generally strongly supportive of a market monitoring mechanism. For the vast majority of risk indicators, there is a significant inter-quintile difference in IRP. With a difference of more than one percent this finding is most

[48] Intercepts are estimated, but not reported.

[49] As in the remainder of Section 3.4.1 we use heteroskedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors with a bandwith of three.

Table 3.4: Correlations

Direct Market Discipline

	IRP	EQUITY	LLR	ROA	ROA_VOL	EFF	PD	CO	LLP	LOANS	INV	COMM	CONS	LIQ	CORE	LARGE	DEP	GAP	SIZE
EQUITY	-0.00																		
	0.69																		
LLR	0.02	0.03																	
	0.00	*0.00*																	
ROA	-0.10	0.13	-0.20																
	0.00	*0.00*	*0.00*																
ROA_VOL	0.06	0.14	0.39	-0.30															
	0.00	*0.00*	*0.00*	*0.00*															
EFFICIENCY	0.11	-0.00	0.06	-0.06	0.06														
	0.00	*0.76*	*0.00*	*0.00*	*0.00*														
PAST_DUE	0.06	0.08	0.21	-0.03	0.13	0.03													
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*													
CHARGEOFFS	0.09	0.07	0.53	-0.42	0.40	0.05	0.23												
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*												
LLP	0.12	0.04	0.45	-0.55	0.30	0.01	0.19	0.81											
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.10*	*0.00*	*0.00*											
LOANS	0.03	0.02	0.28	-0.10	-0.08	-0.01	-0.04	0.09	0.16										
	0.00	*0.04*	*0.00*	*0.00*	*0.00*	*0.29*	*0.00*	*0.00*	*0.00*										
EQU_INV	0.05	0.11	0.02	0.02	0.12	0.01	0.13	0.08	0.06	-0.21									
	0.00	*0.00*	*0.01*	*0.02*	*0.00*	*0.26*	*0.00*	*0.00*	*0.00*	*0.00*									
COMM_LOANS	-0.03	-0.02	0.24	-0.01	-0.03	0.01	0.01	0.10	0.11	0.26	0.02								
	0.00	*0.01*	*0.00*	*0.08*	*0.00*	*0.40*	*0.13*	*0.00*	*0.00*	*0.00*	*0.03*								
CONS_LOANS	-0.12	-0.07	0.07	0.16	-0.14	-0.03	0.14	0.03	-0.01	-0.00	-0.03	-0.02							
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.18*	*0.67*	*0.00*	*0.00*							
LIQUIDITY	-0.03	-0.02	-0.34	0.09	-0.02	-0.04	-0.06	-0.17	-0.21	-0.73	0.08	-0.21	-0.07						
	0.00	*0.01*	*0.00*	*0.00*	*0.05*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*						
CORE_DEP	-0.13	-0.01	0.21	0.00	-0.04	0.01	-0.02	-0.02	-0.05	0.33	-0.31	0.08	0.18	-0.23					
	0.00	*0.22*	*0.00*	*0.80*	*0.00*	*0.19*	*0.01*	*0.01*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*					
LARGE_DEP	0.10	-0.04	0.02	-0.10	-0.03	-0.01	-0.08	0.04	0.12	0.31	-0.10	0.09	-0.23	-0.15	-0.30				
	0.00	*0.00*	*0.05*	*0.00*	*0.00*	*0.25*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*				
DEP_COST	-0.09	-0.25	-0.10	0.04	-0.20	-0.03	-0.06	-0.17	-0.10	0.10	-0.11	-0.00	0.24	-0.18	-0.03	0.08			
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.59*	*0.00*	*0.00*	*0.00*	*0.00*			
GAP	-0.04	-0.11	0.13	0.05	0.02	0.01	0.05	0.03	-0.00	-0.06	0.09	0.30	0.01	-0.03	-0.02	-0.21	-0.10		
	0.00	*0.00*	*0.00*	*0.00*	*0.02*	*0.32*	*0.00*	*0.00*	*0.72*	*0.00*	*0.00*	*0.00*	*0.14*	*0.00*	*0.01*	*0.00*	*0.00*		
SIZE	0.07	-0.04	0.02	-0.03	0.02	0.01	0.22	0.11	0.08	-0.26	0.38	-0.04	0.07	0.12	-0.32	-0.16	-0.10	0.09	
	0.00	*0.00*	*0.03*	*0.00*	*0.01*	*0.07*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	
UNEMPL	0.17	0.14	0.33	-0.22	0.37	0.09	0.23	0.41	0.36	-0.09	0.06	-0.02	-0.14	-0.02	-0.07	0.05	-0.42	0.01	0.07
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.01*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.42*	*0.00*

Indirect Market Discipline

	IRP	DD	RET_VOL	FF_BETA
DD	-0.09			
	0.00			
RET_VOL	0.10	-0.34		
	0.00	*0.00*		
FF_BETA	0.07	-0.21	0.27	
	0.00	*0.00*	*0.00*	
FF_RES_VOL	0.03	-0.33	0.91	0.26
	0.01	*0.00*	*0.00*	*0.00*

The table reports Pearson correlations for the variables used throughout the analysis. Two-tailed p-values in italic.

pronounced for leverage (EQUITY)[50], cost efficiency (EFFICIENCY, measured by the ratio of noninterest expenses to net income), funding stability (CORE_DEP, share of core deposits) and funding cost (DEP_COST, ratio of interest expenses to deposits). We also observe a noticeable relation between the IRP and the level of periodical loan loss provisions (LLP) and the share of liquid assets (LIQUIDITY). However, we find no such effect for the level of accumulated loan loss reserves (LLR), the share of commercial and industrial loans (COMM_LOANS) or the size of a BHC.

Table 3.5: Direct Market Discipline: Analysis of IRP Sensitivity to Public Risk Indicators (Univariate Tests)

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	p-Value
Ranked by **EQUITY**							
EQUITY_mean	6.61	7.95	8.88	9.92	12.36	5.75	
irp_mean	6.42	6.20	5.86	5.63	5.29	-1.13	0.000***
irp_median	5.49	5.48	5.36	5.14	4.78	-0.71	0.000***
Ranked by **LLR**							
LLR_mean	0.55	0.83	1.00	1.20	1.70	1.15	
irp_mean	5.73	5.92	5.98	6.02	5.73	0.00	0.988
irp_median	5.19	5.29	5.36	5.31	5.02	-0.16	0.502
Ranked by **ROA**							
ROA_mean	0.01	0.20	0.25	0.31	0.43	0.42	
irp_mean	6.26	6.23	5.76	5.73	5.41	-0.85	0.001***
irp_median	4.99	5.34	5.25	5.40	5.25	0.26	0.294
Ranked by **ROA_VOL**							
ROA_VOL_mean	0.02	0.04	0.07	0.13	0.38	0.35	
irp_mean	5.49	5.74	6.22	6.04	5.90	0.41	0.042**
irp_median	5.12	5.22	5.40	5.38	5.07	-0.06	0.810
Ranked by **EFFICIENCY**							
EFFICIENCY_mean	-59.56	220.59	295.34	391.31	1031.7	1091.2	
irp_mean	5.58	5.53	5.63	6.07	6.59	1.01	0.000***
irp_median	4.97	5.27	5.34	5.41	5.21	0.23	0.124

(Continued ...)

[50] We find a similar effect using the regulatory Tier 1 capital ratio. However, Tier 1 capital is reported in the FR-Y9C reports only from 1997. To preserve our sample size, we therefore use balance sheet leverage throughout the rest of the analysis.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	p-Value
Ranked by **PAST_DUE**							
PAST_DUE_mean	0.00	0.02	0.07	0.14	0.51	0.51	
irp_mean	6.02	5.73	5.63	5.77	6.23	0.21	0.157
irp_median	5.25	5.23	5.08	5.26	5.58	0.33	0.006***
Ranked by **CHARGEOFFS**							
CHARGEOFFS_mean	0.00	0.03	0.06	0.10	0.24	0.24	
irp_mean	5.66	5.93	5.75	6.01	6.04	0.38	0.162
irp_median	5.14	5.27	5.20	5.34	5.32	0.18	0.498
Ranked by **LLP**							
LLP_mean	0.01	0.05	0.08	0.12	0.27	0.25	
irp_mean	5.42	5.74	5.93	6.09	6.21	0.79	0.003***
irp_median	4.98	5.23	5.29	5.42	5.39	0.41	0.107
Ranked by **LOANS**							
LOANS_mean	43.30	59.33	64.72	69.73	76.85	33.55	
irp_mean	5.82	5.65	5.77	5.92	6.23	0.40	0.105
irp_median	5.30	5.08	5.23	5.25	5.45	0.15	0.259
Ranked by **EQU_INV**							
EQU_INV_mean	-0.01	0.01	0.04	0.04	0.26	0.27	
irp_mean	6.13	5.72	6.61	5.91	6.03	-0.10	0.766
irp_median	5.03	5.11	5.69	5.38	5.63	0.60	0.009***
Ranked by **COMM_LOANS**							
COMM_LOANS_mean	3.45	7.34	10.35	14.04	22.87	19.42	
irp_mean	6.25	5.97	5.63	5.63	5.91	-0.34	0.205
irp_median	5.37	5.28	5.10	5.19	5.40	0.02	0.892
Ranked by **CONS_LOANS**							
CONS_LOANS_mean	0.82	2.78	4.79	7.55	14.36	13.53	
irp_mean	6.27	6.13	5.69	5.73	5.58	-0.69	0.001***
irp_median	5.50	5.30	5.14	5.20	5.30	-0.21	0.151
Ranked by **LIQUIDITY**							
LIQUIDITY_mean	13.77	19.96	24.42	29.72	42.45	28.68	
irp_mean	6.24	5.86	5.86	5.71	5.73	-0.51	0.006***
irp_median	5.53	5.23	5.23	5.06	5.14	-0.39	0.015**
Ranked by **CORE_DEP**							
CORE_DEP_mean	41.20	59.23	65.22	70.17	76.87	35.67	
irp_mean	6.63	5.98	5.70	5.54	5.56	-1.07	0.000***
irp_median	6.02	5.42	5.13	4.93	4.89	-1.13	0.000***
Ranked by **LARGE_DEP**							
LARGE_DEP_mean	3.98	7.07	9.67	13.11	21.21	17.23	
irp_mean	5.86	5.52	5.69	5.82	6.50	0.65	0.020**
irp_median	5.46	5.11	5.06	5.18	5.53	0.07	0.585

(Continued . . .)

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	p-Value
Ranked by **DEP_COST**							
DEP_COST_mean	0.38	0.50	0.57	0.63	0.77	0.39	
irp_mean	5.60	5.59	5.70	5.81	6.70	1.10	0.003***
irp_median	5.24	5.16	5.22	5.13	5.78	0.54	0.002***
Ranked by **GAP**							
GAP_mean	-1.35	0.38	1.30	2.35	4.18	5.53	
irp_mean	6.06	5.74	5.71	5.96	5.93	-0.13	0.661
irp_median	5.27	5.14	5.16	5.37	5.47	0.21	0.122
Ranked by **SIZE**							
SIZE_mean	0.68	1.34	2.53	6.47	136.30	135.62	
irp_mean	6.67	6.26	5.41	5.08	5.98	-0.68	0.217
irp_median	5.59	5.36	4.96	4.89	5.84	0.24	0.477
Ranked by **UNEMPL**							
UNEMPL_mean	4.69	5.70	6.30	6.93	8.22	3.53	
irp_mean	5.82	5.67	5.71	5.90	6.30	0.48	0.003***
irp_median	5.31	5.22	5.21	5.17	5.37	0.06	0.553

The table reports univariate tests on the difference in the IRP between BHCs with low and high values for each risk indicator presented in Panel A of Table 3.1. At each quarter, we divide the sample into five portfolios according to each risk variable. We then compute the mean and median IRP per portfolio and test the difference between the portfolios in the highest (Q5) and lowest quintile (Q1) using Newey and West (1987) standard errors with a bandwidth of 3. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

3.4.1.2 Multivariate Regressions

In the next step, we estimate the joint relation between BHC risk and the IRP in a multivariate regression framework as outlined in Equation (3.3). The regression results (including quarter-fixed effects) are reported in Table 3.6. The first column shows results for the model specification including the full vector of bank accounting risk variables. As suggested by Easton and Sommers (2007), if earnings forecasts are consistently overestimated for a BHC but its price is adjusted downwards accordingly by the market, then the IRP will be overestimated. Therefore, in the second column we follow a similar approach as Hail and Leuz (2009) and include the mean absolute error of forecasts (ERROR), which is calculated as the mean absolute forecast error (EPS forecast minus actual EPS) divided by the mean EPS over the past 36 months (requiring a minimum of 24 months). Gebhardt et al. (2001) recommend the inclusion of a long-term growth variable which can be explained as such. If $T = 15$ is too short (long) for a detailed prediction horizon for growth (mature) BHCs, we might underestimate IRP for growth BHCs and overestimate IRP for mature BHCs. If a BHC characteristic is correlated with growth, this might lead to spurious results. Therefore, in the third column we also add the long-term earnings growth rate (GROWTH) as a further control variable. Finally, in the fourth column, we add BHC-fixed effects to control for any other unobserved heterogeneity.

The regression results generally confirm our findings from the univariate tests. Most coefficients are highly significant and have the expected sign. First, a point of particular interest is whether the cost of equity funding is lower for well-capitalized BHCs as suggested by the Modigliani-Miller theorem (see Admati et al., 2013). Prior studies have produced ambiguous evidence regarding this point. Tsatsaronis and Yang (2012) find that required returns are higher for banks with higher leverage. For a different sample and time period, Baker and Wurgler (2015) establish a low-risk anomaly in the banking industry and find that well-capitalized banks earn the same or even higher realized returns than riskier banks. Using IRP as a measure of expected returns, our results suggest that lower leverage indeed reduces the cost of equity funding. Economically, the effect is rather moderate given a decrease in IRP in the range of 10 to 14 basis points for a one percent increase in the ratio of book equity to total assets (EQUITY), which is inversely proportional to leverage.[51] IRP also decreases with accumulated loan loss reserves (LLR) as a further indicator of capitalization strength. Again, we also find a particularly pronounced effect for asset liquidity (LIQUIDITY), funding stability through core deposits (CORE_DEP) and the cost of funding (DEP_COST). A positive coefficient on the return of assets seems counter-intuitive at first, but is in line with the idea that higher returns can ceteris paribus only be realized through a riskier business model. As for the indicators of credit risk, the cost of equity increases with the share of loan loss provisions (LLP) and past due loans (PAST_DUE), but decreases with net charge-offs (CHARGEOFFS). These findings add to the prior literature on signaling effects of loan loss provisions (e.g., Wahlen (1994); Liu et al. (1997); Ahmed et al. (1999); Kanagaretnam et al.

[51] We find similar results for a risk weighted tier 1 or total capital ratio. However, these ratios are reported in FR Y-9C reports only from 1996. To preserve sample size, we therefore concentrate on book equity.

(2004)) and suggest that investors treat past due loans and loan loss provisions as bad news about the credit quality of the loan portfolio, while high charge-offs are likely perceived as an indicator of proactive portfolio reorganization. Finally, IRP decreases with the share of the loan portfolio (LOANS) and increases with the share of equity investments (EQU_INV), indicating that equity investors apply a lower risk discount to BHCs with a traditional business model. However, our results on details of the loan portfolio composition (consumer loans (CONS_LOANS) vs. commercial/industrial loans (COMM_LOANS)) are inconclusive. All in all, our results provide strong evidence that common public risk indicators are reflected in the risk discount applied by equity investors.

The univariate results from Section 3.4.1.1 suggest a nonlinear relationship between some of the bank accounting risk indicators and IRP. Based on these results we additionally run quantile regressions for the quantiles 10, 30, 50, 70 and 90. The results are presented in Appendix A.2.3 in Table A7 and reveal that, with some variation in significance, most coefficients show the same sign and a similar magnitude compared to the OLS regression. The tenor of our main results therefore remains unchanged.

The forward-looking nature of IRP is a distinct theoretical advantage of its methodology compared to historical measures of expected returns. We challenge this claim by re-estimating the regression model of the last subsection with future accounting risk indicators as outlined in Equation (3.4). We implicitly assume that investors have correct expectations about the BHC's future risk position. The informative value of these tests would be limited when risk indicators are sticky over time, i.e., change very slowly from one observation to the next. Therefore, in these regressions we use a subset of significantly time-variant, i.e., non-sticky, accounting risk indicators. For each risk indicator used in Subsection 3.4.1.2, we calculate the changes between two consecutive quarters and test the mean of the pooled series of changes for being significantly different from zero. We then eliminate all risk indicators identified as being sticky (having a p-value less than 10%) and regress the IRP on leads of 1, 2, 4, 6, 8, 10 and 12 quarters of the remaining indicators. We again include mean average absolute error of forecasts (ERROR) and long-term growth (GROWTH). The results for the subsample of BHCs

Table 3.6: Direct Market Discipline: Analysis of IRP Sensitivity to Public Risk Indicators

	Expected Sign	IRP	IRP	IRP	IRP
EQUITY	-	-0.136***	-0.109***	-0.128***	-0.103***
		0.000	*0.000*	*0.000*	*0.000*
LLR	-	-0.235*	-0.150	-0.167*	-0.619***
		0.085	*0.294*	*0.053*	*0.000*
ROA	+/-	0.537**	0.509**	0.988***	0.802***
		0.018	*0.024*	*0.000*	*0.000*
ROA_VOL	+	-0.608	-1.157***	-1.111***	-0.758***
		0.124	*0.001*	*0.000*	*0.000*
EFFICIENCY	+	0.001***	0.001***	0.000	0.000
		0.000	*0.000*	*0.303*	*0.708*
PAST_DUE	+	0.236	0.252	0.359***	0.201*
		0.210	*0.181*	*0.000*	*0.055*
CHARGEOFFS	+/-	-1.940**	-1.921**	-1.402***	-1.662***
		0.016	*0.027*	*0.006*	*0.001*
LLP	+	1.769**	1.850**	1.212**	1.478***
		0.017	*0.019*	*0.020*	*0.003*
LOANS	-	-0.003	-0.006	0.005	-0.021***
		0.662	*0.382*	*0.352*	*0.009*
EQU_INV	+	0.252	0.438*	0.831***	0.759***
		0.296	*0.078*	*0.000*	*0.002*
COMM_LOANS	+/-	-0.013**	-0.014**	-0.016***	0.010
		0.032	*0.041*	*0.000*	*0.348*
CONS_LOANS	+/-	-0.027***	-0.026***	0.017***	0.025**
		0.000	*0.000*	*0.001*	*0.020*
LIQUIDITY	-	-0.026***	-0.028***	-0.020***	-0.031***
		0.000	*0.000*	*0.000*	*0.000*
CORE_DEP	-	-0.017***	-0.019***	-0.020***	-0.021***
		0.000	*0.000*	*0.000*	*0.000*
LARGE_DEP	+	0.014*	0.017**	-0.028***	-0.011
		0.057	*0.039*	*0.000*	*0.268*
DEP_COST	+	1.481***	1.482***	1.028***	0.436
		0.000	*0.000*	*0.000*	*0.166*
GAP	+	0.015	0.032	0.013	0.050**
		0.527	*0.182*	*0.450*	*0.025*
SIZE	+/-	0.001***	0.001***	0.001***	0.000
		0.005	*0.006*	*0.000*	*0.471*
UNEMPL	+	0.160***	0.161***	0.030	0.048
		0.000	*0.000*	*0.203*	*0.176*
ERROR			0.019	0.040**	0.010
			0.433	*0.026*	*0.574*
GROWTH				29.954***	31.104***
				0.000	*0.000*
N		15791	13341	13341	13341
adj_R2		*0.161*	*0.168*	*0.624*	*0.712*

The table reports OLS coefficient estimates based on robust heteroscedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors with a bandwidth of 3. The base sample comprises 15,791 quarterly observations from 674 BHCs over the time period from 1990 to 2012. The dependent variable is the IRP as presented in Section 3.2. All other variable definitions are given in Table 3.1. We include quarter-fixed effects in the regressions, but do not report the coefficients. In column four, we also include firm-fixed effects. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

with available data are reported in Table 3.7 and confirm our findings from the regression with contemporary indicators. While the sign and significance of most coefficients remains, their magnitude decreases in some cases over longer time periods. However the explanatory power of the the model does not decrease with longer time horizons. Overall these results are supportive of the IRP as a forward-looking measure of bank risk.

Table 3.7: Direct Market Discipline: Analysis of ICC Sensitivity to Future Risk Indicators

	1	2	4	6	8	10	12
EQUITY	-0.054**	-0.047**	-0.036*	-0.016	-0.006	-0.013	-0.017
	0.012	*0.042*	*0.062*	*0.384*	*0.742*	*0.435*	*0.282*
ROA	0.319	0.081	0.036	-0.194	-0.250	-0.290*	-0.181
	0.382	*0.832*	*0.890*	*0.310*	*0.121*	*0.065*	*0.120*
ROA_VOL	-0.634	-0.657	-0.578	-0.700	-0.645	-0.489	-0.416
	0.278	*0.302*	*0.354*	*0.147*	*0.108*	*0.131*	*0.117*
EQU_INV	0.539**	0.571**	0.629***	0.683***	0.565***	0.527***	0.564***
	0.036	*0.028*	*0.009*	*0.002*	*0.007*	*0.010*	*0.004*
COMM_LOANS	-0.017***	-0.017***	-0.019***	-0.019***	-0.020***	-0.020***	-0.020***
	0.002	*0.001*	*0.000*	*0.001*	*0.000*	*0.000*	*0.000*
CONS_LOANS	0.036***	0.036***	0.033***	0.033***	0.033***	0.035***	0.034***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
LIQUIDITY	-0.025***	-0.025***	-0.024***	-0.023***	-0.024***	-0.024***	-0.024***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
CORE_DEP	-0.006**	-0.006**	-0.005	-0.004	-0.004	-0.003	-0.003
	0.028	*0.031*	*0.122*	*0.235*	*0.226*	*0.318*	*0.428*
SIZE	0.002***	0.002***	0.002***	0.002***	0.001***	0.001***	0.001***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
UNEMPL	0.051	0.054	0.061	0.074*	0.068	0.071*	0.062
	0.267	*0.231*	*0.150*	*0.091*	*0.107*	*0.079*	*0.108*
ERROR	0.244***	0.243***	0.244***	0.240***	0.239***	0.235***	0.230***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
GROWTH	26.882***	26.878***	26.930***	26.978***	27.019***	27.049***	27.074***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
N	5005	5005	5005	5005	5005	5005	5005
adj_R2	*0.495*	*0.494*	*0.493*	*0.494*	*0.495*	*0.495*	*0.494*

The table reports OLS coefficient estimates based on robust heteroscedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors with a bandwidth of 3. The sample comprises 5,505 quarterly observations from 262 BHCs over the time period from 1990 to 2009. We employ leads of one to twelve quarters for the risk indicators (see column headers). The dependent variable is the IRP as presented in Section 3.2. All other variable definitions are given in Table 3.1. The risk indicators are a subset of non-sticky variables chosen from those used in Table 3.6. We include quarter-fixed effects in the regressions, but do not report the coefficients. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

3.4.2 Indirect Market Discipline: Predicting Bank Distress Using the IRP

The results presented in Section 3.4.1 show that IRP reflects contemporaneous and forward-looking information about BHC risk. Just like bond spreads, this makes the IRP itself a potentially valuable source of information about the risk of future financial distress from the perspective of indirect market discipline. In this section we gauge the usefulness of the IRP to predict financial distress over different time horizons. We are now also interested in whether the IRP is the most efficient way to extract risk-related information from the stock market. Therefore, we explicitly compare our results for the IRP with the following established market based risk indicators: the distance-to-default measure (DD) as derived in Appendix A.2.1, the market factor coefficient from Fama and French (1993b) regressions (FF_BETA) as a historical measure of (firm-specific) systematic risk, the standard deviation of the residuals of daily returns from Fama and French (1993b) regressions as a historical measure of idiosyncratic (unsystematic) risk (FF_RES_VOL), and the standard deviation of daily returns as a general risk indicator (RET_VOL).

As outlined in Section 3.3.2, we use S&P ratings to determine BHC rating downgrades and upgrades as proxies for financial distress and recoveries. Firms that are severely downgraded are eliminated from the sample until they recover back, since a downgrade is only noted once, and afterwards we would otherwise misleadingly correlate indicators of high risk with non-downgrades ((and vice versa, see Auvray and Brossard, 2012). Accordingly, also BHCs that already initially have a rating of BB+ or lower are eliminated from the analysis of distress prediction and BHCs that initially have a rating of BBB- or higher are eliminated from the recovery analysis. Information about the number of severe downgrades per year can be taken from Panel B of Table 3.2.

3.4.2.1 Descriptive Results

For a first intuition on the informativeness of the IRP, we follow Vassalou and Xing (2004) and use the accuracy ratio proposed by Moody's to measure the ability of IRP to predict severe rating downgrades. For every month in our sample, we rank all observations of rated BHCs in order of decreasing riskiness as indicated by each of the market risk indicators. For every percentile $p \in 0, 1, 2, \ldots, 99, 100$ of a risk indicator, we calculate the percentage of BHCs that are downgraded within the next 12 months out of the n monthly observations. We use the average of these percentages over all months in the sample period to construct the (empirical) cumulative accuracy profile (CAP) of the respective risk indicator, $c(p)$, where $c(0) = 0$ and $c(100) = 1$. The nearer the curve $c(\cdot)$ is to the upper left corner, generally the more accurate is the risk indicator.

The cumulative accuracy profile is benchmarked against a hypothetical perfect risk indicator and a random risk indicator of distress risk. Let there be n observations and m severe downgrades. The hypothetical perfect indicator maps all firms with future downgrades to its lowest percentiles (ranked according to descending order of riskiness), i.e. this indicator perfectly captures future downgrades and assigns more risk to distressed firms than to all other firms. Its cumulative accuracy profile is then given by $c(p) = p * (n/m)$ for $p < m/n$, and $c(p) = 1$ for $p \geq m/n$. The random risk indicator does not contain any information regarding the likelihood of future downgrades. In other words, the observations are ranked randomly. If done repeatedly for different random sequences, the average $c(p)$ for each p converges to $c(p) = p$, i.e., a 45° line. The visual information from the CAPs can then be quantified by computing the area between each CAP and the random 45° line in relation to the area between the CAP of the hypothetical perfect indicator and the random line. This accuracy ratio (AR) of risk indicator i is then equal to the area below its CAP ($area_i$) minus a half divided by the area below the CAP of the perfect indicator ($area_{perfect}$) minus a half.

$$AR_i = \frac{area_i - 0.5}{area_{perfect} - 0.5} \tag{3.8}$$

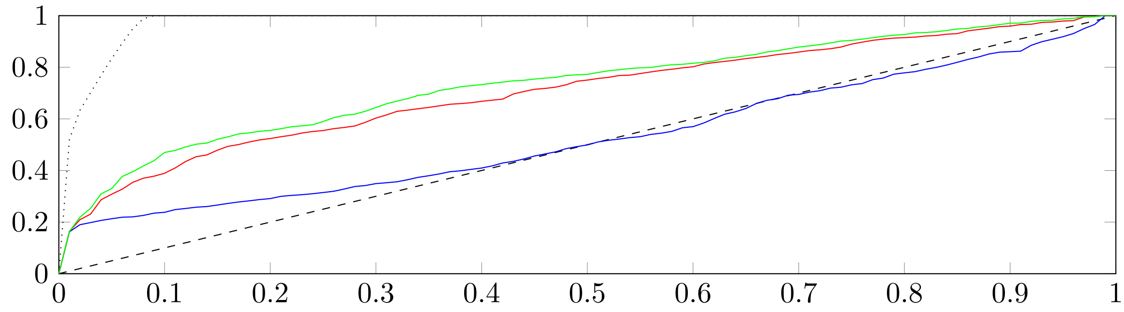
The AR of the random indicator is zero, as it contains no information about the likelihood of future distress, while the AR of the perfect indicator is one. In Figure 3.2 we plot the CAPs of the IRP (blue), DD (red) and the standard deviation of the residuals of daily returns from Fama and French (1993b) (green) regressions along with the random indicator (45° dashed line) and perfect indicator (dotted line). Panel A reports CAPs in levels of IRP, DD[52] and FF_RES_VOL for rating downgrades from a rating equal BBB- or higher to a rating equal to BB+ or lower as our proxy of financial distress. For illustrative purposes, in Panel B we also

[52]DD is ranked in ascending order, since a lower distance to default implies higher distress risk.

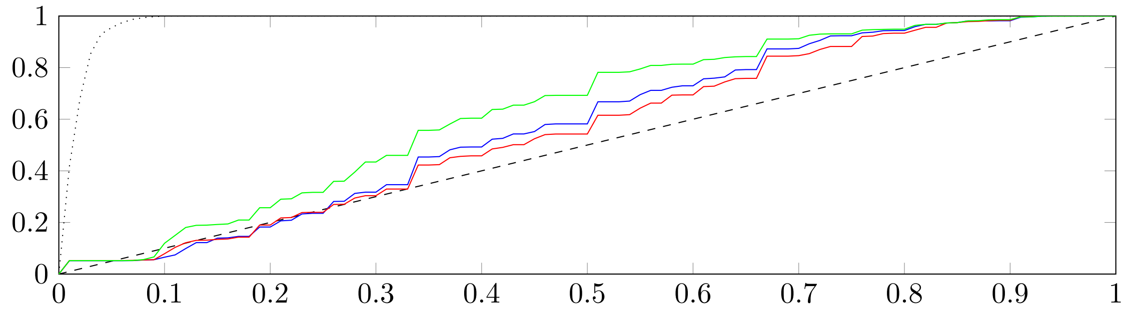
report CAPs in levels of (reversely ranked) IRP, DD and FF_RES_VOL for rating upgrades from a rating equal to BB+ or lower to a rating equal to BBB- or higher as a proxy for recovery.

Figure 3.2: Indirect Market Discipline: Cumulative Accuracy Profiles

Panel A: Defaults / One Year Prediction Horizon



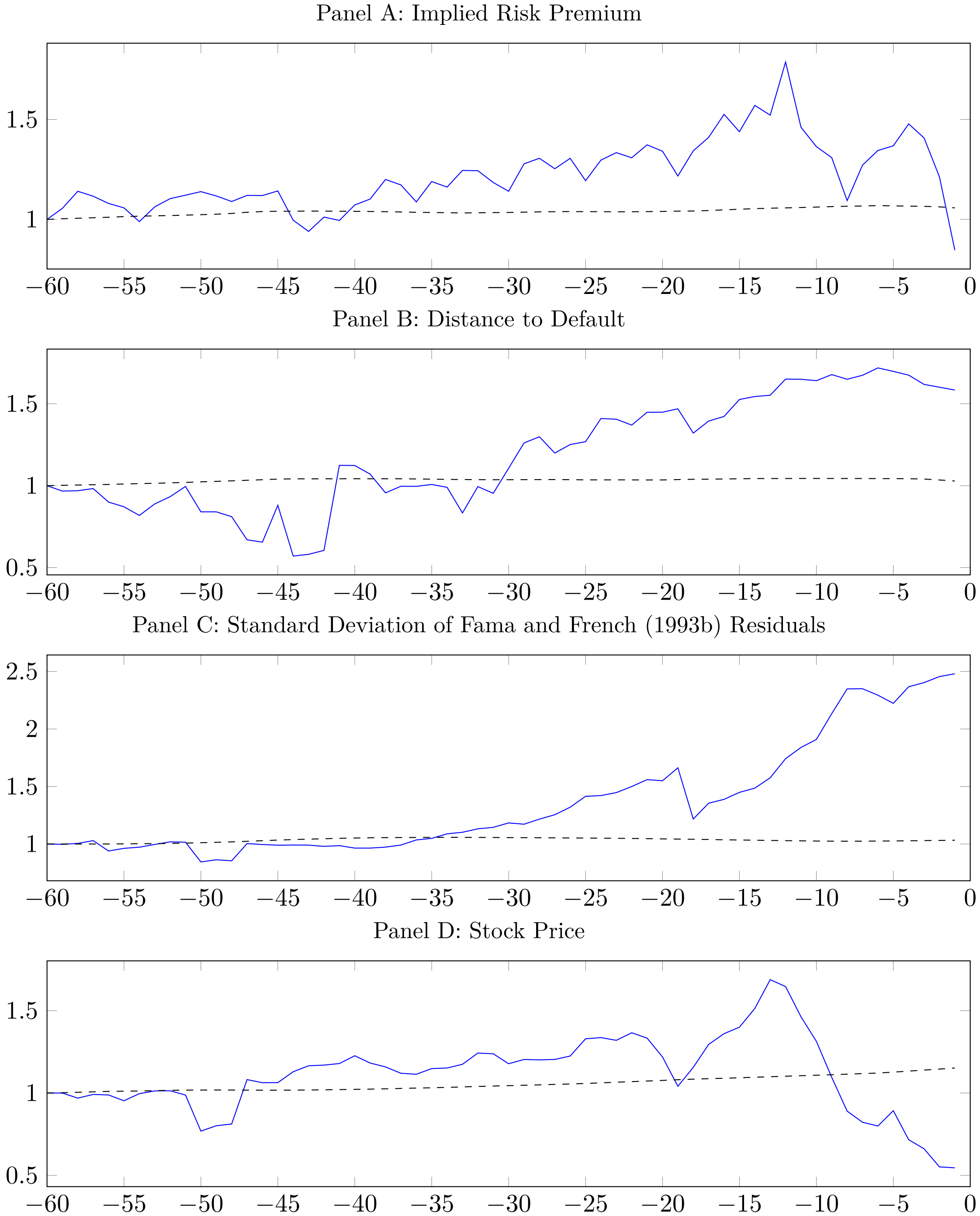
Panel B: Recoveries / One Year Prediction Horizon



The graphs plot the cumulative accuracy profiles (CAPs) for the prediction of severe downgrades/recoveries over a one year prediction horizon. Details on the computation of the CAPs are presented in Section 3.4.2.1. We plot the graphs for the implied risk premium (blue), the distance to default measure (red, see Appendix A.2.1) and the standard deviation of daily return residuals from Fama and French (1993b) regressions (green, see Table 3.1). Panel A reports CAPs for the prediction of downgrades for a sample of 156 BHCs. Panel B reports CAPs for the prediction of recoveries for a sample of 35 BHCs. The dashed 45 ° line represents the CAP of a random risk indicator, while the dotted line represents a hypothetical perfect risk indicator for purposes of comparison.

The CAP of DD clearly dominates that of the IRP in Panel A. Consequently, the AR of DD is 0.435, while that of the IRP is only 0.057, i.e., only slightly better than a random risk indicator. Both risk indicators are however outperformed by FF_RES_VOL with a AR of 0.493. Panel B reveals a higher CAP for the IRP (AR: 0.168) compared to DD (AR: 0.134), while again FF_RES_VOL is the best standalone predictor of recoveries (AR: 0.282). As

Figure 3.3: Indirect Market Discipline: Chronological Development of Risk Indicators



In panel A, we plot the average monthly IRP for each of the sixty months up to the downgrade for the sample BHCs that get downgraded (blue) and have at least 6 IRP observations before their downgrade. As a benchmark, we also plot the average IRP for the sample of non-defaulting BHCs over the sixty months up to each point in time (dashed line). In panel B, C and D, we repeat the analysis for the distance to default measure (see Appendix A.2.1), calculated as 2 - DD for comparison reasons, the standard deviation of daily return residuals from Fama and French (1993b) regressions, and raw stock prices, respectively. All values are scaled by their respective initial values at $t = -60$.

such, while the IRP contains some risk relevant information, at first glance its usefulness as a distress predictor appears limited.

As a further test of the ability of the IRP risk indicator to capture distress risk, in Figure 3.3 we compare the chronological development of the IRP of downgraded BHCs with that of the remaining sample. In Panel A, we plot the average monthly IRP for each of the sixty months up to the downgrade. As a benchmark, we also plot the average IRP for the sample of non-distressed BHCs over the sixty months up to each point in time. Given the above findings, as a comparison we also present the results for DD in Panel B and FF_RES_VOL in Panel C.[53] All values are scaled by their initial values at $t = -60$. We observe that the IRP increases significantly before severe downgrades, while it stays relatively constant in the benchmark observations. However in comparison, DD and FF_RES_VOL show a slightly delayed, but much more pronounced increase. Another noteworthy observation is that the IRP decreases again during the last year before the downgrade. To further investigate this matter, we also document the chronological development of stock prices *per se* in Panel D. It shows that, together with IRP, stock prices first also increase, but ultimately drop again as a consequence of revised cash flow expectations. As the IRP is a measure of systematic rather than idiosyncratic risk, this finding suggests that for firms close to distress idiosyncratic determinants are more relevant than systematic factors (i.e., the underlying factors for the revised cash flow expectations are perceived as firm-specific). This effect also likely accounts for the relatively poor performance of the IRP as a standalone distress predictor as demonstrated by its CAP.

3.4.2.2 Regression Analyses

In the next step we formalize our analysis and estimate the complimentary log-log distress prediction model in Equation (3.5) for leads from one to twelve quarters. As we are interested in the incremental informative value of the IRP, we simultaneously include both the full array

[53] DD is multiplied by (-1) and shifted by 2 upwards to be increasing and comparable with the other two risk indicators.

Table 3.8: Indirect Market Discipline: Discrete Choice Regressions for Distress Prediction

Panel A: Excluding IRP

	1	2	4	6	8	10	12
DD	0.766**	0.489***	0.353***	0.354***	0.617**	1.097	1.115
	0.049	*0.003*	*0.000*	*0.000*	*0.028*	*0.344*	*0.328*
RET_VOL	0.773	0.912	1.034	0.931	1.251	0.970	0.914
	0.264	*0.593*	*0.871*	*0.827*	*0.365*	*0.936*	*0.839*
FF_BETA	1.589	0.244***	0.776	2.296	0.479	1.186	1.387
	0.385	*0.007*	*0.731*	*0.315*	*0.390*	*0.839*	*0.708*
FF_RES_VOL	1.751*	1.298	0.858	0.552	0.655	0.892	1.027
	0.051	*0.276*	*0.637*	*0.209*	*0.332*	*0.825*	*0.962*
EQUITY	1.042	0.965	0.999	1.106	1.178*	1.235**	1.175
	0.789	*0.792*	*0.995*	*0.344*	*0.079*	*0.018*	*0.202*
LLP	1.645	61.690***	2.336	4.743	0.127	0.017	0.004
	0.660	*0.002*	*0.577*	*0.358*	*0.542*	*0.360*	*0.293*
EFFICIENCY	1.000*	1.000	1.000	0.999*	1.000	1.000*	0.999
	0.065	*0.822*	*0.365*	*0.093*	*0.684*	*0.098*	*0.493*
ROA	0.238**	5.208	0.357	0.121	1.926	0.124	0.298
	0.012	*0.156*	*0.241*	*0.102*	*0.751*	*0.177*	*0.527*
LIQUIDITY	0.986	1.022	1.018	1.004	0.982	0.972	0.988
	0.604	*0.354*	*0.490*	*0.886*	*0.526*	*0.302*	*0.637*
SIZE	0.975**	0.984	0.968*	0.966*	0.993	0.995	0.995
	0.028	*0.118*	*0.050*	*0.051*	*0.419*	*0.556*	*0.549*
N	4585	4536	4392	4243	4102	3958	3811
pctevent	0.349	0.353	0.273	0.283	0.268	0.303	0.315
pseudo_R2	0.286	0.29	0.267	0.227	0.093	0.063	0.045
likelihood	153.06	152.10	121.96	127.91	138.31	153.02	155.04
wald	75.486**	59.724**	41.994**	25.344**	14.530	11.057	6.733

Panel B: Including IRP

	1	2	4	6	8	10	12
DD	0.775*	0.528***	0.387***	0.390***	0.633**	1.103	1.112
	0.068	*0.007*	*0.001*	*0.001*	*0.035*	*0.304*	*0.335*
RET_VOL	0.770	0.963	1.030	0.963	1.275	0.962	0.893
	0.261	*0.836*	*0.889*	*0.906*	*0.331*	*0.921*	*0.804*
FF_BETA	1.633	0.206***	0.717	2.042	0.427	1.037	1.269
	0.361	*0.006*	*0.659*	*0.388*	*0.338*	*0.966*	*0.789*
FF_RES_VOL	1.753*	1.165	0.773	0.535	0.617	0.901	1.026
	0.052	*0.557*	*0.444*	*0.173*	*0.278*	*0.844*	*0.965*
IRP	1.019	1.113**	1.228***	1.160	1.166**	1.139**	1.132*
	0.722	*0.016*	*0.000*	*0.114*	*0.023*	*0.046*	*0.066*
EQUITY	1.042	0.970	1.001	1.103	1.167*	1.230**	1.186
	0.790	*0.822*	*0.990*	*0.318*	*0.085*	*0.018*	*0.177*
LLP	1.603	70.971***	4.328	4.078	0.144	0.015	0.004
	0.680	*0.003*	*0.390*	*0.405*	*0.562*	*0.340*	*0.288*
EFFICIENCY	1.000*	1.000	1.000	0.999*	1.000	1.000	0.999
	0.076	*0.776*	*0.695*	*0.063*	*0.660*	*0.123*	*0.475*
ROA	0.227**	4.670	0.223	0.114*	1.430	0.102	0.245
	0.012	*0.185*	*0.103*	*0.089*	*0.858*	*0.142*	*0.471*
LIQUIDITY	0.987	1.024	1.030	1.008	0.987	0.974	0.991
	0.641	*0.309*	*0.281*	*0.760*	*0.642*	*0.340*	*0.734*
SIZE	0.975**	0.985	0.966**	0.966*	0.992	0.994	0.994
	0.028	*0.129*	*0.049*	*0.051*	*0.345*	*0.496*	*0.493*
N	4585	4536	4392	4243	4102	3958	3811
pctevent	0.349	0.353	0.273	0.283	0.268	0.303	0.315
pseudo_R2	0.287	0.31	0.321	0.24	0.113	0.078	0.057
likelihood	152.94	147.75	113.19	125.89	135.36	150.69	153.12
wald	75.940**	63.048**	53.790**	28.596**	18.900**	15.077	9.700

Table 3.8: Indirect Market Discipline: Discrete Choice Regressions for Distress Prediction (Continued)

The table reports the results of discrete choice regressions (using a complimentary log-log model) for the prediction of defaults over leads from one to twelve quarters (see column headers). We estimate the regressions including all market based risk indicators presented in panel C of table 3.1 and a set of CAMEL accounting indicators (for variable definitions see panel A of table 3.1). We report results without (Panel A) and including the IRP (panel B). We include quarter-fixed effects such that the regressions are equivalent to a discrete proportional hazard model. *pctevent* is the percentage of BHC-quarters with an event of default. *pseudo_R2* is the coefficient of determination from Nagelkerke (1991) which measures the relative increase in likelihood of the model when the regressors are included and can take on values from zero to one like the regular coefficient of determination. *likelihood* is computed as $-2\log L$ as a measure of goodness of fit of the model, where L is the likelihood function. *wald* is the χ^2 statistic from testing the null that all coefficients of the regressors are jointly zero. p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

of market based risk indicators and the following accounting risk indicators according to the Federal Reserve's CAMEL rating system: book equity to total assets (Capital Adequacy), loan loss provisions to total assets (Asset Quality), the ratio of non-interest expenditures to net income (Management Capability), return on assets (Earnings), liquid assets to total assets (Liquidity).[54] The estimation results are presented in Table 3.8. For purposes of comparison we show our results both excluding IRP in Panel A and including IRP Panel B. We find that while mostly only DD adds significantly to the reduced model, the IRP enters the model as a highly significant risk indicator for prediction horizons from two to twelve quarters ahead and improves the model's explanatory power.[55] As we present the results as hazard ratios (exponential of the regression coefficients), a coefficient of 1.132 in the last column suggests that an increase of one percent in the IRP reveals the likelihood of distress at the end of the following three years to be 13.2% times higher. These findings suggest that the forward-looking information on systematic risk contained in the IRP does indeed help to evaluate the risk profile of a BHC, however again the informative value seems more present for longer prediction

[54] We also run the regressions of Sections 3.4.2.2 and 3.4.2.3 with past due loans and net charge-offs instead of loan loss provisions for Asset Quality. The results are similar and reported in Appendix A.2.3 in Tables A8, A9, A10 and A11.

[55] The *likelihood* criterion is calculated as (-2) times the log likelihood function value of the model, i.e. a decrease in *likelihood* is an increase in the explanatory power of the model.

horizons.[56]

3.4.2.3 Duration Regressions

To accommodate the findings of the last subsection from a different point of view, we conclude our analysis with a Cox proportional hazard duration model, as in Equation (3.6).[57] While we use the same covariates as in our prior analyses, here we use only the earliest observation per BHC with rating data and all independent variables available, hence maximizing the possible prediction horizon. In other words, we observe the explanatory variables once the BHCs enters the sample, either for the first time or after a recovery, and measure the duration until they are either downgraded or exit the sample. We present the results in Table 3.9 and estimate the model with all market based risk indicators except IRP, only with IRP and finally with the full array of market based risk indicators including the IRP, all including the CAMEL accounting risk indicators from Subsection 3.4.2.2. The results in the first column show that, as already suggested by Table 3.8, the predictive value of the DD measure diminishes in the long run, and that none of the other historical risk indicators enter the model as relevant distress predictors. On the other hand, the IRP as a standalone market-based predictor is highly significant in explaining future downgrades (column two). A hazard ratio of 1.109 implies that an increase of one percent in IRP increases the likelihood of distress by 10.9% for a BHC. This relation persists when the other market based indicators are added to the model (column three), indicating that they capture different aspects of a BHC's risk position. As in the complimentary log-log model, our results point at the usefulness of stock market data to evaluate BHC risk. The IRP reflects future systematic risk in a unique way that makes it an advisable early warning indicator.

[56] As a robustness check, in unreported results we also control for one quarter lagged ERROR and GROWTH (as a remedy against multicollinearity with IRP) as proxies for forecast error and future earnings growth, which both might vary over BHC-quarters and hence have a significant effect on computed ICCs. We find that analyst forecast errors are a relevant distress predictor themselves, likely as they identify BHCs with an unstable business model. Our main results however remain unchanged.

[57] By varying the values of the regressors for each quarter, the complementary log-log regression model from Section 3.4.2.2 would be the discrete counterpart of the proportional hazard model in this Section (see Jenkins, 1995).

Table 3.9: Indirect Market Discipline: Duration Regressions for Distress Prediction

	default	default	default
DD	0.911		0.894
	0.525		*0.491*
RET_VOL	0.641		0.691
	0.279		*0.377*
FF_BETA	0.978		0.649
	0.962		*0.417*
FF_RES_VOL	2.007		1.785
	0.165		*0.266*
IRP		1.109***	1.136***
		0.000	*0.000*
EQUITY	1.214	0.981	1.240*
	0.114	*0.856*	*0.070*
LLP	22.866**	1.467	23.359*
	0.041	*0.774*	*0.059*
EFFICIENCY	1.000	1.000***	1.000
	0.669	*0.002*	*0.449*
ROA	0.131	0.259**	0.058
	0.287	*0.049*	*0.175*
LIQUIDITY	1.050**	1.034*	1.074***
	0.021	*0.091*	*0.002*
SIZE	0.982	0.973	0.984
	0.312	*0.119*	*0.368*
N	151	156	151
pctevent	12.583	14.744	12.583
likelihood	140.53	170.65	131.34
wald	22.581**	31.632**	29.598**

The table reports the results of hazard model regressions for the prediction of BHC defaults. We estimate the regressions including IRP, all market based risk indicators presented in Panel C of Table 3.1 and a set of CAMEL accounting indicators (for variable definitions see Panel A of Table 3.1). All covariates have the values at the beginning of the spell (time of inclusion or of recovery after a default) until eventual default or censorship (exclusion from the sample or end of the sample). *pctevent* is the percentage of BHCs with an event of default. *likelihood* is computed as $-2\log L$ as a measure of goodness of fit of the model, where L is the likelihood function. *wald* is the χ^2 statistic from testing the null that all coefficients of the above regressors are jointly zero. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

3.4.3 Robustness Checks

We perform several (unreported) sensitivity tests to gauge the robustness of our findings. Throughout the paper, we choose to use the IRP model by Pástor et al. (2008) as one of the most sophisticated models proposed in the literature. Nevertheless, we replicate our analysis using IRP estimates from two alternative established models. First, we compute IRPs based on the ICC model proposed by Gebhardt et al. (2001), a variant of the residual income model (RIM), and second we also compute IRPs using the ICC model from Easton (2004), which is based on a rather simple abnormal earnings growth (AEG) model. Just as the discounted earnings model employed by Pástor et al. (2008), the RIM and the AEG models are both variations of the net present value model. In both cases we obtain results very similar to the ones presented in Sections 3.4.1 and 3.4.2.[58]

We further address a technical issue within the Pástor et al. (2008) model concerning the time horizon employed before the period of the terminal value begins (T from Subsection 3.2). We re-estimate the model with time horizons of 10 years and 20 years, respectively, and rerun our main regressions. Again, we obtain very similar results.

An interesting question would be whether stock investors' reaction to bank risk varies over time. We therefore rerun our analyses for alternative sub-periods (e.g., before and after the 2007/2008 financial crisis) but find no evidence for a differential sensitivity across time-periods. Our overall results hold rather constantly over the entire period under observation or weaken when the sample size and hence the power of our test decreases (in particular for the tests on indirect market discipline) .

Finally, we also investigate whether our results are influenced by stock market characteristics. It seems plausible that stock prices should be more informative for stocks that are actively traded compared to less liquid stocks or for stocks with larger market capitalization and hence higher visibility. We therefore split our sample firms according to their relative share turnover and market value and rerun our analyses separately. We find tentative evidence that direct stock market discipline is indeed more pronounced for larger and more liquid firms, however our results for indirect market discipline are again generally weaker due to a lack of variation, and hence statistical power, in the subsamples.

3.5 Conclusion

This paper examines whether the risk position of financial institutions is reflected in the risk discount equity investors apply to their expected cash flows. Using the implied cost of capital methodology offers a convenient way to directly estimate the risk discount and to disentangle it from possibly positive cash flow effects from higher risk taking. Employing a large sample

[58] The model from Gebhardt et al. (2001) requires the availability of more variables than the other two models and hence results in more missing values. This decrease in power reduces the significance of our results.

of U.S. bank holding companies from 1990 to 2012, we find that the implied risk premium varies significantly with publicly available risk information. We are the first to provide such evidence for direct bank market discipline via higher funding costs in the stock market.

We then go on to evaluate the forward-looking informativeness of the implied risk premium with respect to bank financial distress. We find that, in particular in the long run, the implied risk premium adds significantly to models of distress prediction. However, in the short run other market based indicators like the distance to default, which explicitly reflects BHC capitalization, or a measure of idiosyncratic risk like the standard deviation of daily return residuals from Fama and French (1993b) regressions dominate the implied risk premium and also still complement it for longer prediction horizons. All in all, our findings suggest that BHCs' distress risk is neither fully systematic nor idiosyncratic. While the implied cost of capital as a forward-oriented measure of systematic risk captures some risk information, it should be used as a complement to rather than as a substitute for other established risk indicators.

Using the ICC entails some inevitable biases. E.g., steady-state growth rates might differ from the economy-wide growth rate for some firms, and analyst earnings forecasts might not be representative of the market's expectations in particular during times of financial turmoil.[59] It is also important to note that both our study and the applicability of the ICC measure are limited by the input variables required for the calculation of the implied cost of (equity) capital. As we depend on the availability of analyst forecasts (and, in the second part of the paper, rating information), our sample is per se limited to larger and more relevant institutions, which are plausibly more stable and consequentially get into financial difficulties less frequently. As this mechanism however in fact works against our argument, we do not believe it limits the generalizability of our results.

Finally, though we address the issue of share liquidity and size in our robustness checks, we do not explicitly investigate how firm-level characteristics affect the strength of market discipline

[59] Also, we do not account for the information contained in possible equity risk ratings (see Lui et al., 2007, 2012).

for individual BHCs. For example, as shown by Auvray and Brossard (2012), ownership concentration and investor characteristics are likely to influence the risk sensitivity of stock prices. Also, we assume that our accounting indicators are risk relevant a priori, while the market reaction might incorporate the effect of reporting discretion on the informativeness of such indicators (see Beaver et al., 2012). We leave questions like these to future research.

4 An Iterative Approach to Simultaneously Estimate Implied Cost of Capital, Earnings and Dividends

4.1 Introduction

In this chapter, I combine and extend the models from Easton (2004) and Nekrasov and Ogneva (2011) into a new approach to estimate the implied cost of capital (ICC) while endogenously estimating the remaining input variables of the valuation model: expected future earnings, earnings growth and expected future dividends. This approach is of an iterative nature and aims at a methodological equilibrium between the components of the accounting valuation model. The equilibrium is defined through an interplay between two variants of the valuation model, as I explain in 4.3.

Research has pushed earnings based valuation models over the last twenty years, most probably because earnings, compared to cash flows, give a better and broader picture about the present and future activities including value creation and growth. The residual income model (RIM), the abnormal earnings growth (AEG) model and other derivatives have been used primarily to estimate the ICC while assuming some values for the remaining input variables of the models (e.g., Claus and Thomas (2001); Gebhardt et al. (2001); Easton (2004); Ohlson and Juettner-Nauroth (2005); Pástor et al. (2008)). Other papers built RIM and AEG models into a regression framework in order to estimate ICC and earnings growth simultaneously as means of a group of firms (see e.g., Easton et al., 2002; Easton, 2004) or firm-specific values (Nekrasov and Ogneva, 2011).

All previous research, up to my knowledge, assume a constant dividend payout ratio or a deterministic function for it and rely on analyst consensus earnings forecasts (e.g., from I/B/E/S) in order to proxy for expected future earnings and dividend payout ratio respectively. Aside from the unrealistic assumption of a constant dividend payout ratio for future years, analyst earning forecasts have been shown to be biased differently among firms with different characteristics, leading to false estimates of ICC as shown in Easton and Sommers (2007).

Hence, it is important that ICC estimates are in balance (equilibrium) with estimates of earning forecasts and other input variables, such that possible biases in proxies, used as starting values, are reduced to a minimum.

The first contribution of my approach is to estimate ICC, being in a steady state with all other input variables (while estimating the change in earnings growth, similar to Nekrasov and Ogneva (2011)). All the other approaches, including the one by Nekrasov and Ogneva (2011), have concentrated only on estimating or determining a subset of the input variables: ICC (and earnings growth).

The second contribution of my approach is that it allows simultaneous estimation of expected future earnings and expected future dividends if estimates of ICC and earnings growth were given. Up to my knowledge, in the literature so far expected future earnings and expected future dividends are estimated in the literature using different models, i.e. they are not linked together through an accounting based valuation model. In that way my approach extends the literature on earnings and dividends estimation.

The remainder of the chapter is structured as follows. Section 4.2 describes my approach, divided into two direction, the first to estimate ICC and change in earnings growth and the second to estimate earnings forecasts and the dividends forecast. Section 4.3 defines the methodological equilibrium which combines both directions of the approach. Section 4.4 concludes.

4.2 The Approach

In this section I describe and derive the valuation approach which constitutes several steps (and iterations). The output of this approach will be estimates of ICC, expected future earnings, earnings growth and expected future dividends.

In the center of my approach is the AEG model from Easton (2004) which will produce mean results for a group of similar firms. To estimate firm-specific values around the group means, I use the algorithm based on Nekrasov and Ogneva (2011). The approach is divided into two directions. The first direction uses starting values of expected future earnings and expected future dividends to estimate ICC and earnings growth while the second direction uses starting values for ICC and earnings growth to estimate expected future earnings and expected future dividends.

4.2.1 First Direction

Starting with the AEG model from Easton (2004) I get the following pricing formula:

$$p_t = \frac{eps_{t+1}}{r} + \frac{agr_{t+1}}{r(r-g)} \tag{4.1}$$

where $agr_{t+1} = (eps_{t+2} + rdps_{t+1}) - ((1+r)eps_{t+1}) = \Delta eps_{t+2} - r(eps_{t+1} - dps_{t+1})$, i.e. expected cum-dividend earnings less normal earnings. p_t is the market stock price at time t, eps_{t+x} are the earnings per share at time $t+x$ (for $x = 1, 2$), dps_{t+1} are the dividends per share at time $t+1$, r is the cost of equity and g is the rate of change in abnormal growth in earnings, henceforth referred to as change in earnings. Rearranging Equation (4.1) Easton (2004) derives the following relation:

$$\frac{eps_{t+2} + rdps_{t+1}}{p_t} = \gamma_0 + \gamma_1 \frac{eps_{t+1}}{p_t} \tag{4.2}$$

with $\gamma_0 = r(r-g)$ and $\gamma_1 = 1 + g$. Simultaneously solving for r and g requires at least two equations. There is however only one observation per firm at one point in time. Following Easton (2004) I build portfolios of firms, resulting in an overidentified system of equations, which assumes model (4.2) for all firms i in the portfolio.

$$\frac{eps_{i,t+2} + r_i dps_{i,t+1}}{p_{i,t}} = \gamma_{i,0} + \gamma_{i,1} \frac{eps_{i,t+1}}{p_{i,t}}$$

The above identity will only hold with some error when applied to the data, divided into portfolios of firms. Hence I do not solve for r and g deterministically, but through the following regression model:

$$\frac{eps_{i,t+2} + r_i dps_{i,t+1}}{p_{i,t}} = \gamma_0 + \gamma_1 \frac{eps_{i,t+1}}{p_{i,t}} + \epsilon_{i,t} \tag{4.3}$$

where i stands for a specific firm in the portfolio. Regression model (4.3) is hence run for each portfolio and year (more generally, for each cross-sectional unit and time unit). Note that the dependent variable is a function of r_i, which we want to estimate. This issue is tended to by setting a starting value for r_i as explained at the end of this subsection. The derivation of Model (4.3) from Model (4.2) leads to the following three related econometric statements, all of which are to be found in or based on Easton (2004).[60]

1. Regression Model (4.3) is a random coefficients model, since it derives from Model (4.2) without an error term, which makes the error term in (4.3) come from the randomness of $\gamma_{i,0} = \gamma_0 + u_{i,0}$ and $\gamma_{i,1} = \gamma_1 + u_{i,1}$.

2. Looking carefully at the error term $\epsilon_{i,t}$ Easton (2004) makes it clear that heteroscedasticity is at play.

   $$\epsilon_{i,t} = u_{i,0} + u_{i,1} \frac{eps_{i,t+1}}{p_{i,t}}$$

   Hence the heteroscedasticity comes from the varying term $\frac{eps_{i,t+1}}{p_{i,t}}$ for each i and t even though $u_{i,0}$ and $u_{i,1}$ could be assumed to have together a constant variance.

3. $\mathbb{E}[\gamma_{i,0}] = \gamma_0 = r(r-g)$ and $\mathbb{E}[\gamma_{i,1}] = \gamma_1 = 1 + g$, meaning that the estimates of γ_0 and γ_1 are the means of the firm-specific coefficients $\gamma_{i,0}$ and $\gamma_{i,1}$ respectively. This implies that $\hat{\gamma}_0 = \overline{r(r-g)}$ and $\hat{\gamma}_1 = \overline{1+g} = 1 + \bar{g}$.[61]

$\hat{\gamma}_0$ can not be linearly separated into individual means of r and g as was done with $\hat{\gamma}_1$. I

[60] The aim of the regression Model (4.3) is not to study the economic effect of the regressor(s) on the dependent variable. It is merely a technical method to estimate r and g for all the firms in a portfolio.

[61] $\mathbb{E}[X]$ is the expected value of the random variable X and $\bar{x}$ is the sample mean of the realizations of X.

therefore apply a Taylor expansion of γ_0 at some point or starting values (r^0, g^0) to linearize it:

$$\gamma_0 \approx a + br + cg$$

where $a := -r^0(r^0 + g^0)$, $b := -(2r^0 - g^0)$ and $c := r^0$. For simplicity of notation I regard this approximation as an equality from here on, which will hold only in expectation due to the firm-specific nature of γ_0, r, and g respectively. Combining the results from statements 2 and 3, I rewrite $\epsilon_{i,t}$ as a linear combination of the deviation of firm-specific cost of equity r_i from its mean and the deviation of firm-specific change in earnings growth g_i from its mean.

$$\begin{aligned}
\epsilon_{i,t} &= u_{i,0} + u_{i,1}\frac{eps_{i,t+1}}{p_{i,t}} \\
&= (\gamma_{i,0} - \gamma_0) - (\gamma_{i,1} - \gamma_1)\frac{eps_{i,t+1}}{p_{i,t}} \\
&= ((a - a) + b(r_i - \mathbb{E}[r]) + c(g_i - \mathbb{E}[g])) - ((1 - 1) + (g_i - \mathbb{E}[g]))\frac{eps_{i,t+1}}{p_{i,t}} \\
&= b\epsilon^r_{i,t} + \epsilon^g_{i,t}\left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right) \qquad (4.4)
\end{aligned}$$

where $\epsilon^r_{i,t} := r_i - \mathbb{E}[r]$ and $\epsilon^g_{i,t} := g_i - \mathbb{E}[g]$.

Here is where I build a bridge to the algorithm by Nekrasov and Ogneva (2011), who note that just using the estimates $\hat{\gamma}_0$ and $\hat{\gamma}_1$, leaves the firm-specific cost of capital r_i and change in earnings growth in earnings g_i unidentified. They model these firm-specific figures as associated with certain firm characteristics and firm unobservable risk.[62]

[62] Note that I differentiate between the expected values and means of r and g, depending on if I am looking at the random variable or its estimate.

$$r_i = \mathbb{E}[r] + \lambda_r X^r_{i,t} + \epsilon^r_{i,t} \tag{4.5}$$

$$g_i = \mathbb{E}[g] + \lambda_g X^g_{i,t} + \epsilon^g_{i,t} \tag{4.6}$$

where $X^r_{i,t}$ and $X^g_{i,t}$ are observable drivers for r and g respectively. To estimate Equations (4.5) and (4.6) simultaneously Nekrasov and Ogneva (2011) set up an optimization problem, which translates into the following in my setting:

$$\begin{cases} \min\limits_{\hat{\lambda}_r, \hat{\lambda}_g, \epsilon^r_{i,t}, \epsilon^g_{i,t}} & \sum\limits_i w^i_r (\epsilon^r_{i,t})^2 + w^i_g (\epsilon^g_{i,t})^2 \\ \text{s.t.} & r_i = \bar{r} + \hat{\lambda}_r X^r_{i,t} + \epsilon^r_{i,t} \\ & g_i = \bar{g} + \hat{\lambda}_g X^g_{i,t} + \epsilon^g_{i,t} \end{cases} \tag{P}$$

where $\hat{\lambda}_r$ and $\hat{\lambda}_g$ are possible realizations for the coefficient vectors λ_r and λ_g respectively.

Inserting Equations (4.5) and (4.6) into Equation (4.4) and the latter into the regression Model (4.3), analogously to Nekrasov and Ogneva (2011), I get the first weighted least squares (WLS) regression model, with the derivation to be found in Appendix A.3.1.

$$\begin{aligned} \frac{eps_{i,t+2} + r_i dps_{i,t+1}}{p_{i,t}} &= \gamma_0 + \gamma_1 \frac{eps_{i,t+1}}{p_{i,t}} + b(\lambda_r X^r_{i,t} + \epsilon^r_{i,t}) + \left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right)(\lambda_g X^g_{i,t} + \epsilon^g_{i,t}) \\ &= \gamma_0 + \gamma_1 \frac{eps_{i,t+1}}{p_{i,t}} + b\lambda_r X^r_{i,t} + \left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right)\lambda_g X^g_{i,t} + \nu_{i,t} \end{aligned} \tag{WLS(1)}$$

where $\nu_{i,t} = b\epsilon^r_{i,t} + \left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right)\epsilon^g_{i,t}$.[63] and its weights w^i are[64]

[63]Although $\nu_{i,t} = \epsilon_{i,t}$, the left-hand side stems from the model with firm specific characteristics, while the right-hand side stems from the model before introducing these characteristics.

[64]Note that w^i_r and w^i_g are weights which are fixed before estimating the WLS model.

$$w^i = \frac{w_r^i w_g^i}{w_g^i b^2 + w_r^i \left(c + \dfrac{eps_{i,t+1}}{p_{i,t}}\right)^2} \tag{4.7}$$

Before estimating the Model (WLS(1)) I tackle two issues regarding the exogeneity of the regressor $\frac{eps_{i,t+1}}{p_{i,t}}$. The first issue is induced by this regressor being a part of the error term $\nu_{i,t}$. However, conditional on the assumption that $eps_{i,t+1}$ and $p_{i,t}$ are exogenous regarding the cost of equity and growth error terms, $\epsilon_{i,t}^r$ and $\epsilon_{i,t}^g$ respectively, exogeneity with respect to $\nu_{i,t}$ is achieved as well, i.e. $\mathbb{E}[\nu_{i,t}|eps_{i,t+1}, p_{i,t}] = 0$. The second issue stems from including a lagged variable into the model, $eps_{i,t+1}$, which makes it endogenous. Since however $\mathbb{E}[\nu_{i,t}|eps_{i,t-s}] = 0$ for $s \geq 0$ the regressor $eps_{i,t+1}$ is predetermined and hence allows for consistent estimation of the model (see Greene, 2011).

In order to estimate Model (WLS(1)) I set a starting value for r_i, similar to value chosen in Easton (2004). I use the estimated coefficients and related residuals from the Model (WLS(1)), $(\hat{\gamma}_0, \hat{\gamma}_1, \hat{\lambda}_r, \hat{\lambda}_g, \hat{\nu}_{i,t})$, and the following identities to identify firm-specific cost of equity r_i and firm-specific change in earnings growth g_i.

1. I insert $\hat{\gamma}_0$ and $\hat{\gamma}_1$ into the following identities to determine estimates of $\bar{r}$ and $\bar{g}$:

$$\hat{\gamma}_0 = a + b\bar{r} + c\bar{g} \quad \Rightarrow \bar{r} = \frac{\gamma_0 - a - c\bar{g}}{b}$$

$$\hat{\gamma}_1 = 1 + \bar{g} \quad \Rightarrow \bar{g} = \gamma_1 - 1$$

2. I insert the estimates of the residuals from the Model (WLS(1)), $\hat{\nu}_{i,t}$, to get estimates

for the error terms in Equations (4.5) and (4.6):

$$\epsilon^r_{i,t} = \frac{w^i_g b \nu_{i,t}}{w^i_r \left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right)^2 + w^i_g b^2}$$

$$\epsilon^g_{i,t} = \frac{w^i_r \left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right) \nu_{i,t}}{w^i_r \left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right)^2 + w^i_g b^2}$$

3. I then use $\bar{r}$ and $\bar{g}$, the estimates of the residuals $\epsilon^r_{i,t}$ and $\epsilon^g_{i,t}$ and the estimates $\hat{\lambda}_r$ and $\hat{\lambda}_g$ to get estimates for r_i and g_i:

$$r_i = \bar{r} + \hat{\lambda}_r X^r_{i,t} + \epsilon^r_{i,t}$$

$$g_i = \bar{g} + \hat{\lambda}_g X^g_{i,t} + \epsilon^g_{i,t}$$

Based on Easton (2004) I insert r_i into (WLS(1)) and reestimate the model followed by steps one to three until the change in r_i from one iteration to the next is below a given threshold. Getting simultaneous estimates of firm-specific r_i and g_i concludes the first direction of my approach. Although Nekrasov and Ogneva (2011) introduce an approach which ends up with estimates of r_i and g_i, I choose a model which allows for the estimation of the other parameters of the model as well, earnings forecasts and dividends forecasts. This would not be possible with the model used by Nekrasov and Ogneva (2011) since one of their variables is a sum of future earnings forecasts and dividends forecasts which makes single earnings forecasts and the dividends forecast unidentifiable. The following subsection shows how using my approach based on the valuation model from Easton (2004) identifies earnings forecasts as well as the dividends forecast.

4.2.2 Second Direction

I rearrange the AEG Model (4.1) differently than done in Equation (4.2) to arrive at the following:

$$r_t(r_t - g_t)p_t = \beta_0 + \beta_1(-(1 + g_t))\beta_2 r_t \tag{4.8}$$

where $\beta_0 = eps_{t+2}$, $\beta_1 = eps_{t+1}$ and $\beta_2 = dps_{t+1}$. I do not drop the time index from eps_{t+2}, eps_{t+1} and dps_{t+1}, since they resemble the number of leads of these variables. Again I follow Easton (2004) and build portfolios of firms to get a system of equations.

$$r_{i,t}(r_{i,t} - g_{i,t})p_{i,t} = \beta_{i,0} + \beta_{i,1}(-(1 + g_{i,t}))\beta_{i,2} r_{i,t}$$

Note that here the cost of equity $r_{i,t}$ and the rate of change in abnormal growth $g_{i,t}$ are period- and firm-specific since the models assumes that they are known, just like price $p_{i,t}$. Since however the model can only hold for all firms i in a portfolio with some error, I run it analogously to Model (4.3) as a linear regression.[65]

$$r_{i,t}(r_{i,t} - g_{i,t})p_{i,t} = \beta_0 + \beta_1(-(1 + g_{i,t}))\beta_2 r_{i,t} + \eta_{i,t} \tag{4.9}$$

As in the first direction model from 4.2.1, note that regression Model (4.9) is a random coefficients model, the error term $\eta_{i,t}$ is heteroscedastic and by estimating β_0, β_1 and β_2 I would be estimating the means of eps_{t+2}, eps_{t+1} and dps_{t+1} respectively. Analogously to the decomposition of $\epsilon_{i,t}$ in (4.4), I decompose $\eta_{i,t}$ into a linear combination of error terms coming from $\beta_{i,0}$, $\beta_{i,1}$ and $\beta_{i,2}$ being random coefficients.

$$\begin{aligned}
\beta_{i,0} &= \beta_0 + n_{i,0} \quad \Rightarrow n_{i,0} = \beta_{i,0} - \beta_0 = \beta_{i,0} - \mathbb{E}[\beta_{i,0}] \text{ and } \hat{\beta}_0 = \overline{eps_{t+2}} \\
\beta_{i,1} &= \beta_1 + n_{i,1} \quad \Rightarrow n_{i,1} = \beta_{i,1} - \beta_1 = \beta_{i,1} - \mathbb{E}[\beta_{i,1}] \text{ and } \hat{\beta}_1 = \overline{eps_{t+1}} \\
\beta_{i,2} &= \beta_2 + n_{i,2} \quad \Rightarrow n_{i,2} = \beta_{i,2} - \beta_2 = \beta_{i,2} - \mathbb{E}[\beta_{i,2}] \text{ and } \hat{\beta}_2 = \overline{dps_{t+1}}
\end{aligned}$$

[65] Also regression Model (4.9) aims at estimating eps_{t+1}, eps_{t+2} and dps_{t+1} and not interpreting the coefficients of the model economically.

$$\begin{aligned}
\eta_{i,t} &= n_{i,0} + n_{i,1}(-(1+g_{i,t})) + n_{i,2} r_{i,t} \\
&= (\beta_{i,0} - \beta_0) + (\beta_{i,1} - \beta_1)(-(1+g_{i,t})) + (\beta_{i,2} - \beta_2) r_{i,t} \\
&= (eps_{i,t+2} - \mathbb{E}[eps_{t+2}]) + (eps_{i,t+1} - \mathbb{E}[eps_{t+1}])(-(1+g_{i,t})) + (dps_{i,t+1} - \mathbb{E}[dps_{t+1}]) r_{i,t} \\
&= \eta^{e2}_{i,t} + (-(1+g_{i,t}))\eta^{e1}_{i,t} + r_{i,t}\eta^{d}_{i,t} \qquad (4.10)
\end{aligned}$$

where $\eta^{e2}_{i,t} \coloneqq eps_{i,t+2} - \mathbb{E}[eps_{t+2}]$, $\eta^{e1}_{i,t} \coloneqq eps_{i,t+1} - \mathbb{E}[eps_{t+1}]$ and $\eta^{d}_{i,t} \coloneqq dps_{i,t+1} - \mathbb{E}[dps_{t+1}]$.

If I would proceed as in the first direction and minimize the sum of squared error terms $\eta^{e2}_{i,t}$, $\eta^{e1}_{i,t}$ and $\eta^{d}_{i,t}$ respectively, I could not derive a WLS model, since there are three error terms summed into its overall error term, as seen in result (4.10). Hence I have a problem of identification of all error terms here, since only two error terms can be identified using the procedure of the first direction. I solve this problem by assuming that the error terms resulting from the random coefficients $\beta_{i,0}$ and $\beta_{i,1}$ have the same expected value. This is a sound assumption since both random coefficients represent earnings at time periods $t+1$ and $t+2$ respectively. The deviation of $eps_{i,t+1}$ from its mean could be assumed equal in expected value to the deviation of $eps_{i,t+2}$ from its mean. This gives the following result:

$$\eta_{i,t} = -g_{i,t}\eta^{e}_{i,t} + r_{i,t}\eta^{d}_{i,t} \qquad (4.11)$$

where $\eta^{e}_{i,t} \coloneqq \eta^{e1}_{i,t} = \eta^{e2}_{i,t}$.

Analogous to the idea by Nekrasov and Ogneva (2011) and Equations (4.5) and (4.6), I model the firm-specific earnings forecasts and dividends forecasts as follows:

$$eps_{i,t+1} = \mathbb{E}[eps_{t+1}] + \lambda_e X^e_{i,t} + \eta^e_{i,t} \tag{4.12}$$

$$eps_{i,t+2} = \mathbb{E}[eps_{t+2}] + \lambda_e X^e_{i,t} + \eta^e_{i,t} \tag{4.13}$$

$$dps_{i,t+1} = \mathbb{E}[dps_{t+1}] + \lambda_d X^d_{i,t} + \eta^d_{i,t} \tag{4.14}$$

where $X^e_{i,t}$ and $X^d_{i,t}$ are observable drivers for eps_{t+1}, eps_{t+2} and dps_{t+1} respectively. Since I assume the error terms in Equations (4.12) and (4.13) to be identical, I also assume the set of firm characteristics $X^e_{i,t}$ to be identical for both eps_{t+1} and eps_{t+2}. Again, this is a sound assumption, since there is not any reason to suspect significantly different behavior of earnings in two consecutive periods in expectation.

To estimate the above Equations (4.12), (4.13) and (4.14) simultaneously I set up the following optimization problem:

$$\begin{cases} \min\limits_{\hat{\lambda}_e, \hat{\lambda}_d, \eta^e_{i,t}, \eta^d_{i,t}} & \sum\limits_i w^i_e(\eta^e_{i,t})^2 + w^i_d(\eta^d_{i,t})^2 \\ \text{s.t.} & eps_{i,t+1} = \overline{eps_{t+1}} + \lambda_e X^e_{i,t} + \eta^e_{i,t} \\ & eps_{i,t+2} = \overline{eps_{t+2}} + \lambda_e X^e_{i,t} + \eta^e_{i,t} \\ & dps_{i,t+1} = \overline{dps_{t+1}} + \lambda_d X^d_{i,t} + \eta^d_{i,t} \end{cases} \tag{Q}$$

where $\hat{\lambda}_e$ and $\hat{\lambda}_d$ are possible realizations for the coefficient vectors λ_e and λ_d respectively.

Inserting Equations (4.12), (4.13) and (4.14) into Equation (4.11) and the latter into the regression Model (4.9), analogously to Nekrasov and Ogneva (2011) and Model (WLS(1)), I get the second WLS regression model, with the derivation to be found in Appendix A.3.2.

$$r_{i,t}(r_{i,t} - g_{i,t})p_{i,t} = \beta_0 + \beta_1(-(1 + g_{i,t})) + \beta_2 r_{i,t} + (-g_{i,t})\lambda_e X^e_{i,t} + r_{i,t}\lambda_d X^d_{i,t} + \psi_{i,t} \tag{WLS(2)}$$

where $\psi_{i,t} = -g_{i,t}\eta^e_{i,t} + r_{i,t}\eta^d_{i,t}$.[66] and its weights z^i are

$$z^i = \frac{w^i_e w^i_d}{w^i_e r^2_{i,t} + w^i_d g^2_{i,t}} \tag{4.15}$$

As discussed above regarding the exogeneity of all regressors in the Model (WLS(1)), I emphasize here that by assuming $\mathbb{E}[\eta^e_{i,t}|g_{i,t}] = 0$ and $\mathbb{E}[\eta^d_{i,t}|r_{i,t}] = 0$ the regressors $(-(1+g_{i,t}))$ and $r_{i,t}$ become exogenous with respect to $\psi_{i,t}$, $\mathbb{E}[\psi_{i,t}|g_{i,t}, r_{i,t}] = 0$.

After estimating the above Model (WLS(2)), I use the estimates of the coefficients and the residuals $(\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \hat{\lambda}_e, \hat{\lambda}_d, \hat{\psi}_{i,t})$, and the following identities to identify firm-specific earnings forecasts eps_{t+1} and eps_{t+2} and firm-specific dividends forecasts dps_{t+1}.[67]

1. I insert $\hat{\beta}_0$, $\hat{\beta}_1$ and $\hat{\beta}_2$ into the following identities to determine $\overline{eps_{t+1}}$, $\overline{eps_{t+2}}$ and $\overline{dps_{t+1}}$:

$$\hat{\beta}_0 = \overline{eps_{t+2}}$$
$$\hat{\beta}_1 = \overline{eps_{t+1}}$$
$$\hat{\beta}_2 = \overline{dps_{t+1}}$$

2. I insert the estimates of the residuals from the Model (WLS(2)), $\hat{\psi}_{i,t}$, to get estimates for the error terms in Equations (4.12), (4.13) and (4.14):

$$\eta^e_{i,t} = -\frac{w^i_d g_{i,t}\psi_{i,t}}{w^i_e r^2_{i,t} + w^i_d g^2_{i,t}}$$
$$\eta^d_{i,t} = \frac{w^i_e r_{i,t}\psi_{i,t}}{w^i_e r^2_{i,t} + w^i_d g^2_{i,t}}$$

3. I then use $\overline{eps_{t+1}}$, $\overline{eps_{t+2}}$ and $\overline{dps_{t+1}}$, the estimates of the residuals $\eta^e_{i,t}$ and $\eta^d_{i,t}$ and the

[66]Again, although $\psi_{i,t} = \eta_{i,t}$, the left-hand side stems from the model with firm specific characteristics, while the right-hand side stems from the model before introducing these characteristics.

[67]Note that none of the variables of interest here are part of the dependent variable, i.e. one iteration gives the desired estimates.

estimates $\hat{\lambda}_e$ and $\hat{\lambda}_d$ to get estimates for $eps_{i,t+1}$, $eps_{i,t+2}$ and $dps_{i,t+1}$:

$$\begin{aligned}
eps_{i,t+1} &= \overline{eps_{t+1}} + \lambda_e X^e_{i,t} + \eta^e_{i,t} \\
eps_{i,t+2} &= \overline{eps_{t+2}} + \lambda_e X^e_{i,t} + \eta^e_{i,t} \\
dps_{i,t+1} &= \overline{dps_{t+1}} + \lambda_d X^d_{i,t} + \eta^d_{i,t}
\end{aligned}$$

The estimates of $eps_{i,t+1}$, $eps_{i,t+2}$ and $dps_{i,t+1}$ conclude the second step of my approach. Nekrasov and Ogneva (2011) use in their analogous model to (WLS(1)) as the dependent variable a sum of future earnings and dividends. If I would use the same model and rearrange it as I did in Model (4.8), this variable would have become part of the parameters to estimate β. I would then have estimated one value for a sum of variables which can not be separated anymore, i.e. $eps_{i,t+1}$, $eps_{i,t+2}$ and $dps_{i,t+1}$ would have been unidentifiable.

4.3 The Estimation Equilibrium

The first and second directions of the approach in Section 4.2 can be used separately to estimate ICC and the change in earnings growth or earnings forecasts and the dividends forecast. However, since the starting models of both directions originate from the same AEG model by Easton (2004), they can be iterated alternately, starting by the direction for which starting values are available. I iterate then until the implied cost of capital, the estimate of the change in earnings growth, estimates of future earnings and the estimate of future dividends converge to stable values. The combined approach aims at an equilibrium in the components of the original AEG valuation model. This equilibrium is in the sense of the convergence of said components to stable values, denoted as an equilibrium in valuation components.

Definition 1 (Methodological Equilibrium in Valuation Components)**.** *Assume a valuation model M, with a set of known arguments K and a set of unknown arguments U to be estimated. Let M_1, $M_2, \ldots, M_n$ be a set of valuation models equivalent to M, such that M_i can estimate only a subset of U, U_i, where $U_i \cap U_j = \emptyset, \forall i, j \in \{1, \ldots, n\}, i \neq j$. Let $\hat{U}_{i,t}$ denote the* *estimates of all arguments in* U_i *derived in iteration step* t, $t \in \{1, \dots, T\}$. *An equilibrium in the valuation components of* M *is given if and only if,* $\forall t \geq t_0, \exists \epsilon > 0$ *such that*

$$||\frac{\hat{\theta}_t - \hat{\theta}_{t-1}}{\hat{\theta}_{t-1}}|| < \epsilon, \forall \hat{\theta}_t \in \hat{U}_{i,t}, \hat{\theta}_{t-1} \in \hat{U}_{i,t-1}, i \in \{1, \dots, n\}$$

where $|| \cdot ||$ *is a norm.*

The iterations $t \in \{1, \dots, T\}$ are not to confuse with the iterations done at the level of the WLS model in the first direction. This definition of a methodological equilibrium generalizes to all models which can be separated or rearranged into different equivalent versions such that all unknown input variables or parameters become identified.

4.4 Conclusion

In this chapter, I introduce a new approach to simultaneously estimate the implied cost of capital with the other input variables of the valuation model from Easton (2004). I combine this valuation model into an estimation approach similar to the approach from Nekrasov and Ogneva (2011).

The first contribution of my approach is to estimate the implied cost of capital, being in a steady state with all other input variables (while estimating the change in earnings growth). The second contribution of my approach is that it allows simultaneous estimation of expected future earnings and expected future dividends if estimates of ICC and earnings growth were given.

The estimation approach has one main limitation. It strongly depends on the structure of the underlying valuation model. Not every valuation model allows writing it in two different ways (directions), as shown in Section 4.2, such that all variables are identified. I leave the empirical testing of my approach and the transfer of my approach to other suitable valuation models for future research.

A Appendix

A.1 Chapter 2

A.1.1 ACSI Data and COMPUSTAT

Similar to the cleaning procedure suggested in Ittner et al. (2009), a corresponding GVKEY from COMPUSTAT based on the name of each ACSI entity was manually matched. This ACSI - GVKEY match was manually classified into one of the following mutually exclusive categories (0-6 are taken from Ittner et al. (2009)). We report the details with one example per coding in Table A1.

Table A1: Matching between ACSI Data and COMPUSTAT

Coding	Examples	Label / Description	Handling
0	IBM; Twitter.com	No record on COMPUSTAT over the period from 1994-2012	ACSI data is not used (dropped)
1	Cadbury Schweppes; FedEx Corporation	Clean match	ACSI data is used for entity-years covered by COMPUSTAT
2	H. J. Heinz Company (Food Manufacturing and Pet Food)	Multiple divisions (ACSI entities) are assigned to a parent's GVKEY, and the parent is not covered by ACSI over the period 1994-2012	ACSI is averaged across divisions and the average is used for entity-years covered by COMPUSTAT for the parent firm (see coding 8)
3	Apple (Cellular Phones); Lexus (Toyota)	A single division is assigned to the parent's GVKEY, and the parent is covered by ACSI over the period 1994-2011	ACSI data of the single division is not used (dropped)
4	T-Mobile USA, Inc. (Deutsche Telekom AG)	A single division is assigned to the parent's GVKEY, and the parent is not covered by ACSI over the period 1994-2011	ACSI data is used for entity-years of the parent firm covered by COMPUSTAT
5	Gateway, Inc. acquired by ACER in 2007	Merger with overlapping ACSI observations	The overlapping entity-years for the surviving entity are retained
6	Texaco Inc., acquired by Chevron in 2001	Merger with non-overlapping ACSI score data	ACSI data is used for entity-years covered by COMPUSTAT
7	Target Corporation (Department Stores; Discount Stores)	Multiple divisions (ACSI entities) are assigned to a parent's GVKEY, and the parent is covered by ACSI over the period	ACSI data of the multiple divisions are not used (dropped)
8	H. J. Heinz Company	Created average firm out of coded entities coded by 2	ACSI data is used for entity-years covered by COMPUSTAT

The table provides details and examples on merging ACSI data with COMPUSTAT gvkeys.

A.1.2 The Cost of Equity from an Asset Pricing Perspective

In what follows we start by deriving the cost of capital from asset pricing and go on to lay down the valuation model we use to compute ICC. Following Cochrane (2005), the basic pricing formula can be expressed as

$$p_t = \mathbb{E}_t(m_{t+1}x_{t+1}),$$

where t in the index stands for the time at which the variable realizes its value except for t in $\mathbb{E}_t(\cdot)$, which stands for conditioning the expected value on the information up to time t. p_t is the asset price, m_t is the discount factor and x_t is the asset payoff. Using covariance decomposition[68] in the above equation we arrive at the following pricing formula.

$$p_t = \mathbb{E}_t(m_{t+1})\mathbb{E}_t(x_{t+1}) + cov_t(m_{t+1}, x_{t+1}), \tag{A.1}$$

where $cov_t(\cdot, \cdot)$ is the covariance conditioned on information available at time t. In case the covariance is zero, i.e. that the discount factor and asset payoff are uncorrelated, we then have a risk-free case, making 1 unit of an asset at time t payoff $1 + r_f$ units of the same asset at time $t + 1$, where r_f is the risk-free rate. Plugging these values into Equation (A.1) we get

$$1 = \mathbb{E}_t(m_{t+1})(1 + r_f) \Leftrightarrow \mathbb{E}_t(m_{t+1}) = 1/(1 + r_f)$$

[68] $cov(a, b) = \mathbb{E}(ab) - \mathbb{E}(a)\mathbb{E}(b)$.

Going back to Equation (A.1) we see that we correct for risk through the covariance term, which we call systematic risk. Idiosyncratic or unsystematic risk on the other hand is the part of this covariance which drops out for being zero and hence is uncorrelated with the discount factor[69]. The first term is the risk-free value of the asset.

$$p_t = \frac{1}{1+r_f}\mathbb{E}_t(x_{t+1}) + cov_t(m_{t+1}, x_{t+1}) = \frac{1}{r_e}\mathbb{E}_t(x_{t+1}) \tag{A.2}$$

As we demonstrate in the second equation of (A.2) we are interested in a risk correction directly made in the discount factor r_e, which we define in what comes as the cost of equity. We basically transfer the risk from the covariance in the nominator to the cost of equity in the denominator. Summing up, the asset price is the future payoff divided by one plus the cost of equity containing the systematic risk the asset holder has to bear for a high expected return (or the other way around, a discount factor resembling the expected return the asset holder can expect for bearing that much systematic risk). Hence cost of capital can be regarded as a discount rate, expected return or systematic risk interchangeably.[70]

[69] Cochrane (2005) defines idiosnycratic risk as uncorrelated with the discount factor.

[70] Cochrane (2005) shows that if the discount factor can be written as $m = a + b'f$, then the expected return can be written as $\mathbb{E}(R^i) = \alpha + \lambda'\beta_i$ where $b'f$ and $\lambda'\beta_i$ are vector multiplications constituting the systematic risk equivalently. This should give an even clearer image of why it is called systematic risk, if one compares the second representation to the CAPM or other factor models.

A.1.3 Further Tables

Table A2: Analysis of ICC Sensitivity to ACSI (Random Effects)

	(1)	(2)	(3)	(4)
ACSI	-0.058***	-0.059***	-0.062***	-0.062***
	0.007	*0.006*	*0.004*	*0.004*
SIZE	0.007***	0.007***	0.007***	0.007***
	0.004	*0.004*	*0.004*	*0.004*
LEV	0.003	0.004	0.004	0.004
	0.660	*0.632*	*0.595*	*0.588*
BTM	-0.016**	-0.016**	-0.016**	-0.016**
	0.020	*0.017*	*0.018*	*0.016*
ROA	4.737***	4.649***	4.533***	4.514***
	0.001	*0.001*	*0.002*	*0.002*
RD	-17.01***	-16.77***	-15.48***	-15.52***
	0.000	*0.001*	*0.002*	*0.002*
ERROR	-0.154*	-0.155*	-0.155**	-0.156**
	0.055	*0.056*	*0.048*	*0.050*
GROWTH	18.077***	18.148***	18.227***	18.250***
	0.000	*0.000*	*0.000*	*0.000*
FF_BETA		-0.198		-0.102
		0.447		*0.717*
FF_RES_VOL			-0.069	-0.062
			0.288	*0.379*
KAZI	-0.002*	-0.002*	-0.002**	-0.002**
	0.063	*0.063*	*0.043*	*0.045*
N	1738	1738	1738	1738
adj_R2	*0.245*	*0.245*	*0.245*	*0.245*

The table reports the same results as in table 2.5 but with year-fixed and firm-random effects. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A3: Analysis of ICC (Gebhardt et al., 2001) Sensitivity to ACSI

Panel A: Year-Fixed Effects

	(1)	(2)	(3)	(4)
ACSI	0.020	0.029	0.036	0.037
	0.534	*0.363*	*0.243*	*0.235*
SIZE	0.012***	0.012***	0.014***	0.014***
	0.000	*0.000*	*0.000*	*0.000*
LEV	-0.177***	-0.181***	-0.183***	-0.183***
	0.001	*0.001*	*0.001*	*0.001*
BTM	0.421***	0.427***	0.425***	0.425***
	0.000	*0.000*	*0.000*	*0.000*
ROA	-17.81***	-16.52***	-16.05***	-15.97***
	0.000	*0.000*	*0.000*	*0.000*
RD	44.993***	42.587***	37.242***	37.184***
	0.000	*0.000*	*0.000*	*0.000*
ERROR	-0.164*	-0.150	-0.151	-0.150
	0.064	*0.109*	*0.107*	*0.112*
GROWTH	1.428	-0.214	-2.322	-2.392
	0.602	*0.944*	*0.474*	*0.472*
FF_BETA		1.217**		0.106
		0.017		*0.854*
FF_RES_VOL			0.535***	0.524***
			0.000	*0.000*
KAZI	0.005	0.005	0.005	0.005
	0.299	*0.302*	*0.304*	*0.304*
N	1673	1673	1673	1673
adj_R2	*0.6*	*0.602*	*0.61*	*0.609*

Panel B: Year-Fixed and Firm-Fixed Effects

	(1)	(2)	(3)	(4)
ACSI	-0.097***	-0.095***	-0.076**	-0.077**
	0.006	*0.007*	*0.023*	*0.023*
SIZE	-0.001	-0.001	-0.001	-0.001
	0.772	*0.774*	*0.793*	*0.793*
LEV	-0.090**	-0.091**	-0.093**	-0.093**
	0.016	*0.016*	*0.012*	*0.012*
BTM	0.226***	0.227***	0.227***	0.227***
	0.000	*0.000*	*0.000*	*0.000*
ROA	-0.368	-0.233	0.571	0.534
	0.867	*0.917*	*0.799*	*0.813*
RD	16.330	16.576	8.200	7.839
	0.266	*0.269*	*0.596*	*0.614*
ERROR	-0.129	-0.127	-0.129	-0.130
	0.115	*0.122*	*0.154*	*0.154*
GROWTH	-3.011	-3.014	-3.142	-3.144
	0.216	*0.217*	*0.199*	*0.198*
FF_BETA		0.332		-0.158
		0.367		*0.689*
FF_RES_VOL			0.352***	0.363***
			0.000	*0.000*
KAZI	-0.004***	-0.004***	-0.003***	-0.003***
	0.000	*0.000*	*0.004*	*0.004*
N	1673	1673	1673	1673
adj_R2	*0.861*	*0.861*	*0.863*	*0.863*

The table reports OLS coefficient estimates based on robust heteroscedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors (having a bandwidth of 2). The base sample comprises 1,714 yearly observations from 185 firms (we loose firms because of missing values) over the time period from 1994 (1993 after dating ACSI values 3 month backwards) to 2012. The dependent variable is the ICC according to Gebhardt et al. (2001) and the variable of interest is ACSI as presented in section 2.3.4. We include year-fixed effects in the regressions of panel A whereas we include year-fixed and firm-fixed effects in panel B, but do not report their results. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A4: Analysis of ICC (Easton, 2004) Sensitivity to ACSI

Panel A: Year-Fixed Effects

	(1)	(2)	(3)	(4)
ACSI	-0.062***	-0.053***	-0.047***	-0.045**
	0.001	*0.004*	*0.009*	*0.012*
SIZE	0.006***	0.006***	0.007***	0.007***
	0.000	*0.001*	*0.000*	*0.000*
LEV	0.018*	0.015*	0.012	0.012
	0.058	*0.079*	*0.189*	*0.191*
BTM	-0.028**	-0.024**	-0.025**	-0.024*
	0.024	*0.037*	*0.047*	*0.051*
ROA	-6.306***	-5.391***	-5.088***	-4.905***
	0.000	*0.000*	*0.000*	*0.000*
RD	6.553	4.484	0.127	0.013
	0.276	*0.458*	*0.984*	*0.998*
ERROR	0.123*	0.140*	0.152**	0.155**
	0.088	*0.070*	*0.036*	*0.037*
GROWTH	4.713***	3.311*	1.742	1.552
	0.008	*0.073*	*0.398*	*0.456*
FF_BETA		1.081***		0.332
		0.001		*0.322*
FF_RES_VOL			0.420***	0.386***
			0.000	*0.000*
KAZI	0.000	0.000	0.000	0.000
	0.913	*0.865*	*0.759*	*0.754*
N	1553	1553	1553	1553
adj_R2	*0.096*	*0.104*	*0.122*	*0.122*

Panel B: Year-Fixed and Firm-Fixed Effects

	(1)	(2)	(3)	(4)
ACSI	-0.050	-0.051	-0.043	-0.043
	0.113	*0.108*	*0.165*	*0.161*
SIZE	0.010***	0.010***	0.010***	0.010***
	0.004	*0.004*	*0.003*	*0.003*
LEV	0.025**	0.025**	0.023**	0.023**
	0.013	*0.012*	*0.022*	*0.022*
BTM	-0.018	-0.018	-0.017	-0.018
	0.161	*0.157*	*0.180*	*0.172*
ROA	-1.625	-1.654	-1.213	-1.245
	0.299	*0.289*	*0.438*	*0.425*
RD	2.317	2.370	-1.508	-1.873
	0.774	*0.768*	*0.863*	*0.830*
ERROR	0.105*	0.104*	0.115*	0.115*
	0.079	*0.081*	*0.056*	*0.058*
GROWTH	4.948***	4.958***	4.782***	4.791***
	0.004	*0.004*	*0.006*	*0.006*
FF_BETA		-0.083		-0.261
		0.785		*0.391*
FF_RES_VOL			0.132	0.150*
			0.107	*0.070*
KAZI	0.003*	0.003*	0.004*	0.004*
	0.087	*0.088*	*0.054*	*0.053*
N	1553	1553	1553	1553
adj_R2	*0.386*	*0.385*	*0.386*	*0.386*

The table reports OLS coefficient estimates based on robust heteroscedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors (having a bandwidth of 2). The base sample comprises 1,714 yearly observations from 185 firms (we loose firms because of missing values) over the time period from 1994 (1993 after dating ACSI values 3 month backwards) to 2012. The dependent variable is the ICC according to Easton (2004) and the variable of interest is ACSI as presented in section 2.3.4. We include year-fixed effects in the regressions of panel A whereas we include year-fixed and firm-fixed effects in panel B, but do not report their results. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A5: Analysis of the Sensitivity of Monthly Firm Value Decompostion to Interpolated ACSI Values

Panel A: Cash Flow Changes

	(1)	(2)	(3)	(4)	(5)
Δ S_ACSI	-0.003	-0.012***	-0.004	0.010***	0.023***
	0.175	*0.000*	*0.238*	*0.005*	*0.000*
Δ SIZE	0.000	0.000***	0.000***	0.000***	-0.001***
	0.399	*0.000*	*0.000*	*0.000*	*0.000*
Δ BTM	-0.033***	-0.034***	-0.031***	0.016*	0.025***
	0.000	*0.000*	*0.002*	*0.053*	*0.000*
Δ ROA	1.340***	3.359***	4.662***	5.613***	7.189***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
N	9840	9840	9840	9840	9840
adj_R2	*0.084*	*0.16*	*0.165*	*0.16*	*0.163*

Panel B: Cost of Equity Changes

	(1)	(2)	(3)	(4)	(5)
Δ S_ACSI	0.006**	0.016***	0.015***	0.009***	0.003
	0.031	*0.000*	*0.000*	*0.002*	*0.237*
Δ SIZE	0.000	0.000	0.000	0.000**	0.000***
	0.122	*0.338*	*0.405*	*0.017*	*0.000*
Δ BTM	-0.033***	-0.004	0.004	-0.028***	-0.030***
	0.000	*0.386*	*0.626*	*0.000*	*0.000*
Δ ROA	-0.566***	-1.024***	-1.130***	-0.937***	-1.249***
	0.001	*0.000*	*0.000*	*0.000*	*0.000*
N	9840	9840	9840	9840	9840
adj_R2	*0.057*	*0.085*	*0.082*	*0.087*	*0.077*

The table reports OLS coefficient estimates based on robust heteroscedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors (having a bandwidth of 2), similar to the regressions of table 2.6 but with monthly data using interpolated ACSI values as described in a footnote in section 2.5. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A.2 Chapter 3

A.2.1 Derivation of the Distance to Default Measure

In a simple model of a corporate firm with equity and debt investors, Merton (1974) shows that the value of the firm's equity is equal to that of a call option on the assets of the firm, where the strike price is the book value of the debt of the firm. The option matures with the debt of the firm, at T. According to Black and Scholes (1973) the risk-neutral valuation of the option is as follows:

$$E_t = A_t \Phi(d) - D_t \exp(-r_f T)\Phi(d - \sigma_A \sqrt{T}), \tag{A.3}$$

where

$$d = \frac{\log(A_t/D_t) + (r_f + \sigma_A^2/2)T}{\sigma_A \sqrt{T}}$$

The t in the index stands for the time at which the variable realizes its value. E_t is the value of equity of the firm, $\Phi(x)$ is the cumulative standard normal distribution at x, A_t is the value of assets, D_t is the book value of debt, r_f is the risk-free rate and σ_A is the volatility of the assets.

The probability of default here is the probability that the value of the underlying, the assets of the firm, is below the strike price, the book value of the debt of the firm.

$$PD_t = \Phi\left(-\frac{\log(A_t/D_t) + (\mu_A - \sigma_A^2/2)T}{\sigma_A \sqrt{T}}\right) \tag{A.4}$$

where PD_t is the probability of default and μ_A is the drift in the stochastic process of the assets.[71]

The term in the parentheses of the standard normal distribution above is the lower bound below which the firm will default, hence the established the terminology Distance to Default (DD). We take the absolute value though, since the result should resemble a distance.

$$DD_t = \frac{\log(A_t/D_t) + (\mu_A - \sigma_A^2/2)T}{\sigma_A\sqrt{T}} \tag{A.5}$$

Note that although the option is valued risk-neutrally, we use observed and not risk-neutral probabilities, since we are interested in predicting observed default proxies through observed rating downgrades. In other words, options are valued using the expected value of the payoff function at maturity using probabilities, as if all agents were risk-neutral (Black and Scholes, 1973). Using such probabilities would give us though a DD estimate based on theoretical risk-neutral probabilities. Since however our aim is to help predict observed (future realized) defaults, we need to estimate observed probabilities. In this case we are not interested in the theoretically sound valuation of the option, since we only use the valuation formula as a technique to derive DD estimates.[72] We further price the option at date t, assuming that it came into effect at that exact same date. Otherwise T would become $T - t$ in Equations A.4 and A.5.

In order to estimate the (market) value of the assets A_t, the drift μ_a and the volatility σ_A, we go back to the valuation formula of the option in Equation A.3. We further use Itô's Lemma

[71] The assets of the firms are assumed to follow the following geometric Brownian Motion, which explains the use of the standard normal distribution above (W_t is a standard Wiener process).

$$dA_t = \mu_A A_t dt + \sigma_A V_A dW_t$$

[72] A risk-neutral valuation would substitute the drift μ_A with the risk-free rate r_f in Equation (A.5).

(see e.g., McKean, 1969) on the function defined by Equation A.3, $E_t = f(A_t, t)$. From the diffusion term (i.e. the term concerning the Wiener process) we obtain the following second equation for equity volatility σ_E:

$$\sigma_E = \Phi(d)\frac{A_t}{E_t}\sigma_A \tag{A.6}$$

Following Hillegeist et al. (2004) and the SAS code provided in their appendix, we estimate A_t and σ_A using the system of equations of A.3 and A.6. μ_a is then estimated as the asset return, $(A_t - A_{t-1})/A_{t-1}$.[73] However, although we use the algorithm proposed by Hillegeist et al. (2004), we adapt it to daily data along the lines of Distinguin et al. (2006). We define maturity $T = 1$ and the risk-free rate r_f as the 12-month interbank rate[74] (e.g., (Hillegeist et al., 2004; Vassalou and Xing, 2004; Distinguin et al., 2006)). E_t, σ_E and r_f are computed as the 3 month averages of daily values at least 2 month after the fiscal quarter end. To solve the non-linear system of equations of A.3 and A.6 using a Newton search algorithm (minimization heuristic), we set the starting value of A_t to $(E_t + D_t)$ and the starting value of of σ_A to $\sigma_E \cdot E_t/(E_t + D_t)$. We heuristically solve this system of equations for each BHC-quarter and use the results to calculate PD_t and DD_t according to Equations A.4 and A.5, respectively.

[73] If μ_a is less than r_f, it is set to r_f and if μ_a is greater than one it is set to one.

[74] `http://research.stlouisfed.org/fred2/series/USD12MD156N#`. Hillegeist et al. (2004); Vassalou and Xing (2004) use the 1-year T-bill rate.

A.2.2 Details on Downgraded and Upgraded BHCs

Table A6: Downgraded and Upgraded BHCs

BHC Name	Date of Downgrade	BHC Name	Date of Upgrade
Baybanks Inc	Jul 1990	Affiliated Bancshares of Colorado	Nov 1992
MNC Financial	Oct 1990	Equimark Corp	Jan 1993
First City Bancorp of Texas	Oct 1990	Signet Banking Corp	Feb 1993
Baltimore Bancorp	Nov 1990	Colorado National Bancshares	Jun 1993
Midlantic Corp	Dec 1990	Baybanks	Jul 1993
Signet Banking Corp	Jan 1991	Bank South Corp	Nov 1993
Riggs National Corp	Jan 1991	Mark Twain Bancshares	May 1994
First Commerce Corp	Jan 1991	Baltimore Bancorp	Nov 1994
Bank South Corp	Nov 1991	Midlantic	Jan 1995
Magna Group	Jan 1992	Magna Group	Jul 1998
Riggs National Corp	Oct 2000	Riggs National Corp	Aug 1998
Provident Banking Corp	Mar 2003	Huntington Bancshares	Dec 2010
Doral Financial Corp	Apr 2005	Associated Banc Corp	May 2011
First Bancorp	Dec 2005	Wilmington Trust Corp	May 2011
Colonial Bancgroup	Jan 2009	Regions Financial Corp	Mar 2012
BanPonce Corp	Apr 2009		
Huntington Bancshares	Jun 2009		
Synovus Financial Corp	Jun 2009		
Whitney Holding Corp	Jun 2009		
Citizens Republic Bancorp	Jun 2009		
Associated Banc Corp	Nov 2009		
Wilmington Trust Corp	Feb 2010		
Marshall & Ilsley Corp	Oct 2010		
Regions Financial Corp	Nov 2010		

This table provides detailed information on banks that experience a downgrade to non-investment grade status (BB+ or worse) or an upgrade to investment grade status (BBB- or better) during the sample period together with the respective date of the downgrade (upgrade). Such downgrades (upgrades) are recorded as ‘distress’ (‘recovery’) events in Section 3.4.2.

A.2.3 Further Tables

Table A7: Direct Market Discipline: Nonlinear Analysis of IRP Sensitivity to Public Risk Indicators

	ols	p10	p30	p50	p70	p90
EQUITY	-0.128***	-0.071*** °	-0.097*** °	-0.094*** °	-0.104*** °	-0.160*** °
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
LLR	-0.167*	-0.158**	-0.170***	-0.141***	-0.143**	-0.158**
	0.053	*0.033*	*0.001*	*0.002*	*0.011*	*0.040*
ROA	0.988***	1.520*** °	1.140***	0.577*** °	0.471*** °	0.821***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.003*
ROA_VOL	-1.111***	-2.232*** °	-1.403***	-1.029***	-0.546*** °	-0.363°
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.107*
EFFICIENCY	0.000	0.000*** °	0.000*** °	0.000** °	0.000	0.000
	0.303	*0.000*	*0.006*	*0.014*	*0.481*	*0.769*
PAST_DUE	0.359***	0.295***	0.258***	0.297***	0.380***	0.280**
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.033*
CHARGEOFFS	-1.402***	-0.979**	-0.890***	-0.831*** °	-0.883**	-0.505
	0.006	*0.021*	*0.007*	*0.003*	*0.015*	*0.323*
LLP	1.212**	-0.421°	0.140°	0.417°	0.777**	3.059*** °
	0.020	*0.407*	*0.664*	*0.104*	*0.029*	*0.000*
LOANS	0.005	-0.006°	0.002	0.005	0.010**	0.012**
	0.352	*0.179*	*0.639*	*0.114*	*0.015*	*0.043*
EQU_INV	0.831***	0.823***	0.627*** °	0.326*** °	0.071°	-0.128°
	0.000	*0.000*	*0.000*	*0.000*	*0.601*	*0.569*
COMM_LOANS	-0.016***	0.004°	-0.009*** °	-0.011*** °	-0.007** °	-0.025***
	0.000	*0.166*	*0.000*	*0.000*	*0.011*	*0.000*
CONS_LOANS	0.017***	0.025*** °	0.025*** °	0.020***	0.012***	-0.012** °
	0.001	*0.000*	*0.000*	*0.000*	*0.000*	*0.015*
LIQUIDITY	-0.020***	-0.037*** °	-0.025***	-0.020***	-0.013***	-0.004°
	0.000	*0.000*	*0.000*	*0.000*	*0.002*	*0.498*
CORE_DEP	-0.020***	-0.015*** °	-0.018***	-0.024*** °	-0.030*** °	-0.040*** °
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
LARGE_DEP	-0.028***	-0.014*** °	-0.033***	-0.042*** °	-0.048*** °	-0.060*** °
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
DEP_COST	1.028***	0.376** °	0.435*** °	0.661*** °	0.888***	1.357***
	0.000	*0.039*	*0.001*	*0.000*	*0.000*	*0.000*
GAP	0.013	0.021*	0.004	-0.018* °	-0.013°	0.020
	0.450	*0.058*	*0.629*	*0.059*	*0.287*	*0.245*
SIZE	0.001***	0.001*** °	0.001***	0.001***	0.001***	0.001*
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.084*
UNEMPL	0.030	0.049**	0.015	0.004°	0.011	0.040
	0.203	*0.028*	*0.224*	*0.732*	*0.452*	*0.133*
ERROR	0.040**	0.024*	0.033**	0.049***	0.047***	0.042**
	0.026	*0.068*	*0.036*	*0.001*	*0.001*	*0.040*
GROWTH	29.954***	16.300*** °	23.661*** °	28.783*** °	33.100*** °	42.529*** °
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
N	13341	13341	13341	13341	13341	13341

The table reports quantile regression coefficient estimates for the quantiles 10, 30, 50, 70 and 90 respectively (see column headers) which are compared to OLS coefficient estimates with robust heteroscedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors (having a bandwidth of 3) and quarter-fixed effects in the first column. The sample comprises 13,341 quarterly observations from 551 BHCs over the time period from 1992 to 2012 (we loose years because of missing values). The dependent variable is the IRP as presented in Section 3.2. All other variable definitions are given in Table 3.1. ° means that the estimator for the corresponding quantile is signifincantly different from the OLS estimator with p-value less than 0.05. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A8: Indirect Market Discipline: Discrete Choice Regressions for Distress Prediction with PAST_DUE

Panel A: Excluding IRP

	1	2	4	6	8	10	12
DD	0.832	0.617**	0.371***	0.403***	0.606**	1.119	1.143
	0.170	*0.029*	*0.001*	*0.003*	*0.028*	*0.308*	*0.238*
RET_VOL	0.933	1.093	0.955	1.030	1.215	1.101	0.928
	0.752	*0.633*	*0.829*	*0.937*	*0.474*	*0.845*	*0.864*
FF_BETA	1.350	0.135**	0.868	3.919	0.342	0.527	0.876
	0.663	*0.015*	*0.850*	*0.152*	*0.247*	*0.538*	*0.883*
FF_RES_VOL	1.382	1.189	0.974	0.479	0.625	0.486	0.877
	0.236	*0.503*	*0.936*	*0.182*	*0.337*	*0.329*	*0.831*
EQUITY	0.952	1.183*	0.980	1.112	1.154	1.294**	1.144
	0.779	*0.095*	*0.861*	*0.324*	*0.168*	*0.016*	*0.323*
PAST_DUE	3.114	0.612	1.118	1.192	1.631	9.603*	6.475
	0.223	*0.754*	*0.917*	*0.869*	*0.738*	*0.063*	*0.238*
EFFICIENCY	1.000*	0.999*	1.000	0.999**	1.000	1.000	1.000
	0.053	*0.064*	*0.303*	*0.025*	*0.607*	*0.334*	*0.553*
ROA	0.241**	1.468	0.280*	0.097*	2.889	0.113	0.617
	0.024	*0.624*	*0.089*	*0.060*	*0.613*	*0.338*	*0.824*
LIQUIDITY	0.984	1.033	1.011	0.995	0.977	0.956	0.991
	0.584	*0.219*	*0.673*	*0.880*	*0.459*	*0.190*	*0.740*
SIZE	0.979*	0.992	0.968*	0.974*	0.992	0.991	0.993
	0.066	*0.360*	*0.054*	*0.086*	*0.381*	*0.313*	*0.406*
N	3521	3486	3348	3210	3074	2938	2807
pctevent	0.341	0.316	0.358	0.312	0.325	0.34	0.392
pseudo_R2	0.28	0.277	0.266	0.238	0.098	0.11	0.047
likelihood	116.12	108.09	117.45	103.69	121.64	119.19	137.33
wald	58.575**	37.531**	37.843**	21.264**	11.543	12.660	5.767

Panel B: Including IRP

	1	2	4	6	8	10	12
DD	0.818	0.604**	0.412***	0.452***	0.648*	1.124	1.149
	0.152	*0.026*	*0.003*	*0.008*	*0.054*	*0.268*	*0.213*
RET_VOL	0.928	1.074	0.966	1.058	1.304	1.232	0.952
	0.732	*0.713*	*0.876*	*0.876*	*0.338*	*0.672*	*0.911*
FF_BETA	1.357	0.139**	0.842	3.296	0.246	0.248	0.642
	0.657	*0.017*	*0.826*	*0.219*	*0.159*	*0.245*	*0.647*
FF_RES_VOL	1.395	1.219	0.862	0.450	0.527	0.383	0.811
	0.224	*0.475*	*0.659*	*0.121*	*0.209*	*0.212*	*0.736*
IRP	0.969	0.965	1.242***	1.303**	1.331**	1.283***	1.195**
	0.698	*0.718*	*0.001*	*0.021*	*0.011*	*0.002*	*0.019*
EQUITY	0.957	1.191*	0.974	1.093	1.151	1.303**	1.167
	0.801	*0.092*	*0.815*	*0.381*	*0.148*	*0.011*	*0.251*
PAST_DUE	3.140	0.642	1.220	0.995	1.802	13.574**	6.972
	0.224	*0.777*	*0.837*	*0.996*	*0.683*	*0.038*	*0.227*
EFFICIENCY	1.000*	0.999*	1.000	0.999**	1.000	1.000	1.000
	0.051	*0.081*	*0.624*	*0.013*	*0.552*	*0.398*	*0.541*
ROA	0.253**	1.494	0.146**	0.077**	1.797	0.078	0.451
	0.032	*0.607*	*0.019*	*0.044*	*0.771*	*0.267*	*0.715*
LIQUIDITY	0.982	1.033	1.019	1.000	0.976	0.950	0.991
	0.557	*0.218*	*0.496*	*0.994*	*0.457*	*0.164*	*0.758*
SIZE	0.979*	0.992	0.965*	0.973*	0.990	0.989	0.992
	0.071	*0.366*	*0.058*	*0.056*	*0.258*	*0.214*	*0.329*
N	3521	3486	3348	3210	3074	2938	2807
pctevent	0.341	0.316	0.358	0.312	0.325	0.34	0.392
pseudo_R2	0.281	0.278	0.321	0.272	0.137	0.153	0.07
likelihood	115.98	107.97	108.88	99.100	116.47	113.53	134.05
wald	58.337**	36.102**	51.177**	27.111**	17.420*	18.783**	10.465

Table A8: Indirect Market Discipline: Discrete Choice Regressions for Distress Prediction with PAST_DUE (Continued)

The table reports the results of discrete choice regressions (using a complimentary log-log model) for the prediction of defaults over leads from one to twelve quarters (see column headers). We estimate the regressions including all market based risk indicators presented in panel C of table 3.1 and a set of CAMEL accounting indicators (for variable definitions see panel A of table 3.1). We report results without (Panel A) and including the IRP (panel B). We include quarter-fixed effects such that the regressions are equivalent to a discrete proportional hazard model. *pctevent* is the percentage of BHC-quarters with an event of default. *pseudo_R2* is the coefficient of determination from Nagelkerke (1991) which measures the relative increase in likelihood of the model when the regressors are included and can take on values from zero to one like the regular coefficient of determination. *likelihood* is computed as $-2\log L$ as a measure of goodness of fit of the model, where L is the likelihood function. *wald* is the χ^2 statistic from testing the null that all coefficients of the regressors are jointly zero. p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A9: Indirect Market Discipline: Duration Regressions for Distress Prediction with PAST_DUE

	default	default	default
DD	0.771		0.777
	0.230		*0.210*
RET_VOL	1.691		1.653
	0.227		*0.267*
FF_BETA	0.542		0.478
	0.178		*0.120*
FF_RES_VOL	0.527		0.536
	0.242		*0.258*
IRP		1.172**	1.113
		0.038	*0.131*
EQUITY	1.158	1.126	1.158
	0.224	*0.206*	*0.214*
PAST_DUE	8.771	4.682	5.729
	0.121	*0.179*	*0.242*
EFFICIENCY	1.000	1.000	1.000
	0.486	*0.415*	*0.446*
ROA	0.017**	0.170***	0.015***
	0.010	*0.000*	*0.010*
LIQUIDITY	1.046*	1.059**	1.053**
	0.063	*0.017*	*0.041*
SIZE	0.982	0.985	0.982
	0.213	*0.260*	*0.208*
N	145	145	145
pctevent	10.345	10.345	10.345
likelihood	108.47	108.10	106.40
wald	18.162*	20.792**	19.417*

The table reports the results of hazard model regressions for the prediction of BHC defaults. We estimate the regressions including IRP, all market based risk indicators presented in Panel C of Table 3.1 and a set of CAMEL accounting indicators (for variable definitions see Panel A of Table 3.1). All covariates have the values at the beginning of the spell (time of inclusion or of recovery after a default) until eventual default or censorship (exclusion from the sample or end of the sample). *pctevent* is the percentage of BHCs with an event of default. *likelihood* is computed as $-2\log L$ as a measure of goodness of fit of the model, where L is the likelihood function. *wald* is the χ^2 statistic from testing the null that all coefficients of the above regressors are jointly zero. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A10: Indirect Market Discipline: Discrete Choice Regressions for Distress Prediction with CHARGEOFFS

Panel A: Excluding IRP

	1	2	4	6	8	10	12
DD	0.742**	0.504***	0.350***	0.359***	0.623**	1.106	1.120
	0.019	*0.003*	*0.000*	*0.000*	*0.031*	*0.295*	*0.316*
RET_VOL	0.755	0.955	1.014	0.917	1.231	0.925	0.897
	0.215	*0.796*	*0.946*	*0.795*	*0.397*	*0.842*	*0.807*
FF_BETA	1.642	0.265***	0.814	2.481	0.511	1.423	1.599
	0.337	*0.010*	*0.781*	*0.265*	*0.437*	*0.683*	*0.600*
FF_RES_VOL	1.872**	1.287	0.892	0.586	0.675	1.009	1.062
	0.029	*0.298*	*0.730*	*0.254*	*0.367*	*0.986*	*0.917*
EQUITY	1.066	0.986	1.007	1.100	1.180*	1.238**	1.168
	0.686	*0.920*	*0.948*	*0.379*	*0.073*	*0.020*	*0.227*
CHARGEOFFS	0.488	27.687**	0.590	1.790	0.031	0.000	0.000
	0.690	*0.021*	*0.808*	*0.813*	*0.412*	*0.112*	*0.176*
EFFICIENCY	1.000*	1.000	1.000	0.999*	1.000	1.000*	0.999
	0.071	*0.752*	*0.378*	*0.079*	*0.672*	*0.091*	*0.553*
ROA	0.219***	2.300	0.250	0.087**	1.928	0.097	0.293
	0.007	*0.371*	*0.110*	*0.040*	*0.751*	*0.132*	*0.540*
LIQUIDITY	0.980	1.019	1.013	1.000	0.980	0.966	0.985
	0.458	*0.430*	*0.633*	*0.991*	*0.472*	*0.191*	*0.536*
SIZE	0.977**	0.983*	0.969*	0.966*	0.994	0.996	0.996
	0.042	*0.099*	*0.058*	*0.058*	*0.463*	*0.637*	*0.613*
N	4586	4537	4393	4244	4103	3959	3812
pctevent	0.349	0.353	0.273	0.283	0.268	0.303	0.315
pseudo_R2	0.286	0.271	0.266	0.223	0.096	0.078	0.052
likelihood	153.07	156.07	122.19	128.58	137.88	150.60	153.90
wald	73.560**	58.951**	42.496**	25.240**	14.995*	12.646	7.450

Panel B: Including IRP

	1	2	4	6	8	10	12
DD	0.753**	0.540***	0.388***	0.395***	0.636**	1.110	1.115
	0.033	*0.008*	*0.001*	*0.001*	*0.037*	*0.272*	*0.330*
RET_VOL	0.754	1.007	1.035	0.949	1.258	0.922	0.880
	0.215	*0.971*	*0.877*	*0.871*	*0.357*	*0.840*	*0.779*
FF_BETA	1.683	0.221***	0.735	2.175	0.448	1.216	1.433
	0.317	*0.007*	*0.683*	*0.338*	*0.370*	*0.826*	*0.691*
FF_RES_VOL	1.871**	1.151	0.794	0.561	0.629	0.995	1.049
	0.030	*0.589*	*0.502*	*0.204*	*0.300*	*0.993*	*0.935*
IRP	1.020	1.124***	1.228***	1.164*	1.162**	1.129*	1.124*
	0.702	*0.008*	*0.000*	*0.097*	*0.027*	*0.068*	*0.081*
EQUITY	1.065	0.986	0.997	1.095	1.167*	1.230**	1.176
	0.687	*0.917*	*0.974*	*0.363*	*0.083*	*0.022*	*0.204*
CHARGEOFFS	0.488	35.065**	1.522	2.115	0.048	0.000	0.000
	0.693	*0.015*	*0.864*	*0.767*	*0.469*	*0.129*	*0.184*
EFFICIENCY	1.000*	1.000	1.000	0.999*	1.000	1.000	0.999
	0.081	*0.876*	*0.685*	*0.053*	*0.665*	*0.109*	*0.528*
ROA	0.210***	2.021	0.170**	0.085**	1.498	0.088	0.260
	0.007	*0.449*	*0.048*	*0.037*	*0.839*	*0.121*	*0.497*
LIQUIDITY	0.982	1.022	1.025	1.006	0.985	0.969	0.988
	0.500	*0.358*	*0.348*	*0.839*	*0.600*	*0.234*	*0.642*
SIZE	0.977**	0.983	0.966*	0.967*	0.992	0.996	0.995
	0.042	*0.108*	*0.056*	*0.056*	*0.378*	*0.575*	*0.560*
N	4586	4537	4393	4244	4103	3959	3812
pctevent	0.349	0.353	0.273	0.283	0.268	0.303	0.315
pseudo_R2	0.287	0.295	0.317	0.237	0.115	0.091	0.064
likelihood	152.94	150.95	113.80	126.40	135.10	148.61	152.13
wald	74.218**	66.438**	54.554**	28.181**	19.081**	16.085*	10.319

Table A10: Indirect Market Discipline: Discrete Choice Regressions for Distress Prediction with CHARGEOFFS (Continued)

Panel B: Including IRP

The table reports the results of discrete choice regressions (using a complimentary log-log model) for the prediction of defaults over leads from one to twelve quarters (see column headers). We estimate the regressions including all market based risk indicators presented in panel C of table 3.1 and a set of CAMEL accounting indicators (for variable definitions see panel A of table 3.1). We report results without (Panel A) and including the IRP (panel B). We include quarter-fixed effects such that the regressions are equivalent to a discrete proportional hazard model. *pctevent* is the percentage of BHC-quarters with an event of default. *pseudo_R2* is the coefficient of determination from Nagelkerke (1991) which measures the relative increase in likelihood of the model when the regressors are included and can take on values from zero to one like the regular coefficient of determination. *likelihood* is computed as $-2\log L$ as a measure of goodness of fit of the model, where L is the likelihood function. *wald* is the χ^2 statistic from testing the null that all coefficients of the regressors are jointly zero. p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A11: Indirect Market Discipline: Duration Regressions for Distress Prediction with CHARGEOFFS

	default	default	default
DD	0.916		0.898
	0.554		*0.512*
RET_VOL	0.622		0.646
	0.268		*0.320*
FF_BETA	1.072		0.682
	0.885		*0.484*
FF_RES_VOL	2.059		1.911
	0.164		*0.231*
IRP		1.110***	1.145***
		0.000	*0.000*
EQUITY	1.266*	0.976	1.291**
	0.050	*0.823*	*0.030*
CHARGEOFFS	7.512	0.484	12.785
	0.254	*0.703*	*0.155*
EFFICIENCY	1.000	1.000***	1.000
	0.442	*0.001*	*0.327*
ROA	0.020**	0.189***	0.009***
	0.018	*0.008*	*0.006*
LIQUIDITY	1.046**	1.032	1.074***
	0.037	*0.117*	*0.003*
SIZE	0.978	0.975	0.979
	0.278	*0.168*	*0.315*
N	151	156	151
pctevent	12.583	14.744	12.583
likelihood	142.95	170.57	132.88
wald	19.907**	31.935**	27.354**

The table reports the results of hazard model regressions for the prediction of BHC defaults. We estimate the regressions including IRP, all market based risk indicators presented in Panel C of Table 3.1 and a set of CAMEL accounting indicators (for variable definitions see Panel A of Table 3.1). All covariates have the values at the beginning of the spell (time of inclusion or of recovery after a default) until eventual default or censorship (exclusion from the sample or end of the sample). *pctevent* is the percentage of BHCs with an event of default. *likelihood* is computed as $-2\log L$ as a measure of goodness of fit of the model, where L is the likelihood function. *wald* is the χ^2 statistic from testing the null that all coefficients of the above regressors are jointly zero. Two-tailed p-values in italic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A.3 Chapter 4

A.3.1 Derivation of the First Weighted Least Squared Model (WLS(1))

In this subsection of the appendix I derive the Model (WLS(1)) along the lines of Nekrasov and Ogneva (2011). Integrating the regression Model (4.3) and the related equations into the optimization Problem (P), I get the following expanded optimization problem:

$$\begin{cases} \min\limits_{\hat{\gamma}_0,\hat{\gamma}_1,\hat{\lambda}_r,\hat{\lambda}_g,\epsilon^r_{i,t},\epsilon^g_{i,t}} & \sum\limits_i w^i_r(\epsilon^r_{i,t})^2 + w^i_g(\epsilon^g_{i,t})^2 \\ \text{s.t.} & \dfrac{eps_{i,t+2} + r_i dps_{i,t+1}}{p_{i,t}} = \hat{\gamma}_0 + \hat{\gamma}_1 \dfrac{eps_{i,t+1}}{p_{i,t}} + \epsilon_{i,t} \\ & \epsilon_{i,t} = b(r_i - \bar{r}) + \left(c + \dfrac{eps_{i,t+1}}{p_{i,t}}\right)(g_i - \bar{g}) \\ & r_i = \bar{r} + \hat{\lambda}_r X^r_{i,t} + e^r_{i,t} \\ & g_i = \bar{g} + \hat{\lambda}_g X^g_{i,t} + e^g_{i,t} \end{cases} \tag{P1}$$

where $\hat{\gamma}_0$ and $\hat{\gamma}_1$ are possible realizations for the coefficient vectors γ_0 and γ_1 respectively. I substitute the corresponding equations for $\epsilon_{i,t}$, r_i and g_i into the first condition of the optimization Problem (P1) and arrive at the following equivalent problem:

$$\begin{cases} \min\limits_{\hat{\gamma}_0,\hat{\gamma}_1,\hat{\lambda}_r,\hat{\lambda}_g,\epsilon^r_{i,t},\epsilon^g_{i,t}} & \sum\limits_i w^i_r(\epsilon^r_{i,t})^2 + w^i_g(\epsilon^g_{i,t})^2 \\ \text{s.t.} & \dfrac{eps_{i,t+2} + r_i dps_{i,t+1}}{p_{i,t}} = \hat{\gamma}_0 + \hat{\gamma}_1 \dfrac{eps_{i,t+1}}{p_{i,t}} + b\hat{\lambda}_r X^r_{i,t} + \left(c + \dfrac{eps_{i,t+1}}{p_{i,t}}\right)\hat{\lambda}_g X^g_{i,t} + \nu_{i,t} \\ & \nu_{i,t} = b\epsilon^r_{i,t} + \left(c + \dfrac{eps_{i,t+1}}{p_{i,t}}\right)\epsilon^g_{i,t} \end{cases} \tag{P2}$$

I then rearrange the second condition of the optimization Problem (P2) and use its first order condition (FOC)[75] to derive an optimization problem which is equivalent to a WLS model.

[75]Note that the target function I am optimizing is a sum of non-negative terms. Hence the FOC of the sum is equivalent to the set of FOCs of its summands.

$$\Rightarrow\ \epsilon^g_{i,t} = \frac{\nu_{i,t} - b\epsilon^r_{i,t}}{\left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right)} \tag{A.7}$$

$$\Rightarrow\ \frac{\partial}{\partial \epsilon^r_{i,t}} \left[w^i_r (\epsilon^r_{i,t})^2 + w^i_g \left(\frac{\nu_{i,t} - b\epsilon^r_{i,t}}{\left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right)} \right)^2 \right] \stackrel{!}{=} 0$$

$$\Leftrightarrow\ 2w^i_r \epsilon^r_{i,t} - 2w^i_g b \frac{\nu_{i,t} - b\epsilon^r_{i,t}}{\left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right)^2} = 0$$

$$\Leftrightarrow\ \epsilon^r_{i,t} = \frac{w^i_g b \nu_{i,t}}{w^i_r \left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right)^2 + w^i_g b^2} \tag{A.8}$$

Inserting the result from Equation (A.8) into Equation (A.7) yields the following expression for $\epsilon^g_{i,t}$:

$$\epsilon^g_{i,t} = \frac{w^i_r \left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right) \nu_{i,t}}{w^i_r \left(c + \frac{eps_{i,t+1}}{p_{i,t}}\right)^2 + w^i_g b^2} \tag{A.9}$$

Finally, inserting the results from Equations (A.8) and (A.9) into the target function of the optimization Problem (P2), I arrive the following optimization problem which is equivalent to the Model (WLS(1)) with weights w^i.

$$\begin{cases} \min\limits_{\hat{\gamma}_0,\hat{\gamma}_1,\hat{\lambda}_r,\hat{\lambda}_g,\epsilon^r_{i,t},\epsilon^g_{i,t}} & \sum\limits_i w^i(\nu_{i,t})^2 \\ \text{s.t.} & \dfrac{eps_{i,t+2}+r_i dps_{i,t+1}}{p_{i,t}} = \hat{\gamma}_0 + \hat{\gamma}_1\dfrac{eps_{i,t+1}}{p_{i,t}} + b\hat{\lambda}_r X^r_{i,t} + \left(c+\dfrac{eps_{i,t+1}}{p_{i,t}}\right)\hat{\lambda}_g X^g_{i,t} + \nu_{i,t} \\ & w^i = \dfrac{w^i_r w^i_g(\nu_{i,t})^2}{w^i_r\left(c+\dfrac{eps_{i,t+1}}{p_{i,t}}\right)^2 + w^i_g b^2} \end{cases} \tag{P3}$$

A.3.2 Derivation of the Second Weighted Least Squared Model (WLS(2))

In this subsection of the appendix I derive the Model (WLS(2)) in my approach as done in Nekrasov and Ogneva (2011) and in Subsection A.3.1. Integrating the regression Model (4.9) and the related equations into the optimization Problem (Q), I get the following expanded optimization problem:

$$\begin{cases} \min\limits_{\hat{\beta}_0,\hat{\beta}_1,\hat{\beta}_2,\hat{\lambda}_e,\hat{\lambda}_d,\eta^e_{i,t},\eta^d_{i,t}} & \sum\limits_i w^i_e(\eta^e_{i,t})^2 + w^i_d(\eta^d_{i,t})^2 \\ \text{s.t.} & r_{i,t}(r_{i,t}-g_{i,t})p_{i,t} = \hat{\beta}_0 + \hat{\beta}_1(-(1+g_{i,t}))\hat{\beta}_2 r_{i,t} + \eta_{i,t} \\ & \eta_{i,t} = -g_{i,t}\eta^e_{i,t} + r_{i,t}\eta^d_{i,t} \\ & eps_{i,t+1} = \overline{eps_{t+1}} + \lambda_e X^e_{i,t} + \eta^e_{i,t} \\ & eps_{i,t+2} = \overline{eps_{t+2}} + \lambda_e X^e_{i,t} + \eta^e_{i,t} \\ & dps_{i,t+1} = \overline{dps_{t+1}} + \lambda_d X^d_{i,t} + \eta^d_{i,t} \end{cases} \tag{Q1}$$

where $\hat{\beta}_0$, $\hat{\beta}_1$ and $\hat{\beta}_2$ are possible realizations for the coefficient vectors β_0, β_1 and β_2 respectively.I substitute the corresponding equations for $\eta_{i,t}$, $eps_{i,t+1}$, $eps_{i,t+2}$ and $dps_{i,t+1}$ into the first condition of the optimization Problem (Q1) and arrive at the following equivalent problem:[76]

[76]Note that I assume that $eps_{i,t+1}$ and $eps_{i,t+2}$ behave identically regarding their deviation from their respective mean. This means that their related condition in the optimization model is treated as one.

$$\begin{cases} \min\limits_{\hat{\beta}_0,\hat{\beta}_1,\hat{\beta}_2,\hat{\lambda}_e,\hat{\lambda}_d,\eta^e_{i,t},\eta^d_{i,t}} & \sum\limits_i w^i_e(\eta^e_{i,t})^2 + w^i_d(\eta^d_{i,t})^2 \\ \text{s.t.} & r_{i,t}(r_{i,t}-g_{i,t})p_{i,t} = \hat{\beta}_0 + \hat{\beta}_1(-(1+g_{i,t})) + \hat{\beta}_2 r_{i,t} \\ & \qquad + (-g_{i,t})\lambda_e X^e_{i,t} + r_{i,t}\lambda_d X^d_{i,t} + \psi_{i,t} \\ & \psi_{i,t} = -g_{i,t}\eta^e_{i,t} + r_{i,t}\eta^d_{i,t} \end{cases} \tag{Q2}$$

I then rearrange the second condition of the optimization Problem (Q2) and use its first order condition (FOC)[77] to derive an optimization problem which is equivalent to a WLS model.

$$\Rightarrow \; \eta^d_{i,t} = \frac{\psi_{i,t} + g_{i,t}\eta^e_{i,t}}{r_{i,t}} \tag{A.10}$$

$$\Rightarrow \; \frac{\partial}{\partial \eta^e_{i,t}}\left[w^i_e(\eta^e_{i,t})^2 + w^i_d\left(\frac{\psi_{i,t}+g_{i,t}\eta^e_{i,t}}{r_{i,t}}\right)^2\right] \stackrel{!}{=} 0$$

$$\Leftrightarrow \; 2w^i_e\eta^e_{i,t} + 2w^i_d g_{i,t}\frac{\psi_{i,t}+g_{i,t}\eta^e_{i,t}}{r^2_{i,t}} = 0$$

$$\Leftrightarrow \; \eta^e_{i,t} = -\frac{w^i_d g_{i,t}\psi_{i,t}}{w^i_e r^2_{i,t} + w^i_d g^2_{i,t}} \tag{A.11}$$

Inserting the result from Equation (A.11) into Equation (A.10) gives the following expression for $\eta^d_{i,t}$:

$$\eta^d_{i,t} = \frac{w^i_e r_{i,t}\psi_{i,t}}{w^i_e r^2_{i,t} + w^i_d g^2_{i,t}} \tag{A.12}$$

Finally, inserting the results from Equations (A.11) and (A.12) into the target function of the optimization Problem (Q2), I arrive the following optimization problem which is equivalent to the Model (WLS(2)) with weights z^i.

[77] Again here the target function is a sum of non-negative terms. Hence the FOC of the sum is equivalent to the set of FOCs of its summands.

$$
\begin{cases}
\min\limits_{\hat{\beta}_0,\hat{\beta}_1,\hat{\beta}_2,\hat{\lambda}_e,\hat{\lambda}_d,\eta^e_{i,t},\eta^d_{i,t}} & \sum\limits_i z^i(\psi_{i,t})^2 \\
\text{s.t.} & r_{i,t}(r_{i,t}-g_{i,t})p_{i,t} = \hat{\beta}_0 + \hat{\beta}_1(-(1+g_{i,t})) + \hat{\beta}_2 r_{i,t} \\
& \qquad + (-g_{i,t})\lambda_e X^e_{i,t} + r_{i,t}\lambda_d X^d_{i,t} + \psi_{i,t} \\
& z^i = \dfrac{w^i_e w^i_d}{w^i_e r^2_{i,t} + w^i_d g^2_{i,t}}
\end{cases}
\tag{P3}
$$

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