High Risk, Low Returns?

An Empirical Study of Default Risk and Expected Returns in the Nordics

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Abstract

The traditional risk-return relationship suggests that higher risk should yield higher returns, yet this pattern does not consistently hold in the case of default risk. Hence, this thesis examines the relationship between default risk and expected stock returns in the Nordics between 2005 and 2023. In contrast to most prior studies that rely on realized returns, this study uses expected returns proxied by the implied cost of capital (ICC). The analysis is based on 3,058 firm-year observations for listed Nordic manufacturing and industrial firms and proceeds in two steps. Firstly, portfolio sorts and cross-sectional regressions are applied to examine general patterns. Secondly, piecewise linear regressions are used to explore potential nonlinearity. The first analysis reveals a statistically significant but economically negligible relationship between default risk and expected returns. However, allowing for nonlinearity in the second analysis reveals that expected returns decline across the bottom 85% of the default risk distribution and flatten for the top 15% of firms. This turning point occurs at a probability of failure of approximately 1.15%, suggesting that beyond this threshold, further increases in default risk no longer translate into meaningfully lower expected returns.

Keywords:

Risk-return relationship, Default risk, Implied cost of capital (ICC)

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1. Introduction

> "Investors should always keep in mind that the most important metric is not the returns achieved, but the returns weighed against the risks incurred." (Seth Klarman, 2007)[1]

The above quote relates to the risk-return tradeoff, a concept that lies at the core of asset pricing. First formalized by Markowitz (1952), the principle suggests that investors demand higher expected returns as compensation for taking on greater risk. Within the topic of risk, a critical distinction arises between two key types: variability risk and default risk.[2] Variability risk reflects fluctuations in firm performance due to changes in the operating environment, while default risk captures the likelihood that a firm fails to meet its financial obligations and subsequently enters financial distress. While asset pricing theory has reached consensus on how variability risk is priced, typically as a systematic component captured by models such as CAPM, there is considerably less agreement on the nature of default risk. Some argue it is largely idiosyncratic and therefore diversifiable and unpriced, while others maintain that it has systematic elements linked to macroeconomic conditions.

In empirical applications, the pricing of default risk also remains contested, with much of the disagreement arising from the method used to estimate expected returns. Most studies adopt one of two approaches: 1) backward-looking realized returns, or 2) a forward-looking implied cost of capital (ICC).[3] The majority of research employing the first approach finds a negative relationship between default risk and realized stock returns (e.g., Dichev, 1998; Griffin & Lemmon, 2002; Campbell et al., 2008; Fama & French, 2006; Breig & Elsas, 2009; George & Hwang, 2010). This finding is commonly referred to as the financial distress risk anomaly. Given these results, several studies raise methodological concerns, pointing to potential measurement errors associated with the realized return approaches (e.g., Garlappi & Yan, 2011; Von Kalckreuth, 2005; Campbell et al., 2008; Sharpe, 1978).

To investigate this further, various studies turn to the ICC, which Pastor et al. (2008) argue offers stronger evidence of a positive intertemporal risk-return trade-off than realized return measures. Similarly, Chava and Purnanandam (2010) argue that while a negative relationship between bankruptcy risk and realized stock returns can indicate market inefficiency, it is unclear why rational investors are not exploiting this. They instead suggest that the relationship arises from the reliance on noisy ex post realized returns in prior studies to estimate the ex ante expected return. By employing the ICC, Chava and Purnanandam find a strong and statistically significant positive relationship between default risk and expected returns in the U.S. market.

The conflicting findings suggest that the choice of expected return proxy plays an important role in shaping the observed risk-return relationship. Although the ICC-based evidence aligns more closely with theoretical predictions, research on the pricing of default risk using this

[1] Seth Klarman is a billionaire investor, hedge fund manager, and author, widely recognized as a leading advocate of value investing.

[2] The terms default risk, bankruptcy risk, and financial distress risk will be used interchangeably in this study, as is done by Dichev (1998), despite not having the exact same meaning (Altman & Hotchkiss, 2006).

[3] For a given company and year, the ICC is computed as the internal rate of return (IRR) that equates the present value of estimated cash flows to the current market value.

method remains relatively limited. Chava and Purnanandam's (2010) study remains the only prominent application of the ICC in this context. However, since their analysis focuses solely on the U.S. market and covers data only up to 2005, it remains uncertain whether their findings generalize to other markets and/or more recent periods.

This study aims to address this research gap by examining the relationship between expected returns, proxied as the ICC, and default risk on the Nordic market between 2005 and 2023. The analysis is guided by the following research question: *What is the relationship between default risk and expected returns in the Nordic market when expected returns are proxied by the ICC?* The ICC is estimated using the residual income valuation (RIV) model. Skogsvik's (1987) accounting-based default risk model will be used to estimate a probability of failure for each firm-year.[4] To ensure robustness, alternative valuation models and default risk measures are also employed.

The remainder of this paper is structured in the following way. Part 2 reviews the literature on the relationship between expected returns and default risk. Part 3 explains the methodological choices of the paper and presents the sample. Part 4 presents the empirical findings and a corresponding analysis of these. Lastly, part 5 and 6 covers a discussion of the results and a part on concluding remarks, respectively.

[4] Skogsvik (1987) originally developed his bankruptcy model for Swedish firms; however, due to the standardized IFRS accounting framework and the similar institutional and legal environments across the Nordic region, it is considered suitable for the broader Nordic market.

2. Literature Review and Hypotheses

This section outlines key literature underlying the relationship between default risk and expected returns. It is organized into five main parts:

- **2.1. Risk in Asset Pricing**: Establishes the theoretical foundation by examining how asset pricing models conceptualize the risk-return relationship.
- **2.2. Default Risk and Expected Return: Evidence Based on Realized Returns**: Reviews empirical studies that rely on realized stock returns as a proxy for expected returns, with a majority documenting a negative relationship between default risk and returns, commonly referred to as the financial distress risk anomaly.
- **2.3. Default Risk and Expected Return: Evidence Based on the ICC:** Presents studies that employ the ICC as a forward-looking proxy for expected returns, with a focus on whether this method yields findings more aligned with theoretical predictions.
- **2.4. Summary of Existing Evidence**: Summarizes the main insights from prior literature and outlines the rationale for investigating the Nordic market.
- **2.5. Research Question and Hypotheses:** States the research question and the two hypotheses that guide the empirical analysis.

2.1. Risk in Asset Pricing

The risk-return tradeoff is a foundational concept in asset pricing, based on the notion that higher risk should lead to higher returns. This principle was first formalized by Markowitz (1952), who demonstrated how investors could construct efficient portfolios by balancing risk and return. Risk is commonly categorized into two types: systematic risk, which affects the entire market, and idiosyncratic risk, which is specific to individual assets. The Capital Asset Pricing Model (CAPM), developed by Sharpe (1964) and Lintner (1965), builds on this foundation by explaining expected returns as compensation for exposure only to systematic risk. Idiosyncratic risk, on the other hand, can be eliminated through diversification and is therefore not compensated. However, not all risks fall cleanly into these two categories. Some may contain elements of both, making their pricing implications less clear. Default risk is one such case. It reflects the possibility that a firm fails to meet its financial obligations, and it remains uncertain whether this risk is fully diversifiable or whether it includes a systematic component that may be priced in the cross-section of returns.

2.1.1. Is Default Risk Systematic or Idiosyncratic?

The classification of default risk as systematic or idiosyncratic remains a subject of debate in asset pricing literature. Some studies suggest that default risk is primarily idiosyncratic, and thus not priced in the same way as systematic risks. For instance, Asquith and Gertner (1994) emphasize how bankruptcy is often driven by inefficient capital structures and firm-level decisions, suggesting that default risk primarily stems from idiosyncratic factors. Similarly,

Avramov et al. (2009) find that credit risk is not significantly associated with systematic risk factors, suggesting that distress is not priced in the same way as variability risk.

Conversely, some research points to systematic elements in distress risk. Denis and Denis (1995) argue that widespread distress in the late 1980s was driven primarily by unanticipated macroeconomic developments, implying a systematic component. George and Hwang (2010) find that firms with high expected distress costs strategically reduce leverage but still remain vulnerable to downturns, indicating ongoing exposure to market-wide risk. Almeida and Philippon (2007) further demonstrate that distress costs increase during recessions, raising risk-adjusted default probabilities and influencing firm value, further supporting the systematic nature of default risk. This raises an important question for empirical asset pricing: is default risk actually rewarded with higher returns?

2.2. Default Risk and Expected Return: Evidence Based on Realized Returns

Empirical studies have taken different approaches to evaluate whether default risk is associated with higher expected returns. A substantial body of empirical research proxies expected returns with realized stock returns, based on the assumption that historical returns converge to expectations over time.

Studying the U.S. market from 1981 to 1995 and estimating default risk via both Altman's (1968) Z-score model and Ohlson's (1980) O-score model, Dichev (1998) finds a negative relationship between default risk and realized returns. This finding contradicts the traditional risk-return relationship developed by Markowitz (1952) and implies that expected returns decline as default risk rises. Griffin and Lemmon (2002) also find a negative relationship between default risk and realized return using Ohlson's (1980) O-score model. Their findings also demonstrate that the low returns of firms with high distress risk are primarily driven by weak stock price performance of these low book-to-market (B/M) firms. Campbell et al. (2008) further complements the literature by employing a dynamic hazard rate estimation methodology and likewise finds that financially distressed stocks generated unexpectedly low returns in the U.S. in the post-1980 period. Fama and French (2006) support these findings by showing that default risk remains negatively associated with realized returns also in a multifactor framework. Drawing on the above studies, Breig and Elsas (2009) extend the analysis by comparing the U.S. to the German market. Their findings show that, consistent with U.S. evidence, default risk in Germany is also negatively correlated with realized returns.

While most studies report a negative association between default risk and realized returns, a few suggest that the relationship may be positive under certain conditions. Vassalou and Xing (2004) find that the relationship between distress risk and returns is positive for small firms and those with high B/M ratios. George and Hwang (2010) conduct a similar study and reinforce this finding. They further show that the positive relationship turns negative when stocks priced below 5 USD are excluded from the sample. Moreover, Ng (2005) finds that higher distress risk is associated with higher future returns, after controlling for size and B/M. Penman et al. (2007) reiterates this finding in a subset of regressions in their study aiming to

explore whether default risk is the underlying driver of the negative relationship between leverage and returns. Here, they show that returns are positively correlated with a probability of failure based on Altman's (1968) Z-score model. To provide greater clarity on the evidence based on realized returns, Table 1 below summarizes key information from each study mentioned above.

Table 1. Summary of Previous Literature on the Relationship Between Default Risk and Realized Returns

This table summarizes key studies on the relationship between default risk and realized returns. It highlights the test specifications, control variables, and findings most relevant to our analysis. Industry is set to "All industries" if unspecified in the study. Control variables include standard regression factors and key firm characteristics like size (MV), B/M, and leverage (D/A). RM denotes market excess return (CAPM); SMB, HML, and UMD represent size, value, and momentum factors from Fama-French models. Approximate no. of observations ("~") is estimated based on the average no. of firms per period multiplied by the duration of the sample period.

Author(s)	Sample Period	No. of Observations	Industry	Country	Default Risk Model	Method	Control variables	Risk-return Relationship
Dichev (1998)	1981-1995	237,628	Industrials	U.S.	Altman's (1968) Z-Score and Ohlson's (1980) O-Score	Fama-MacBeth (1973) regressions on decile portfolios sorted by default risk	MV & B/M	Negative
Griffin & Lemmon (2002)	1965-1996	~39,700	Non-financials	U.S.	Ohlson's (1980) O-Score	Buy-and-hold returns on quintile portfolios sorted by B/M and default risk	MV & B/M	Negative
Campbell et al. (2008)	1981-2003	1,695,036	All industries	U.S.	Dynamic Hazard Rate	Monthly excess returns and alphas from 1) CAPM, 2) 3-factor, and 3) 4-factor regressions on decile portfolios sorted by default risk	1) RM, 2) RM, SMB, HML, 3) RM, SMB, HML, UMD	Negative
Fama & French (2006)	1963-2004	~1,108,500	Non-financials	U.S.	Ohlson's (1980) O-Score	Standard Fama-MacBeth (1973) on monthly cross-section regressions	MV & B/M	Negative

Breig & Elsas (2009)	1990-2006	6,249	Non-financials	Germany	Merton's (1974) Option Pricing	Cross-sectional regressions of portfolio returns on Fama-French factors and a default risk factor, using portfolios sorted by size, B/M, and default risk	MV & B/M	Negative
Vassalou & Xing (2004)	1971-1999	93,702	All industries	U.S.	Merton's (1974) Option Pricing	Plain portfolio analysis of the average return of quintile portfolios double-sorted by size and default risk	MV & B/M	Positive, but only among small firms or firms with high B/M ratios
George & Hwang (2010)	1966-2002	70,633	Non-financials	U.S.	Merton's (1974) Option Pricing	Plain portfolio analysis of the average return of quintile portfolios double-sorted by size and default risk	D/A	Negative; Vassalou & Xing (2004) results not robust after excluding stocks below 5 USD
Ng (2005)	1989-2001	17,832	Non-financials	U.S.	Altman's (1968) Z-Score, Ohlson's (1980) O-Score, and the Black-Scholes Merton Bankruptcy Score (Hillegeist et al., 2004)	Buy-and-hold returns on quintile portfolios sorted by default risk and level of accruals	MV & B/M	Positive, but only if the control variables are included
Penman et al. (2007)	1962-2011	89,795	Non-financials	U.S.	Altman's (1968) Z-Score	Standard cross-sectional regressions on annual raw stock returns	MV	Positive

2.2.1. The Financial Distress Risk Anomaly

The commonly observed negative relationship between default risk and expected returns is known as the financial distress risk anomaly, and challenges the traditional view that higher risk should be rewarded with higher returns. This raises questions about whether the anomaly reflects mispricing or stems from how expected returns are measured. While mispricing is difficult to verify directly, the anomaly has prompted further investigation into whether the pattern instead reflects issues with how expected returns are measured. In this context, researchers highlight three potential sources of measurement related error.

2.2.1.1. Alternative Shareholder Incentives

One of the key concerns with estimating the cost of equity for distressed stocks is that traditional asset pricing models do not account for shareholder incentives beyond stock returns. Garlappi et al. (2008) argue that the default risk-return relationship is affected by shareholder influence. When shareholders have significant influence in distressed firms, they may accept lower stock returns since they can benefit in other ways, such as retaining control of assets and influencing debt restructuring terms. Expanding on this idea, Garlappi and Yan (2011) establish a hump-shaped relationship between distress risk and expected returns. Their findings suggest that while firms with moderate default probabilities tend to generate higher returns, those with extreme distress risk experience declining returns due to shareholder interventions. Furthermore, Von Kalckreuth (2005) notes that for firms close to bankruptcy, non-cash ownership returns, such as strategic influence, restructuring opportunities, or tax advantages may outweigh traditional financial returns.

2.2.1.2 Distortion from Portfolio Dynamics

A second key challenge in evaluating this anomaly is the significant volatility observed in the realized returns of high default risk portfolios. These portfolios are naturally more exposed to firm failures, which imply that overall portfolio performance depends heavily on a small number of stocks that manage to recover or perform well despite their distress risk. This imbalance increases return volatility, as gains from a few outperforming stocks are diluted by the losses from many failing ones, making it difficult to establish a clear risk-return relationship. Rebalancing further distorts return patterns. As firms default or become delisted, they are removed from the portfolio, while stocks that recover and are no longer classified as high default risk also exit. This constant turnover alters the composition of the portfolio, preventing a stable risk-return assessment over time (Chava & Purnanandam, 2010).

2.2.1.3 Noise Associated with Sample Periods

A third possibility is that the negative relationship between financial distress risk and returns is driven by specific conditions within the sample period rather than representing a persistent trend. Campbell et al. (2008) suggest that underperformance could be attributed to adverse macroeconomic conditions or an unexpected shift in equity ownership from individuals to institutions during the analysis period. Rather than structural factors, temporary market fluctuations may drive this pattern, necessitating a longer time horizon to reduce distortions. Sharpe (1978) analyzes a six-year period and argues that unexpected market shocks introduce

noise into asset returns. However, even when extending the analysis to longer sample periods, the relationship between realized returns and risk can still appear negative. Supporting this concern, Mehra and Prescott (1985) show that expected returns derived from forward-looking general equilibrium models are significantly lower than those based on historical returns.

2.3. Default Risk and Expected Return: Evidence Based on the ICC

Given the potential measurement errors inherent in using realized returns as a proxy for expected returns, several researchers advocate for the use of the ICC. The following section outlines literature that either studies the usefulness of the ICC or employs it to examine the relationship between default risk and expected returns.

2.3.1. Introduction to the ICC

The ICC is a forward-looking estimate of expected return based on market prices and expectations of future performance. Rather than relying on historical returns, the ICC is a discount rate derived by reverse engineering from valuation models. Given a firm's current stock price and forecasted future cash flows, the ICC is the internal rate of return that makes the present value of those cash flows equal to the observed market price. This return reflects the market's required compensation for holding the asset. Importantly, the ICC reflects a bankruptcy calibrated cost of equity, as the cash flows used in its estimation are conditional on firm survival. Common valuation models used to estimate the ICC include the dividend discount model (DDM), the RIV model, and the abnormal earnings growth (AEG) model.

To assess the usefulness of the ICC in practice, Gebhardt et al. (2001) examine how it varies with specific firm characteristics. They find that approximately 60% of the cross-sectional variation in future ICC can be attributed to factors such as industry classification, B/M ratio, forecasted long-term growth, and the dispersion in analyst earnings forecasts. Based on these findings, the authors argue for the ICC as the best means to estimate a firm's expected return. This claim is supported by Pastor et al. (2008), who provides strong evidence of a positive intertemporal risk-return trade-off using the ICC as a proxy for expected returns. Nevertheless, the ICC approach is subject to certain limitations. Results can vary depending on model choice, input assumptions, and data quality, with analyst forecasts often subject to bias. Lee et al. (2010) critically evaluate various ICC estimation methods and show that small differences in assumptions can lead to substantial variation in results. They emphasize that terminal value estimates depend heavily on the assumed perpetual growth rate, while earnings forecasts are sensitive to forecast bias. To address concerns about forecast bias, Hou et al. (2012) propose an alternative estimation method based on historical accounting data rather than analyst projections. They find that such a method provides a more reliable estimate for expected returns rather than an ICC based on analyst forecasts.

2.3.2. Evidence of a Positive Default Risk-Return Relationship

Recognizing the ICC as the best proxy for expected return, Chava and Purnanandam (2010) examine its relationship with default risk in the U.S. market between 1980 and 2006. The paper uses two different models to calculate the default risk; the Hazard Rate model which estimates default probability using historical bankruptcy data (inspired by e.g., Shumway, 2001; Chava & Jarrow, 2004; Campbell et al., 2008), and a Merton (1974) inspired option pricing-based model, which translates a distance-to-default to an expected default frequency (EDF). Chava and Purnanandam (2010) estimate the ICC using the DDM. While the ICC serves as the basis for expected returns, the authors subtract the prevailing risk-free rate to arrive at the implied expected risk premium (ERP), which is then used as the return proxy in their analysis.

Using the above method, the authors conduct two types of tests; univariate tests and cross-sectional regressions. In the univariate tests, stocks are sorted into deciles based on default risk, and the ERP is computed for each portfolio. The average probability of failure for the full sample, estimated by the hazard rate model, amounts to 0.5%. Moreover, they find a positive and linear relationship between default risk and ERP, with investors anticipating an annual premium of 8.15% for stocks in the top decile of default risk, compared to 3.24% for those in the bottom decile, under the Hazard Rate model.

Table 2. Univariate Tests: Expected Returns by Default Risk Decile (Chava & Purnanandam, 2010)

This table presents the findings of Chava and Purnanandam's (2010) univariate tests, where 10 portfolios are formed on the basis of default risk (1 = lowest risk, 10 = highest risk) under the EDF and Hazard Rate model, respectively. For each decile portfolio and year, the ERP is first calculated. These annual ERP values are then averaged over time to obtain the portfolio-level expected return, reported as the time-series mean in the table.

Decile	Hazard Rate (%)	EDF (%)
1	3.24	3.16
2	3.41	3.59
3	3.77	3.84
4	3.99	4.25
5	4.47	4.53
6	4.69	4.89
7	5.24	5.27
8	5.77	5.74
9	6.26	6.46
10	8.15	8.06

The cross-sectional regressions further analyze this relationship by regressing the ERP on default risk percentile (DRP) while controlling for size, relative valuation, and one-month lagged stock returns. These results are slightly less pronounced than those from the univariate tests, indicating a smaller but still notable difference in ERPs between high and low default risk stocks. They show that investors expect to earn an additional risk premium of 3.64% per year from stocks that fall in the top 1% of the DRP compared with the bottom 1% stocks.[5] This positive cross-sectional relationship between default risk and stock returns holds after conducting multiple robustness tests to ensure the accurate measurement of the ICC.

[5] In Table 3, Hazard Rate, the DRP coefficient represents the change in ERP per percentile increase in default risk. With 100 portfolios, the top 1% vs. bottom 1% reflects a 99-percentile spread. Multiplying the coefficient (0.0364) by 100 gives an annual ERP difference of 3.64%, representing the added risk premium for the riskiest stocks.

Table 3. Cross-sectional Regressions: Default Risk and Expected Returns (Chava & Purnanandam, 2010)

This table presents the findings of Chava and Purnanandam's (2010) cross-sectional regression, Model 1, where the ERP serves as the dependent variable. DRP is the annual percentile rankings based on the Hazard Rate model and the EDF model, respectively, and serves as the key independent variable. Control variables include; logta, the natural logarithm of total assets; M/B, the market-to-book ratio of the firm; and $ret_{t-1,t}$, one-month lagged stock returns. The authors employ the Fama-MacBeth estimation approach, in which annual cross-sectional regressions are estimated and the time-series average of the resulting coefficients is reported. Coefficients are reported with t-statistics in parentheses below. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.[6]

	EDF	**Hazard Rate**
DRP	0.0360*** (11.11)	0.0364*** (8.98)
$logta$	-0.5468*** (-5.66)	-0.4748*** (-3.87)
M/B	-0.1566 (-1.04)	-0.1873 (-1.43)
$ret_{t-1,t}$	-4.9148*** (-10.90)	-4.2579*** (-8.96)
$intercept$	6.5243*** (6.98)	6.0368*** (5.49)

[6] The estimate and t-stat is taken directly from their study; however, the authors do not explicitly provide p-values. Significance levels have thus been estimated from the t-values using two-tailed tests and assuming infinite degrees of freedom. This is appropriate given the large sample size in their study, which allows the t-distribution to approximate the standard normal distribution. P-values were calculated $p = 2 * (1 - \Phi(|t|))$, where Φ denotes the cumulative distribution function of the standard normal distribution.

2.4. Summary of Existing Evidence

The mixed evidence in prior research on the relationship between default risk and expected returns largely stems from how expected returns are defined and measured. While most studies relying on realized returns find a negative relationship that contradicts theoretical predictions, Chava and Purnanandam (2010) use the ICC and instead report a positive relationship between default risk and expected returns. These differing results suggest that the choice of measurement approach can influence the conclusions drawn. However, these findings are largely limited to the U.S. market, raising the question of whether the observed relationships generalize beyond that context. The Nordic region offers a compelling setting to address this gap. Although Nordic equity markets are smaller in size and less liquid compared to the U.S. (Euronext, 2024), they are characterized by strong political institutions, high levels of transparency, and robust regulatory frameworks.

2.5. Research Question and Hypotheses

Building on the literature review, this study aims to answer the following research question by testing the corresponding hypotheses:

What is the relationship between default risk and expected returns in the Nordic market when expected returns are proxied by the ICC?

> **H1:** The relationship between default risk and ICC-estimated expected stock returns in the Nordics is positive.
>
> **H2:** The relationship between default risk and ICC-estimated expected stock returns in the Nordics is linear.

These hypotheses build on the findings of Chava and Purnanandam (2010), who document a strong positive and linear relationship between default risk and ICC-estimated expected returns in the U.S. market. While this contrasts with the negative relationship reported in most studies using realized returns (see table 1 in section 2.2.), the discrepancy is likely due to realized returns being a flawed proxy for expected returns.

3. Method

This section outlines the methodological approach taken to examine the relationship between default risk and expected returns in the Nordic market. The overall design builds on the study by Chava and Purnanandam (2010), with adaptations to suit our sample. The method is organized into four main parts:

- **3.1. Default Risk Estimation:** Default risk is estimated using Skogsvik's (1987) accounting-based model. Robustness is tested with Ohlson's (1980) O-score, and a recalibration formula is applied to correct for sample bias in both models.
- **3.2. ICC and ERP Estimation**: The ICC is estimated using the RIV model. Robustness checks include alternative models (DDM and composite model). Forecasting is based on historical accounting data.
- **3.3. Data and Sample:** The sample includes Nordic industrial and manufacturing firms from 2005 to 2023. The period is selected to ensure consistency in accounting standards and firms are chosen to align with model requirements.
- **3.4. Empirical Approach: Univariate and Multivariate Tests:** The analysis includes portfolio sorts, traditional cross-sectional regressions, and piecewise linear regressions. Model specifications broadly follow Chava and Purnanandam, with adjustments for sample size and context.

3.1. Default Risk Estimation

3.1.1. Choice of Primary Bankruptcy Model: The Skogsvik Model

When selecting a bankruptcy model, one can use either a market-based approach, e.g., the EDF model used by Chava and Purnanandam (2010), or an accounting-based approach. This study adopts the latter approach, given the stronger empirical performance of accounting-based models (Agarwal & Taffler, 2008), which offer three key advantages:

1) Bankruptcy is usually the result of several years of poor performance, rather than sudden economic shocks, and is therefore often captured in a firm's financial statements.
2) The double-entry accounting system helps ensure that window dressing or changes in accounting policies have low impact on ratios combining multiple accounting variables.
3) Since loan covenants are typically based on accounting figures, models using accounting ratios are more likely to reflect the information relevant to creditors.

An appropriate bankruptcy model is then selected, ideally one calibrated on similar Nordic firms within a comparable time period. While no such model exists, the one developed by

Skogsvik (1987) provides a close fit and is therefore used as the primary model.[7] This model estimates the probability of failure based on a set of financial ratios derived from historical accounting data. Skogsvik's study is based on a Swedish sample of 51 failure firms and 328 surviving firms operating within manufacturing. The sample was restricted to limited liability companies (i.e., Aktiebolag) that, during any year between 1966 and 1971, had either a minimum of 200 employees or total assets of at least 20 MSEK (measured in 1970 price levels). Based on this sample, Skogsvik uses multivariate probit analysis to develop a bankruptcy prediction model. The model covers forecast horizons ranging from one to six years, with variations in the coefficients depending on the forecast period. Since we are interested in how overall bankruptcy risk relates to the ICC, each firm's probability of failure is calculated as the average of the average of the one-, three-, and five-year estimates. These three models are summarized below:

Table 4. Summary of Skogsvik's (1987) Failure Prediction Model Coefficients for Forecast Horizons 1, 3, and 5 Years

	Forecast Horizon		
Financial Ratio	**1**	**3**	**5**
R_A	-4.3		
R_L	+22.6	+13.2	+13.5
$t(1)$		+0.2	
TIV	+1.6	+1.3	+0.9
LI		-0.5	-1.0
ER	-4.5	-3.3	-1.8
E'	+0.2		
$Diff(R_L)$	-0.1		
$Constant$	-1.5	-1.1	-1.1

where:

$$R_A = \frac{EBIT}{Average\ assets}$$

$$R_L = \frac{Interest\ cost}{Average\ liabilities}$$

[7] See section 3.3. for a further discussion on the suitability of the Skogsvik (1987) model and the methodological choices made to ensure maximum comparability with his original sample.

$$t(1) = \frac{Tax\ cost}{EBT}$$

$$TIV = \frac{Average\ inventory}{Revenue}$$

$$LI = \frac{Cash\ assets}{Current\ liabilities}$$

$$ER = \frac{Owners'\ equity}{Assets}$$

$$E' = \frac{Change\ in\ owners'\ equity}{Owners'\ equity}$$

$$Diff(R_L) = \frac{R_{L,t} - \overline{R}_{L,t-1}}{\left[\sum_{\tau=t-4}^{t-1} (R_{L,\tau} - \overline{R}_{L,t-1})^2 / 3\right]^{0.5}}\ where:\ \overline{R}_{L,t-1} = \sum_{\tau=t-4}^{t-1} R_{L,\tau} / 4$$

However, since diff(R_L) is relatively complex to compute and was found to have limited influence in the original study, it is excluded from the model.[8]

3.1.2. Robustness: Alternative Bankruptcy Model

To assess robustness against the choice of bankruptcy model, an alternative bankruptcy model is applied. We maintain an accounting-based approach, but instead use Ohlson's O-score model (1980), based on a logit estimation technique. This model is based on data from U.S. manufacturing firms between 1970 and 1976. Thus, while the sample shares certain firm characteristics with those examined in this study, its geographical context limits its representativeness for Nordic firms. Nonetheless, the O-score is yet today one of the most widely used bankruptcy prediction models in the academic literature and provides a well-established benchmark. See Table 14 in Appendix 2 for a detailed description of the model.

3.1.3. Adjustment for Sample Selection Bias

Both Skogsvik (1987) and Ohlson (1980) estimate their models using samples that overrepresent bankrupt firms in order to ensure a sufficient number of failure cases. This sampling approach introduces selection bias, resulting in upward-biased failure probabilities. To address this, the recalibration formula proposed by Skogsvik and Skogsvik (2013) is employed, adjusting the estimated probabilities to better reflect a representative population context:

$$P(Fail)POP = P(Fail)ES \times \frac{\pi \times (1-prop)}{prop \times (1-\pi) + P(Fail)\ ES \times (\pi - prop)} \quad (1)$$

where:

$$\pi = proportion\ of\ failure\ companies\ in\ the\ population\ of\ companies$$

[8] Diff(RL) was found to have an effect only in the 1-year model, where its coefficient was -0.1, indicating a very limited impact on the estimated probability of failure.

$$prop \;=\; proportion\ of\ failure\ companies\ in\ the\ estimation\ sample\ of\ companies$$

$$P(Fail)POP \;=\; The\ probability\ of\ failure\ in\ the\ population\ of\ companies$$

$$P(Fail)ES \;=\; The\ probability\ of\ failure\ in\ the\ estimation\ sample\ of\ companies$$

We approximate the population-level probability of failure (π) using historical data from 2006-2015 reported by Bărbuță-Mișu and Madaleno (2020), who estimate insolvency rates of 3.8% in Denmark, 3.3% in Sweden, 2.4% in Norway, and 1.5% in Finland. Given the distribution of sample observations across countries, a population level failure probability of 3% is considered a reasonable estimate for the recalibration. This is a simplified assumption, as recalibration should ideally rely only on data available at each individual forecasting date (i.e., for each point in time during 2005-2023 in our sample) to avoid hindsight bias. Nonetheless, this simplification is not expected to compromise the validity of the study, as the focus lies in examining how different levels of default risk relate to the ICC rather than in precisely estimating failure probabilities. Moreover, the failure rate in the estimation sample of companies (prop) is given by Skogsvik's (1987) sample composition of 51 failure firms out of a total of 379 firms studied (i.e., 13.5%).

3.2. ICC and ERP Estimation

3.2.1. Choice of Primary Valuation Model: The RIV Model

Deriving the ICC requires the use of an equity valuation model, with the RIV model, the DDM, and the AEG model being the most commonly applied frameworks. This thesis employs the RIV model as the primary model for the ICC estimation. The choice is motivated by the findings of Anesten et al. (2020), who evaluate the pricing accuracy of these three models for Scandinavian firms over the period 2005 to 2014. Their results show that the RIV model provides the most accurate pricing when value drivers are forecasted using historical financial data, which is the approach applied in this study. Although prior research suggests that extending the forecast horizon beyond five years does not enhance pricing accuracy, a ten-year forecast horizon is adopted to maintain consistency with the DDM robustness test. As Penman and Sougiannis (1998) note, longer horizons are important for the DDM reliability, making a comparable period necessary for a meaningful comparison with the RIV model.

Moreover, the RIV model was originally developed by Preinreich (1938) and states that a firm's equity value can be expressed as the sum of its book value of equity and the present value of expected residual incomes.[9] Residual income is defined as net income minus the required return. The ICC is calculated as the discount rate that makes the observed market value of equity equal to the sum of the book value of equity and the present value of expected residual incomes.

A general formula of the RIV model, with truncation time t = T, is defined as follows:

[9] The RIV model is derived from the DDM under the assumption that the clean surplus relation holds in expectation.

$$V_0(RIV) = BV_0 + \sum_{t=1}^{T} \frac{E_0(NI_t - \rho_E \times BV_{t-1})}{(1+\rho_E)^t} + \frac{E_0(NI_{T+1} - \rho_E \times BV_T)}{(\rho_E - g_{Ri})(1+\rho_E)^T} \quad (2)$$

where:

$BV_0 = reported\ book\ value\ of\ owners'\ equity\ at\ time\ t = 0,\ valuation\ point\ in\ time$

$NI_t = net\ income\ in\ period\ t$

$BV_t = book\ value\ of\ owners'\ equity\ (ex\ dividend)\ at\ time\ t$

$\rho_E = cost\ of\ equity$

$g_{Ri} = growth\ rate\ of\ residual\ income\ (NI_t - \rho_E \times BV_{t-1})\ in\ period\ t = T+1\ and\ onward$

The standard formula has a strong reliance on an assumed long-term growth rate of residual income in the terminal value. To mitigate this dependence, the approach proposed by Anesten et al. (2020) is applied, whereby the truncation value is calculated by multiplying the book value at the end of the final forecast year by a permanent measurement bias. This bias captures the extent to which conservative accounting practices systematically understate asset values and, consequently, the underlying equity value (Brainard & Tobin, 1968; Tobin, 1969). As this understatement varies across sectors, industry-specific biases are employed. Estimates are drawn from Runsten (1998), whose sample of Swedish firms broadly matches our sample. See Table 15-16 in Appendix 3 for a summary of the estimated PMB's per industry in Runsten, as well as a comprehensive description of the measurement bias mapping.

Based on the above adjustments, the employed RIV model, with a 10-year explicit forecast period is defined as:

$$V_0(RIV(T=10)) = BV_0 + \sum_{t=1}^{10} \frac{\widehat{NI}_t - \rho_{E^*} \times \widehat{BV}_{t-1}}{(1+\rho_{E^*})^t} + \frac{\hat{q}_T \times \widehat{BV}_{10}}{(1+\rho_{E^*})^{10}} \quad (3)$$

where:

$\widehat{NI}_t = forecasted\ net\ income\ in\ period\ t$

$\widehat{BV}_t = forecasted\ book\ value\ of\ owners'\ equity\ (ex\ dividend)\ at\ time\ t$

$\rho_{E^*} = ICC = bankruptcy\ calibrated\ cost\ of\ equity$

$\hat{q}_T = forecasted\ measurement\ bias\ of\ equity\ at\ the\ end\ of\ period\ t = T$

As mentioned in section 2.3.1., the estimated ICC represents the bankruptcy calibrated cost of equity, as the firm cash flows in this model are conditioned on firm survival.

3.2.2. Robustness: Alternative Valuation Models

To assess the robustness of the results to the choice of valuation model, alternative methods for estimating the ICC are employed. First, we apply the DDM with a 10-year forecast horizon. This robustness test draws on the findings of Anesten et al. (2020), who demonstrated that the model achieves the second-highest pricing accuracy when forecasts rely on historical financial statements. Second, we apply a composite model, calculated as the equally weighted average of estimates from the RIV, DDM, and AEG models. This robustness test follows the approach of Hou et al. (2012), who argues that an ICC based on multiple valuation models improves the reliability of return predictions. A 10-year forecast horizon is used for both the RIV and the DDM, while the AEG model is estimated using the core model from Ohlson and Juettner-Nauroth (2005). See Equations 10-11 in Appendix 3 for comprehensive model specifications of the DDM and the AEG model.

3.2.3. Forecasting of Value Drivers

Forecasting the value drivers in both the RIV model and the alternative models can be done either using analyst forecasts or historical accounting data. This study applies the latter method, based on two main reasons. First, using historical data ensures consistency across all sample firms, as reliable analyst estimates are typically only available for larger companies. Second, as argued by Hou et al. (2012), relying on historical accounting information reduces forecast bias and enhances the reliability of the ICC as a proxy for expected returns. The accounting-based approach used in this thesis is based on the methodology of Anesten et al. (2020), with modifications to suit the current setting. The approach is outlined below.

Step 1: Historical averages of return on equity ($\overline{ROE}_t$) and payout share ($\overline{PS}_t$) are computed based on up to four years of historical data.[10] The ratios are calculated for each year during the historical period as below, and then averaged across the years:

$$ROE_t = NI_t \,/\, BV_{t-1} \tag{4}$$

$$PS_t = DIV_t \,/\, BV_{t-1} \tag{5}$$

where:

$$DIV_t = dividend\ payment\ during\ year\ t,\ based\ on\ the\ results\ of\ calendar\ year\ t-1$$

While Anesten et al. (2020) use the historical average of the payout ratio, relating dividends to net income, we take an alternative approach. We follow Skogsvik and Skogsvik (2010) and use the payout share ratio, defined as dividends divided by the book value of equity. This provides a more stable basis for forecasting dividends than the payout ratio, which uses net

[10] The historical averages of the key drivers used to estimate the ICC and the ERP are as follows: the mean (median) ROE is 18.78% (16.23%), and the mean (median) PS is 7.26% (5.72%).

income as the denominator. Negative net income results in negative payout ratios even when firms distribute dividends, thereby introducing distortions in forecast accuracy. Conversely, book value of equity is rarely negative, offering a more stable denominator and enabling more consistent and reliable dividend projections. Lastly, dividends are measured as gross dividends, excluding share buybacks and new equity issues, as these are infrequent and not reflective of ongoing operations.

Step 2: Starting from the reported book value of equity at time t-1 (i.e., t = 0), we forecast net income and dividend paid out for year t (i.e., t = 1) using the above averages of ROE and PS.

$$\widehat{NI}_t = \overline{ROE}_t \times BV_{t-1} \tag{6}$$

$$\widehat{Div}_t = \overline{PS}_t \ * \ BV_{t-1} \tag{7}$$

Step 3: Using above forecasts of net income and dividend, we can now use a re-ordered and simplified version of the clean surplus relation to forecast book value of equity at time t.

$$\widehat{BV}_t = BV_{t-1} + \widehat{NI}_t - \widehat{Div}_t \tag{8}$$

Where book value of equity is ex dividend, and the formula is excluding new equity issues and share buybacks as these are assumed to be zero during the forecast period.

Step 4: Steps 2 and 3 are repeated for each year to produce annual forecasts of net income, dividends, and book value of equity over the 10-year forecast horizon.

Step 5: After completing the forecasts for each year, the ICC is reverse-engineered using Excel's Goal Seek function.

3.2.4. ERP Estimation

Once all value drivers are forecasted and the ICC is derived, the final step involves calculating the ERP, which serves as the dependent variable in the main regressions, following Chava and Purnanandam (2010). The ERP is defined as the ICC less the ten-year government bond yield prevailing at the time of estimation.[11] Subtracting the risk-free rate isolates the portion of the ICC that compensates investors specifically for bearing risk. This adjustment is beneficial to ensure comparability over time, as it removes variation in the ICC driven by changes in interest rates rather than changes in risk. This is highly relevant for the sample period of 2005 to 2023, during which interest rates fluctuated significantly. A country-specific risk-free rate is used for this purpose.

3.2.5. Estimation Point in Time

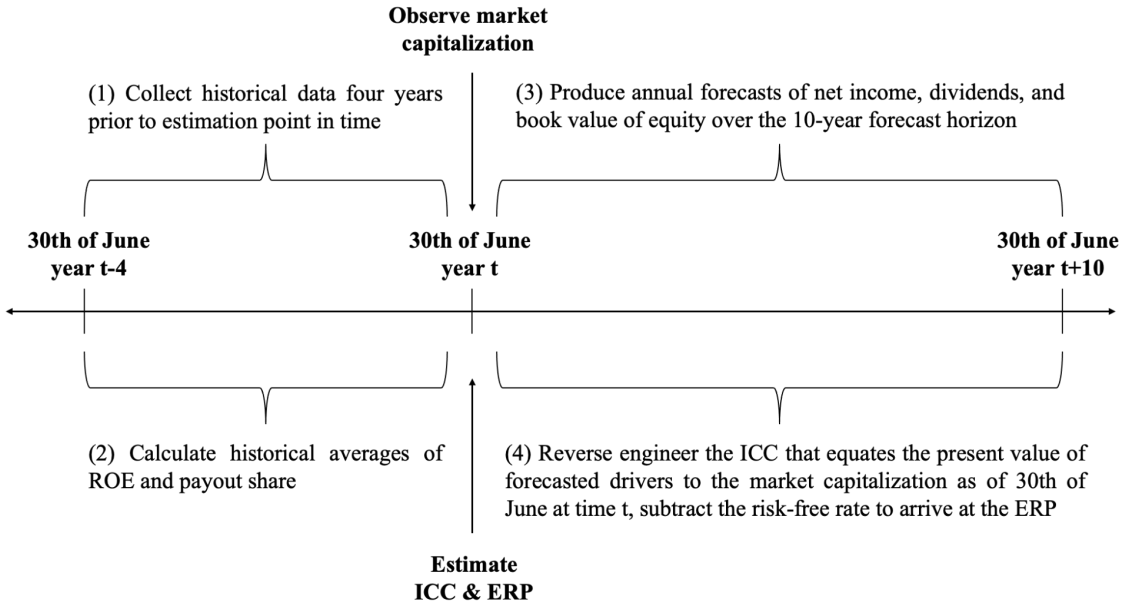
The ICC and ERP estimation date for each firm is set to June 30th of the year following the most recent calendar year, in line with Chava and Purnanandam (2010). For example, if a firm has full-year financial statements for 2019, the valuation date is set to June 30th 2020.

[11] This approach differs from Chava and Purnanandam (2010), who use the 1-year risk-free rate. However, the use of a longer-term yield ensures consistency with the 10-year forecast horizon.

This timing ensures that financial data used in the estimation is up to date and comparable across firms. The observation is based on the simplifying assumption that all companies have reported by June 30th, as collecting firm-specific reporting dates was not feasible due to data and time constraints. Likewise, dividends for calendar year t = 0 are assumed to be distributed to equity holders on June 30th of t = 1. While firm-specific dividend payment dates would be preferable, this was also not possible. Although these are simplifying assumptions, they are unlikely to materially affect the results, given the 10-year explicit forecast horizon.

An illustration of the estimation process is summarized below:

Fig. 1. Summary of the ICC and ERP Estimation Process



3.3. Data and Sample

3.3.1. Time Period

The sample covers the period from 2005 to 2023, motivated by two main reasons. First, while Chava and Purnanandam (2010) analyze the relationship between default risk and expected returns using the ICC for the period 1952 to 2005, there are no comparable studies covering more recent years. The lower bound is set at 2005 to ensure consistency in accounting standards across years, and 2023 represents a natural upper bound, as it is the latest calendar year with complete financial data for all firms in the sample. Beginning in 2005, all listed firms in the Nordics were required to replace country-specific GAAP with IFRS. This shift toward uniform accounting standards reduces variation in financial statement comparability. This consistency is particularly important for the validity of the default risk estimation, as prior research (Beaver, McNichols, & Rhie, 2005) shows that the predictive accuracy of bankruptcy models is highly sensitive to changes in accounting standards. Thus, studying a

period with consistent financial reporting standards minimizes structural noise and enhances the validity of the model used to derive our independent variable.

3.3.2. Industry and Firm Criteria

The sample covers observations of firms listed on Nordic stock exchanges between 2005 and 2023.[12] Firms listed in Iceland are excluded due to limited data availability and concerns about market comparability. Although Skogsvik (1987) based his analysis solely on Swedish firms, the model should be applicable to the broader Nordic sample, as firms in the region apply the same accounting standard (IFRS) and operate under similar institutional and legal frameworks (Nordea, 2021).

To ensure the Skogsvik (1987) model remains applicable, the sample includes firms from comparable industries. As the SNI classification used by Skogsvik applies only to Swedish firms and has changed since the 1980s, industry definitions are instead based on the Global Industry Classification Standard (GICS) to allow for consistency across countries. GICS, developed by S&P Dow Jones Indices and MSCI, categorizes firms into 11 sectors and 68 industries. To reflect Skogsvik's manufacturing focus and ensure a sufficient sample size, we include firms classified in sectors 15 (*Materials*) and 20 (*Industrials*). In addition, we add firms in *Automobiles & Components*, *Technology Hardware & Equipment*, and *Semiconductors & Semiconductor Equipment*, which also reflect manufacturing activity. Moreover, firms are excluded based on Skogsvik's (1987) size criteria, which require total assets exceeding 20 million SEK (in 1970 price levels) or more than 200 employees. To ensure consistency over time, the asset requirement has been inflation-adjusted using each country's respective consumer price index.

3.3.3. Model-Specific Assumptions

When estimating the ICC, a set of criteria is applied to retain sufficient observations while excluding outliers:

1) Four-year averages are calculated for ROE and payout share, requiring at least two historical observations to be valid, following Anesten at al. (2020).

2) In cases where both net income and book value of equity are negative, the resulting ROE is mathematically positive (see Equation 4 in section 3.2.3). In such instances, the sign is reversed to negative, as this more appropriately reflects the firm's inability to generate returns for equity holders.

3) Average ROE values are restricted to the range of -25% to +150%, as in Anesten et al.

4) Observations with a negative payout share are excluded, following Anesten et al.

[12] To avoid sample selection bias, we include all firms that were publicly listed at any point during the period. For example, a company that was listed in 2012 and went bankrupt in 2017 is included in the sample for all years in which it reported data.

5) Firms reporting a negative book value of equity in a given year are assumed not to pay dividends for that year, as such payments would not be economically justifiable.

Based on these restrictions and the previously mentioned forecasting methodology, the ICC is reverse engineered for each observation. Thereafter, two additional criterias are implemented.

6) In line with Hou et al. (2012), negative ICC values are excluded.[13] This adjustment ensures the sample accurately reflects economic reality, since a negative ICC implies that investors are accepting a negative return, which is not a realistic assumption.

7) Lastly, as in Chava and Purnanandam (2010), all variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers.

3.3.4. Data Collection

All financial and market data are collected from S&P Capital IQ. To ensure comparability across years, calendar-year data is used. Random checks are performed on firms of varying sizes across all countries to verify the accuracy and reliability of the collected data. Consumer price index data is obtained from the official statistical agencies of the respective countries (Statistiska Centralbyrån, n.d.; Statistisk Sentralbyrå, n.d.; Statistics Denmark, n.d.; Statistikcentralen, n.d.). 10-year government bond yields are retrieved from the Swedish Central Bank (Riksbanken, n.d.), which reports both domestic and international yields.

3.3.5. Sample Summary

Table 5. Sample Selection Process

The sample selection process described in section 3.3 is summarized below. The final sample consists of 3,058 firm-year observations across 348 unique firms.[14]

Step	Criteria	Observations
Start	All firm-year observations of industrial/manufacturing firms listed in the Nordics between 2005-2023	**6,459**
Step 1	Exclude firm-years not meeting Skogsvik's (1987) size criteria (≥ 200 employees and/or inflation-adjusted total assets ≥ 20 million SEK)	**5,878**
Step 2	Exclude firm-years with insufficient data for the ICC estimation, average ROE outside -25% to +150%, or negative payout share values	**4,226**
Final	Exclude firm-years where the ICC estimates are negative	**3,058**

[13] A negative ICC arises when the market capitalization is significantly higher than what can be justified by the firm's current forecasted value drivers. In such cases, a negative discount rate (i.e., the ICC) is the only way to reconcile the present value of expected future cash flows with the observed market value.
[14] All tests and regressions are conducted on this same sample of firm-year observations.

Moreover, a summary of the sample divided by country and GICS industry, respectively, can be found in Tables 12-13 in Appendix 1.

3.4. Empirical Approach: Univariate and Multivariate Tests

3.4.1. Univariate Tests: Portfolio Sorting

Following Chava and Purnanandam (2010), the empirical analysis starts with univariate tests where firms are sorted into decile portfolios based on their estimated probability of failure, with decile 1 containing the lowest-risk firms and decile 10 the highest. Chava and Purnanandam compute the portfolio-level expected return by first calculating the mean return for each year and then averaging across years, yielding a time-series mean. In contrast, this analysis pools all firm-year observations and directly computes the overall average and median ERP for each decile. This adjustment is motivated by our smaller sample size and ensures that each portfolio is sufficiently populated.

3.4.2. Multivariate Tests: Cross-Sectional Regressions

To further examine whether firms with higher default risk are associated with higher expected returns, we conduct various types of multivariate cross-sectional regressions.[15] In these regressions, default risk deciles (ranging from 1 to 10) serve as the main independent variable, and the ERP as the dependent variable. Although the general regression framework of Chava and Purnanandam (2010) is followed, two deviations are made to account for the relatively smaller sample size. First, all firm-year observations are pooled, and a single cross-sectional regression is estimated, rather than applying the Fama-MacBeth (1973) method.[16] This approach allows for full use of the available cross-sectional variation and provides more stable coefficient estimates. Second, while Chava and Purnanandam transform each firm's default probability into a percentile ranking based on the annual cross-sectional distribution, we instead use decile rankings.[17] This choice ensures sufficient observations within each portfolio while retaining the benefits of rank-based transformations, such as mitigating outliers and improving interpretability.

Chava and Purnanandam (2010) employ three regression specifications with progressively more control variables. The first model includes the natural logarithm of total assets (as a firm size proxy), the M/B ratio, and one-month lagged stock returns. The second model adds financial leverage, and the third further incorporates return volatility. This analysis adopts the first specification as the baseline, with two modifications to better reflect conventions in the asset pricing literature. First, the firm size proxy is adjusted to the natural logarithm of market capitalization, which has been shown to be a reliable predictor of expected returns (Fama &

[15] See Exhibit 1 in Appendix 4 for a discussion regarding the diagnostic tests used to assess the underlying regression assumptions.
[16] Since we use ERP as the dependent variable, calculated by adjusting the ICC with date-specific risk-free rates, much of the year-specific variation is already accounted for.
[17] Initial tests using percentile rankings of default risk, following the approach of Chava and Purnanandam (2010), yielded very low explanatory power.

French, 1992). Second, the M/B ratio is inverted to the B/M ratio to align with standard practice in empirical asset pricing research (see table 1 in section 2.2.).

While Chava and Purnanandam (2010) expand their models by including leverage and return volatility, these variables are excluded from the current specification. This decision is motivated by Traczynski (2017), who shows that financial leverage and market return volatility are the primary factors explaining default risk across industries. As the main independent variable already captures default risk, adding variables that are highly correlated with it would be redundant and risk inflating multicollinearity.

3.4.2.1. Model Specification

In our primary model specification, the ERP is derived from the ICC estimated using the 10-year RIV model and serves as the dependent variable. Control variables are introduced stepwise across regression columns to illustrate their incremental effect on the estimated relationship between default risk and expected returns. This is presented in 4.2.1 Primary Model Specification. The estimation model with all control variables included is presented below, and will be referred to as the primary model specification for the remainder of this method.

$$ERP_{10Y\ RIV} = \alpha_1 + \beta_1 P(Fail)_{Dec.,t} + \beta_2 Size_t + \beta_3 B/M_t + \beta_4 ret_{t-1,t} + \varepsilon_{i,t} \qquad (9)$$

where:

$ERP_{10Y\ RIV} = ICC\ estimated\ for\ the\ 10Y\ RIV\ model,\ less\ the\ risk\ free\ rate\ at\ time\ t$

$\alpha_1 = constant$

$\beta_{1,2,3,4} = regression\ coefficients\ for\ the\ independent\ variables$

$P(Fail)_{Dec.,t} = probability\ of\ failure\ decile\ rankings$

$Size_t = natural\ logarithm\ of\ firm\ market\ capitalization\ at\ time\ t$

$B/M_t = \frac{Book\ value\ of\ equity_t}{Market\ capitalization_t}$

$ret_{t-1,t} = One\ month\ lagged\ stock\ returns$

$\varepsilon_{i,t} = error\ term$

Robustness is tested with respect to both the independent and dependent variable specifications. First, the ERP estimated from the 10-year DDM is used in the regressions. Next, a composite ERP is calculated as the average of the ICC estimates produced by the RIV, DDM, and AEG OJ Core models. Finally, robustness to the choice of default risk model is evaluated using the Ohlson (1980) model and forming deciles based on its estimated

default probabilities. The findings from these alternative regressions are presented in Table 9 in section 4.2.2.

Finally, the analysis investigates potential nonlinearities in the relationship between default risk and the ICC, motivated by patterns observed in earlier tests. To do this, the primary regression specification is first re-estimated with a high-risk dummy variable (e.g., for the top decile). To further examine whether the relationship between default risk and ERP varies across risk levels, a piecewise linear regression is conducted. In this specification, interaction terms containing a high-risk dummy variable is used. The primary coefficient on default risk then captures the slope for firms below the threshold, while the interaction term identifies any incremental change in slope for firms above it (Gujarati, 2003). This approach enables a test of whether the relationship between default risk and expected returns shifts once the specified threshold is exceeded. Testing various thresholds, in this case the top 20%, 15%, and 10% of the default risk distribution, allows a test of where this threshold is. The findings from these regressions are presented in Table 10-11 in section 4.2.3.[18]

[18] The RIV-derived ICC serves as the primary dependent variable in all tests; however, to assess robustness, the regressions are also estimated using the DDM and the composite valuation model.

4. Empirical Findings and Analysis

4.1. Univariate Tests: Portfolio Sorting

Table 6. Mean and Median Probability of Failure by Default Risk Decile

This table presents a summary of the default risk distribution within our sample under the Skogsvik (1980) bankruptcy model. Decile portfolios are constructed by sorting firms based on default risk, with decile 1 representing the lowest 10% and decile 10 representing the highest 10%. The mean and median probabilities of failure are reported for each decile. The sample includes 3,058 firm observations, with each decile containing 305-306 observations.

Decile	**Mean (%)**	**Median (%)**
1	0.10	0.10
2	0.20	0.20
3	0.28	0.29
4	0.37	0.37
5	0.47	0.47
6	0.58	0.58
7	0.74	0.74
8	0.88	0.88
9	1.12	1.11
10	2.33	1.93
Total Sample	**0.71**	**0.53**

The full sample exhibits a mean (median) probability of failure of 0.71% (0.53%). These values are broadly in line with Chava and Purnanandam (2010), who report an average probability of failure of 0.5%. In our sample, the median default risk increases gradually across deciles 1 to 9, ranging from 0.10% to 1.11%. In decile 10, however, the failure probability rises more sharply to 1.93%.

Table 7. Mean and Median ERP (10-year RIV Model) by Default Risk Decile

This table presents univariate test results, showing the mean and median ERP for each decile portfolio from Table 6. The ERP is calculated by first deriving the ICC from the 10-year RIV model, and subsequently subtracting the risk-free rate at the estimation point in time.

Decile	Mean (%)	Median (%)
1	13.46	8.45
2	11.91	8.72
3	11.59	8.40
4	11.18	8.13
5	10.71	7.84
6	10.08	7.05
7	10.04	7.05
8	10.54	7.69
9	9.77	6.67
10	13.41	8.82
Total Sample	**11.27**	**7.97**

The full sample exhibits a mean (median) ERP of 11.27% (7.97%), with a few high-ERP observations in each decile causing the mean to consistently exceed the median.[19] We therefore focus on median values, as they better represent the typical observation in each decile. Overall, our ERP values are notably higher than those reported by Chava and Purnanandam (2010), who document a mean ERP of 5.1% in their base model. A potential contributing factor could be the lower liquidity of the Nordic markets compared to the U.S. market (Euronext, 2024), which may partly explain the higher return expectations observed in our sample.

Moreover, we observe a generally linear decline in ERP from deciles 2 to 9, suggesting that as default risk increases, investors adjust their expected returns downward, contrary to our hypothesis of a positive relationship. This distribution is different to that reported by Chava and Purnanandam (2010), whose findings indicate a linear increase in ERP as default risk rises, consistent across all deciles. In contrast, our univariate results align more closely with much of the literature on realized returns, which often points to a negative relationship between default risk and stock performance (see table 1 in section 2.2.).

[19] The total sample mean (median) ERP is 11.38% (6.00%) under the 10-year DDM model and 10.10% (7.12%) under the composite valuation model.

Another noteworthy point concerns the divergence in deciles 1 and 10. In decile 1, the ERP is slightly higher than in decile 2, suggesting a modest deviation at the lower end of the distribution. In contrast, decile 10 shows a more pronounced jump, with the ERP increasing from 6.67% in decile 9 to 8.82%. This is particularly relevant given that the most substantial increase in default risk, as presented in Table 6, also occurs between decile 9 and 10. This could imply that once a firm reaches the top end of the default risk distribution, investors respond by increasing their required returns. This may suggest that the relationship between default risk and ERP follows a V-shaped relationship, contrary to our hypothesis of a linear relationship. This observation will be explored further in section 4.2.3.

4.2. Multivariate Tests: Cross-Sectional Regressions

4.2.1. Primary Model Specification

Table 8. Cross-Sectional Regressions Using 10-year RIV ERP and Skogsvik Default Risk Deciles

This table reports the results of cross-sectional regressions using the primary valuation and default risk models. In all specifications, the dependent variable is the ERP derived from the 10-year RIV model. The key independent variable is the decile ranking of default risk, $P(Fail)_{Dec}$, derived from the Skogsvik (1987) model.[20] Control variables are introduced stepwise to illustrate the incremental effect of each addition, with Model (4) representing the main specification, referred to as the primary model in the methodology section. Column (1) estimates the model without any control variables. Column (2) adds firm size (log market capitalization) as the sole control variable. Column (3) adds the B/M ratio to the control variables in (2). Column (4) further includes one-month lagged stock returns. All coefficients are estimated using pooled OLS regressions with heteroskedasticity-robust standard errors. Coefficients are reported with t-statistics in parentheses below. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

[20] Table 17 in Appendix 4 reports the Pearson pairwise correlation coefficients among the independent variables used in the cross-sectional regression analysis, indicating no excessive correlation between any of the variables.

	(1)	(2)	(3)	(4)
$P(Fail)_{Dec}$	-0.0002 (-0.18)	-0.0007 (-0.75)	-0.0026*** (-2.91)	-0.0027*** (-3.04)
$Size_t$		-0.009*** (-9.14)	-0.0034*** (-3.21)	-0.0027** (-2.46)
B/M_t			0.0488*** (10.33)	0.0477*** (9.74)
$ret_{t-1,t}$				-0.0428 (-1.57)
$intercept$	0.1133*** (20.66)	0.1816*** (18.97)	0.1148*** (10.66)	0.1109*** (9.45)
N R^2	*3,058* *0.0000*	*3,058* *0.0214*	*3,058* *0.0841*	*3,058* *0.0872*

The coefficient of -0.0027 in Model (4) indicates a negative relationship between default risk and expected returns, significant at the 1% level.[21] This suggests that a firm moving up a decile is associated with a 0.0027 percentage point decrease in ERP. Despite being statistically significant, the low coefficient estimate makes the effect economically negligible. Compared to the univariate results, the cross-sectional regressions thus show the same negative direction, but with a much smaller economic relevance. These findings contrast Chava and Purnanandam (2010) and our hypothesis of a positive relationship. Instead, the direction of our results is more consistent with the realized return literature (see table 1 in section 2.2.), although with a considerably smaller magnitude.

The relationship is not statistically significant in Model (1), which includes no control variables, or in Model (2) where firm size is the sole control. However, once the B/M ratio is added in Model (3), the coefficient becomes statistically significant, and the results remain stable in Model (4) with the inclusion of one-month lagged stock returns. Overall, this stepwise inclusion of control variables highlight the important role of size and the B/M ratio in explaining the observed relationship.

[21] Regressing the raw default probabilities as the independent variable instead of decile ranks yields a coefficient of -0.097 with a p-value of 0.849, indicating limited explanatory power. This further motivates the use of ranked deciles as the independent variable when assessing the overall sample.

4.2.2. Robustness: Alternative Model Specifications

Table 9. Cross-Sectional Regressions Using Alternative Model Specifications

This table reports alternative cross-sectional regressions with modified variables to test the robustness of the main results. In Panel A, the dependent variable ERP has been estimated using two alternative valuation models; the 10-year DDM and a composite model that combines estimates from the RIV, DDM, and AEG models. The key independent variable, $P(Fail)_{Dec,S}$ is the annual decile rank of firm-level default risk derived from the Skogsvik (1987) bankruptcy model. In Panel B, we keep the ERP based on the 10-year RIV model (i.e., the primary valuation model), and instead test for robustness in the independent variable. Here, the independent variable is the decile ranking of default risk, $P(Fail)_{Dec}$, derived from the Ohlson (1980) bankruptcy model. In all estimations, control variables include firm size (log market capitalization), B/M ratio, and one-month lagged stock returns. All coefficients are estimated using pooled OLS regressions with heteroskedasticity-robust standard errors. Coefficients are reported with t-statistics in parentheses below. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Panel A: Alternative Valuation Model		**Panel B: Alternative Bankruptcy Model**
	DDM	**Composite Model**	**Ohlson Model**
$P(Fail)_{Dec}$	-0.0012 (-1.38)	-0.0018** (-2.34)	-0.0038*** (-3.59)
$Size_t$	-0.0115*** (-10.99)	-0.0021** (-2.33)	-0.0054*** (-4.63)
B/M_t	0.0203*** (4.77)	0.0301*** (6.80)	0.0457*** (9.84)
$ret_{t-1,t}$	-0.0305 (-1.10)	-0.0427* (-1.80)	-0.0509* (-1.89)
$intercept$	0.1911*** (16.95)	0.1031*** (10.13)	0.1385*** (9.91)
N	*3,058*	*3,058*	*3,058*
R^2	*0.0670*	*0.0543*	*0.0541*

Under the DDM, the relationship between default risk and ERP loses significance, which is notable given that DDM is the valuation model used by Chava and Purnanandam (2010). In contrast, the composite model is in line with our primary model specification, as the ERP remains slightly negative and significant at the 5% level. A firm moving up a decile is associated with a 0.0018 percentage point decrease in expected returns, an even smaller effect

than under the RIV model. Overall, the findings suggest that the relationship between default risk and expected returns is not consistent across all valuation models. Similarly, to assess the robustness of our results to the choice of default risk estimation model, we re-estimate the regressions using the Ohlson (1980) bankruptcy model. The results remain robust to this alternative specification, with the coefficient on default risk remaining statistically significant and of a similar magnitude to that obtained under the Skogsvik (1987) model in table 8, model (4). However, these regressions may fail to capture nonlinear patterns in the data, thus limiting the ability to assess the potential V-shaped relationship discussed earlier.

4.2.3. Cutoff Point Analysis

Table 10. Cross-Sectional Regressions Testing a Potential Cutoff Point: High-risk Dummy

This table presents the results from cross-sectional regressions conducted to provide an initial assessment of the potential V-shaped relationship between default risk and expected returns. To test the robustness of the findings, three separate regressions are estimated using alternative measures of the ERP, derived from the 10-year RIV, 10-year DDM, and composite valuation models. The regression specification builds on the baseline model from Table 8, model (4), and introduces a dummy variable for high-risk firms, defined as those in decile 10 of default probability based on the Skogsvik (1987) model. The key independent variable is the decile ranking of default risk, $P(Fail)_{Dec}$, also derived from the Skogsvik model. Control variables include firm size (log market capitalization), B/M ratio, and one-month lagged stock returns. All regressions are estimated using pooled OLS with heteroskedasticity-robust standard errors. Coefficients are reported with t-statistics in parentheses below. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	RIV	DDM	Composite
$P(Fail)_{Dec}$	-0.0035*** (-3.64)	-0.0025*** (2.61)	-0.0026*** (-3.12)
$Decile\ 10\ Dummy$	0.0195* (1.85)	0.0267** (2.49)	0.0173* (1.95)
$Size_t$	-0.0031*** (-2.90)	-0.0113*** (-10.85)	-0.0024*** (-2.72)
B/M_t	0.0477*** (9.93)	0.0174** (4.01)	0.0286*** (6.53)
$ret_{t-1,t}$	-0.0559** (-2.09)	-0.0349 (-1.26)	-0.0513** (-2.23)
$intercept$	0.1161*** (10.74)	0.1956*** (17.66)	0.1097*** (12.00)
N	*3,058*	*3,058*	*3,058*
R^2	*0.0872*	*0.0638*	*0.0514*

As highlighted in the univariate tests, the sharp rise in ERP from decile 9 to 10 stands out as a key deviation from the overall trend. This increase coincides with the most substantial increase in the probability of failure across all deciles, suggesting that investors may only adjust their required returns once default risk crosses a certain threshold. To begin examining this possibility, we re-estimate the primary model specification with the addition of a dummy variable for high-risk firms, defined as those in decile 10. For all three valuation models, the coefficient on default risk remains consistent with previous findings; negative, statistically significant at the 1% level, but economically negligible. For the RIV model, the default risk coefficient is -0.0035, whereas the high-risk dummy yields a positive and statistically significant coefficient at the 10% level (0.0195), suggesting a potential reversal in the pricing of default risk at the top end of the distribution. While this provides evidence of a potential V-shaped relationship, the magnitude of the dummy coefficient is low, implying that the economic relevance of this shift remains limited.

To further investigate the possibility of a nonlinear relationship, we implement a piecewise linear regression that allows the slope of default risk to vary across different parts of the distribution.

Table 11. Cross-Sectional Regressions Using Piecewise Linear Regression

This table reports the results of cross-sectional regressions analyzing the relationship between default risk and the ERP using piecewise linear specifications. The sample is segmented by percentiles to enable a more focused examination of the transition between deciles 9 and 10. The dependent variable is the ERP derived from the 10-year RIV model. The key independent variable is the raw annual default probability, $P(Fail)_{Raw}$, calculated using the Skogsvik (1987) model. Control variables include firm size (log market capitalization), B/M ratio, and one-month lagged returns. All regressions are estimated using pooled OLS with heteroskedasticity-robust standard errors. Coefficients are reported with t-statistics in parentheses below. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. The coefficient on $P(Fail)_{Low}$ captures the slope of the relationship between default risk and ERP below the specified threshold (e.g., up to the top 10%), while the coefficient on $P(Fail)_{High}$ captures the change in slope above that threshold, indicating how the relationship differs among firms in the top x% of default risk.

	Percentiles		
	Top 20%	**Top 15%**	**Top 10%**
$P(Fail)_{Low}$	-0.7476 (-1.11)	-2.8178*** (-3.33)	-2.0945*** (-2.86)
$P(Fail)_{High}$	0.7734 (1.23)	2.6198*** (3.67)	2.0786*** (3.00)
$Size_t$	-0.0027** (-2.45)	-0.0023** (-2.05)	-0.0024** (-2.12)
B/M_t	0.0467*** (9.38)	0.0464*** (9.42)	0.0464*** (9.38)
$ret_{t-1,t}$	-0.0461* (-1.68)	-0.0465* (-1.70)	-0.0458* (-1.68)
$intercept$	0.0993*** (8.39)	0.1061*** (9.15)	0.1044*** (9.01)
N	*3,058*	*3,058*	*3,058*
R^2	*0.0844*	*0.0876*	*0.0868*

When the threshold is set at the top 20% of the default risk distribution (i.e., decile 9), no statistically significant relationship is revealed between default risk and expected returns, neither below nor above the threshold. This suggests that the chosen cutoff does not capture a shift in the underlying relationship, indicating that a potential change in trend may occur further along the distribution. In contrast, when the threshold is set at the top 10% of the

default risk distribution (i.e., decile 10), the piecewise linear regression produces statistically significant estimates both below the threshold and for the incremental effect above it. This suggests a shift in the pricing of default risk within the top decile. To examine whether this shift emerges earlier, a midpoint threshold is introduced at the top 15%. At this level, the results again show strong and statistically significant relationships on both sides of the cutoff.

These results suggest that the turning point in the relationship between default risk and ERP lies around the top 15% of the default risk distribution, corresponding to a default probability of approximately 1.15%.[22] Below this threshold, the coefficient on default risk is -2.8178 (significant at the 1% level), indicating that an increase in default probability within the lower end of the distribution (e.g., from 0% to 1%) is associated with a 2.82 percentage point decline in the ERP. This finding marks a clear shift from earlier results, where statistically significant relationships were economically negligible. Here, the magnitude of the effect suggests that default risk substantially reduces expected returns at the lower end of the distribution. These results are also robust across alternative valuation models, including the 10-year DDM and the composite model, as shown in Table 18 in Appendix 4.

Above the threshold, the slope changes by +2.6198 (also significant at the 1% level), resulting in an implied slope of -0.1980.[23] This implies that for firms in the top 15% of the default risk distribution, a one percentage point increase in default probability is, on average, associated with a 0.20 percentage point decline in ERP. Taken together, the results do not support a V-shaped relationship. The findings instead suggest a different type of nonlinear pattern, where ERP declines at the lower end of the distribution but flattens beyond the top 15% of the distribution. This indicates that investors adjust expected returns in response to rising default risk only up to a certain point, beyond which further increases appear to have marginal effect. Although additional refinement of the threshold could be pursued, the actual bankruptcy probabilities around this range are relatively low and show limited variation.

[22] The mean (median) probability of failure in the top 15% of firms is 1.97% (1.62%).

[23] In piecewise regressions, the slope below the threshold is the baseline slope, while the coefficient above reflects the change. The slope above the threshold is thus the sum of the two (i.e., -2.8178 + 2.6198 = -0.1980).

5. Discussion

5.1 Comparison of Findings to Prior Literature

The hypotheses underlying this study is that default risk is positively related to expected returns, as well as follows a linear pattern, when expected returns are proxied by the ICC. However, initial results from the primary regression indicate a negative but economically negligible relationship. Further analysis using piecewise linear regressions suggests that this regression may obscure important variation across the default risk distribution. In particular, the relationship appears to be driven by firms in the upper end of the distribution. Once this nonlinearity is accounted for, the regression shows that the ERP declines in the bottom end of the default risk distribution and then flattens among firms in the upper end.

At first glance, our findings therefore deviate from both the predictions of standard asset pricing theory and the results of prior empirical studies, suggesting an alternative interpretation of how default risk is priced. However, when restricting the sample to firms below the top 15% of the default risk distribution, our results align with the realized return literature (see table 1 in section 2.2.), which overall documents a negative and economically meaningful relationship between default risk and expected returns. It is only when ignoring the nonlinear structure, as in the primary model specification, that the relationship appears economically insignificant across the full sample. Moreover, our results differ from Chava and Purnanandam (2010) not only when the full sample is used, but also when the distribution is segmented. This is particularly notable since both studies rely on ICC-based measures of expected returns. Hence, the divergence is more likely to stem from differences in the measurement of default risk, the valuation model used to estimate the ICC, or the sample composition.

However, the choice of default risk model is unlikely to account for the difference. The findings are robust to the use of both Skogsvik's (1987) and Ohlson's (1980) models, indicating that the observed patterns are not sensitive to the specific measure of default probability. Furthermore, the distribution of estimated default probabilities in our sample is broadly comparable to that reported by Chava and Purnanandam (2010), suggesting that differences in the underlying risk assessments are unlikely to drive the contrasting results.

Differences in valuation models may instead contribute to the observed divergence, particularly when the full sample is used without accounting for nonlinearity. Our findings are robust to both the RIV and the composite models, but not to the DDM under the primary model specification. This is noteworthy given that Chava and Purnanandam (2010) rely on the DDM in their analysis. However, when the piecewise regression framework is applied, our results remain robust across all three valuation models, including the DDM. While all employed valuation models are theoretically equivalent under infinite forecast horizons and identical long-term growth assumptions, they often diverge in practice due to simplifying assumptions made in implementation (Anesten et al., 2020). These practical differences in how future growth and value creation are captured may contribute to variation in ICC estimates across models. Although model choice may partially explain differences from

Chava and Purnanandam, the consistency of our findings across all models under the piecewise specification suggests this is unlikely to be the primary factor.

A more plausible explanation for the discrepancy between previous literature may instead relate to differences in sample composition. This study focuses on Nordic industrial and manufacturing firms, whereas their analysis covers a broader set of U.S. non-financial firms. In addition, the time periods differ, with our sample concentrated in the post-2000 era and theirs largely pre-2000. These distinctions point to the possibility that structural differences in market dynamics or firm characteristics may influence how default risk is priced across regions and time periods. Differences in market liquidity may also play a role, as the Nordic equity markets are smaller and less liquid than the U.S. market (Euronext, 2024), which may affect how default risk is incorporated into prices.

5.2 Interpretation of the Nonlinear Relationship

Although the results initially appear inconsistent with theoretical expectations, the observed nonlinearity calls for a more nuanced interpretation. The cutoff point analysis reveals a pricing structure where expected returns decline with increasing default risk only up to a certain threshold. Beyond this point, approximately the top 15% of the default risk distribution, the relationship flattens. This pattern challenges the notion that default risk is a continuously priced systematic factor. Although systematic risks do not necessarily require linearity, they are generally expected to affect expected returns across the entire risk distribution. The observed flattening suggests that the pricing of default risk may be constrained at the upper end.

One possible interpretation draws on behavioral explanations discussed in prior literature. Garlappi and Yan (2011) propose that investors' pricing of distress risk may follow a hump-shaped pattern due to shareholder incentives. Although this study does not find such a pattern, the notion that investors treat firms differently across the default risk distribution remains relevant. In particular, firms in the upper end of the distribution may be perceived as already distressed, leading to a form of return inelasticity. Once a certain level of default risk is reached, further increases have marginal effect on pricing because perceived risk is already high. This idea is consistent with Von Kalckreuth (2005), who suggests that at extreme levels of distress, non-financial considerations (e.g., strategic positioning, tax shields, or political implications) may influence investor behavior. However, such interpretations are unlikely to fully explain the results, as the mean (median) probability of failure in the top 15% of firms is only 1.97% (1.62%), which is not extreme in absolute terms. Instead, the observed flattening may reflect that investors become less responsive to variation in default risk beyond a certain relative threshold within the distribution.

6. Conclusion

This thesis investigates how default risk is priced in the Nordic equity market from 2005 to 2023, using the ICC as a proxy for expected returns. Motivated by the findings of Chava and Purnanandam (2010), our hypotheses proposes a positive and linear relationship between default risk and expected returns. The results indicate that default risk is negatively related to expected returns for firms with a probability of failure below approximately 1.15%, corresponding to the bottom 85% of the default risk distribution in our sample. This relationship is both statistically and economically significant. However, beyond this threshold, the relationship changes. For firms in the top 15% of the default risk distribution, further increases in default risk have little additional effect on expected returns, indicating a flattening of the relationship.

These results contradict the findings of Chava and Purnanandam (2010) and reject both hypotheses of this study. In contrast, our results align more towards a majority of the realized return literature (see table 1 in section 2.2.), which finds a negative relationship. Beyond the direction of the relationship, our findings point to a nonlinear structure. Garlappi and Yan (2011) also find a nonlinear relationship, specifically a hump-shaped pattern. However, our results suggest a different structure, where expected returns decline with increasing default risk up to a certain point, after which the relationship flattens. This observed flattening may reflect that investors become less responsive to further increases in risk once a certain relative threshold is exceeded.

Taken together, this thesis contributes to the literature on default risk pricing by providing evidence from a recent time period and a previous unexplored market. By using the ICC as a forward-looking proxy for expected returns, this study addresses concerns that the financial distress anomaly arises from measurement error in realized returns. Nevertheless, the findings are inconsistent with the predictions of standard asset pricing theory. The observed nonlinear relationship suggests that differences in how expected returns are measured may not entirely account for the results. The nonlinear finding also serves as a reminder to future research not to rely solely on linear models when examining the pricing of default risk.

However, it is important to note that our study focuses exclusively on industrial and manufacturing firms, a choice necessitated by the requirements of the Skogsvik (1987) accounting-based bankruptcy model. A key limitation of this approach is that the analysis focuses on a specific segment of the market, and the conclusions drawn may not generalize beyond these industries. Thereto, the sample primarily covers firms in the lower range of the default risk distribution. Unlike studies such as Garlappi and Yan (2011), the analysis is hence not able to capture the full spectrum of failure probabilities. Future research could address this by applying a market-based default risk model to include a wider set of Nordic firms (e.g., all listed non-financials).

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Appendices

Appendix 1. Summary of Sample Firms Characteristics

Table 12. Sample Composition by Country

This table presents the sample divided by countries.

Country	No. of Observations	% of Total
Sweden	1,724	56%
Finland	600	20%
Norway	402	13%
Denmark	332	11%
Total Sample	**3,058**	**100%**

Table 13. Sample Composition by GICS Industry

This table presents the sample divided by GICS industries, where all industries below 5% of total have been aggregated into the "Others" category.

GICS Industry	No. of Observations	% of Total
Machinery	500	16%
Technology Hardware and Equipment	366	12%
Commercial Services and Supplies	237	8%
Construction and Engineering	224	7%
Professional Services	209	7%
Trading Companies and Distributors	185	6%
Metals and Mining	176	6%
Others	1,161	38%
Total Sample	**3,058**	**100%**

Appendix 2. Default Risk Estimation: Alternative Model

This appendix presents the Ohlson (1980) O-score model, which is used as an alternative default risk estimation model to test for robustness against the Skogsvik (1987) model.

Table 14. Ohlson (1980) O-Score Model

Ohlson (1980) presented the results for three different models, which aimed at predicting bankruptcy; 1) one year in advance, 2) two years in advance, conditioned on firm survival in year one, and 3) either one or two years in advance. Thus, the prediction horizons are shorter than for the Skogsvik (1987) model, making it impossible to construct an average of the years one, three, and five, like was done for his model. Since this only serves as a robustness test, we made the choice to only include the one-year model. This model, which yields a so-called O-score for a given firm, is presented below:

Financial Ratio / Dummy Variable	**Forecast Horizon**
	1
$SIZE$	-0.407
$TLTA$	+6.03
$WCTA$	-1.43
$CLCA$	+0.0757
$OENEG$	-1.72
$NITA$	-2.37
$FUTL$	-1.83
$INTWO$	+0.285
$CHIN$	-0.521
$Constant$	-1.32

where:

$SIZE = log(\frac{Total\ assets}{GNP\ price\ level\ index})$, where the index assumes a base value of 100 for 1968. Total assets are as reported in dollars. The index year is as of the year prior to the year of the balance sheet date. The procedure assures a real-time implementation of the model. The log transform has an important implication. Suppose two firms, A and B, have a balance sheet date in the same year, then the sign of PA - PB is independent of the price-level index. (This will not follow unless the log transform is applied.) The latter is, of course, a desirable property.

$$TLTA = \frac{Total\ liabilities}{Total\ assets}$$

$$WCTA = \frac{Working\ capital}{Total\ assets}$$

$$CLCA = \frac{Current\ liabilities}{Current\ assets}$$

$$OENEG = 1\ if\ Total\ liabilities > Total\ assets,\ 0\ if\ otherwise$$

$$NITA = \frac{Net\ income}{Total\ assets}$$

$$FUTL = \frac{Funds\ provided\ by\ operations}{Total\ liabilities}$$

$$INTWO = 1\ if\ Net\ income\ was\ negative\ for\ the\ last\ two\ years,\ 0\ if\ otherwise$$

$CHIN = \frac{(NI_t - NI_{t-1})}{(|NI_t| + |NI_t - 1|)}$, where NI_t is net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure change in net income.

Moreover, to convert the resulting O-score into a probability of failure, we applied the inverse logit transformation to the O-score, which states that:

$$P(Fail) = \frac{1}{1 + e^{-O}}$$

Appendix 3. ICC and ERP Estimation: Implied Measurement Bias and Alternative Valuation Models

This appendix outlines the estimation of the implied measurement bias used in the RIV model. It also presents the DDM and the AEG OJ Core model, which are used to assess the robustness of the results to alternative valuation models.

Table 15. Summary of the Estimated PMB's per Industry in Runsten (1998)

This table presents the total estimated permanent measurement bias in Runsten's (1998) original study. For each industry, the total PMB is estimated as the sum of the measurement bias for: 1) machinery, equipment, and ships, 2) buildings, 3) trading property, 4) land, 5) investment in shares, 6) R&D expenses, 7) personal development expenses, 8) marketing expenses, and 9) deferred taxes. For simplicity, we only report and use the total PMB.

Industry	**Total PMB**
Pharmaceutical	1.74
Capital-intensive service	0.76
Consumer goods	0.72
Investment companies	0.68
Pulp and paper	0.67
Shipping	0.65
Other service	0.62
Consultants and computer	0.59
Real estate	0.56
Mixed building and real estate	0.55
Trading and retail	0.47
Chemical industry	0.44
Building and construction	0.38
Engineering	0.33
Other production	0.31
Conglomerate and mixed inv.	0.28

Table 16. Mapping of GICS Industries to Runsten's (1998) Table to Derive Implied PMBs

This table presents the mapping-approach used to match Runsten's (1998) estimated total PMBs to the firms in our sample, resulting in the implied PMBs applied in the RIV model. The first column lists the GICS sector classifications of the firms in our sample, which are further divided into their respective GICS industries (e.g., Construction Materials within the Materials sector). Each GICS industry is then manually matched to the most comparable industry category in Runsten's (1998) study, shown in column two. The corresponding implied PMB, shown in column three, is then applied in the calculation of terminal value for all firms assigned to that sector classification.

GICS Sector (Number)	Matched Runsten (1998) Industry	Implied PMB
Materials (15)		
Chemicals	Chemical industry	0.44
Construction Materials	Building and construction	0.38
Containers and Packaging	Other production	0.31
Metals and Mining	Building and construction	0.38
Paper and Forest Products	Pulp and paper	0.67
Industrials (20)		
Aerospace and Defense	Engineering	0.33
Building Products	Building and construction	0.38
Construction and Engineering	Engineering	0.33
Electrical Equipment	Engineering	0.33
Industrial Conglomerates	Conglom. & mix. inv.	0.28
Machinery	Engineering	0.33
Trading Companies and Dist.	Conglom. & mix. inv.	0.28
Commercial Services and Supplies	Other service	0.62
Professional Services	Other service	0.62
Air Freight and Logistics	Shipping	0.65
Passenger Airlines	Shipping	0.65
Marine Transportation	Shipping	0.65
Ground Transportation	Shipping	0.65
Transportation Infrastructure	Building and construction	0.38
Miscellaneous		
Automobiles and Components	Other production	0.31
Technology Hardware and Equipment	Other production	0.31
Semicons. and Semicon. Equipment	Other production	0.31

Equation 10. The DDM (Bauman, 1969)

This equation presents the DDM developed by Bauman (1969), which is employed as an alternative approach to estimate the ICC, enabling a robustness check of the results obtained using the RIV model. The forecasting of value drivers follows the same methodology described in Section 3.2.3 (Forecasting of Value Drivers).

$$V_0(DDM(T = 10)) = \sum_{t=1}^{10} \frac{\widehat{Div}_t}{(1 + \rho_{E^*})^t} + \frac{\widehat{Div}_{10}(1+\widehat{g}_{Div})}{(\rho_{E^*} - \widehat{g}_{Div})(1 + \rho_{E^*})^{10}} \quad (10)$$

where:

$\widehat{Div}_t = \ forecasted\ dividend\ at\ time\ t$

$\widehat{g}_{Div} = \ forecasted\ growth\ rate\ of\ dividends\ from\ t = 11\ onward$

$\rho_{E^*} = ICC = \ bankruptcy\ calibrated\ cost\ of\ equity$

Following Courteau et al. (2000), we assume $\widehat{g}_{Div} = 2\%$.

Equation 11. AEG OJ Core Model (Ohlson & Juettner-Nauroth, 2005)

This equation presents the AEG valuation model developed by Ohlson and Juettner-Nauroth (2005). While this model is not used directly to estimate the ICC, its output is incorporated into the composite ICC measure, which averages the ICC estimates produced by the RIV model, the DDM, and the AEG model. The forecasting of value drivers is consistent with the methodology outlined in Section 3.2.3 (Forecasting of Value Drivers).

$$V_0(AEG(OJ)) = \frac{\widehat{NI}_1}{\rho_{E^*}} + \frac{\left[\widehat{NI}_2 + \widehat{Div}_1 \times \rho_{E^*} - \widehat{NI}_1 \times (1+\rho_{E^*})\right] / \rho_{E^*}}{(\rho_{E^*} - \widehat{g}_{AEG})} \quad (11)$$

where:

$\widehat{NI}_1, \widehat{NI}_2 = \ forecasted\ net\ income\ in\ periods\ t = 1\ and\ t = 2$

$\widehat{Div}_1 = \ forecasted\ dividend\ at\ time\ t = 1$

$\widehat{g}_{AEG} = \ forecasted\ growth\ rate\ of\ capitalized\ abnormal\ earnings\ growth\ from\ t = 1\ onward$

$\rho_{E^*} = ICC = \ bankruptcy\ calibrated\ cost\ of\ equity$

As suggested in Skogsvik and Juettner‐Nauroth (2013), we assume that the consequences of business competition and conservative accounting are offsetting, and thus set $\widehat{g}_{AEG} = 0$.[24]

The terminal value is thus calculated as:

$$\frac{\left[\widehat{NI}_2 + \widehat{Div}_1 \times \rho_{E^*} - \widehat{NI}_1 \times (1+\rho_{E^*})\right] / \rho_{E^*}}{\rho_{E^*}} \qquad (12)$$

[24] While it is common in valuation theory to assume the same long-term growth rate for all value drivers (e.g., both AEG and DIV), this assumption typically does not hold in simplified valuation models with shorter forecast periods, as is the case here.

Appendix 4. Empirical Results: Diagnostics and Robustness

This appendix presents additional analyses conducted to assess the validity and robustness of the empirical results.

Table 17. Pairwise Pearson Correlations Between Independent Variables

This table reports the Pearson pairwise correlation coefficients among the primary independent variables used in the cross-sectional regression analysis. The main variable of interest is the decile ranking of default risk, $P(Fail)_{Dec}$, based on the Skogsvik (1987) model. Additional independent variables include firm size (log market capitalization), B/M ratio, and one-month lagged stock returns. Correlation coefficients are reported along with their statistical significance levels, indicated by ***, and * for the 1%, 5%, and 10% significance levels, respectively.

	$P(Fail)_{Dec}$	$Size_t$	B/M_t	$ret_{t-1,t}$
$P(Fail)_{Dec}$	1.0000			
$Size_t$	-0.0767***	1.0000		
B/M_t	0.1835***	-0.3520***	1.0000	
$ret_{t-1,t}$	0.0127	0.0561***	-0.1236***	1.0000

Exhibit 1. Assessment of Regression Assumptions: Diagnostic Tests

To evaluate the validity of the regression assumptions underpinning our empirical analysis, we conducted four diagnostic tests related to the classical linear regression model: 1) multicollinearity, tested for through variance inflation factors (VIF); 2) heteroskedasticity, tested for via the Breusch-Pagan test; 3) first-order autocorrelation, tested for using the Durbin-Watson statistic; and 4) normality of residuals, tested for through the Jarque-Bera skewness-kurtosis test. The outcomes and implications of each test are discussed below.

1) **Multicollinearity**: All independent variables displayed low VIF values, ranging from 1.01 to 1.17, with a mean of 1.09. These results suggest that multicollinearity is not a concern, and no corrective measures were thus deemed necessary. This is further illustrated by the low pairwise correlation reported in Table 17 above.

2) **Heteroskedasticity**: The Breusch-Pagan test strongly rejected the null hypothesis of homoscedastic residuals ($p = 0.000$), indicating the presence of heteroskedasticity in the error terms. To address this, all regressions were estimated using heteroskedasticity robust standard errors, ensuring valid inference despite the violation of constant variance.

3) **Autocorrelation**: The Durbin-Watson test revealed statistically significant first-order autocorrelation in the residuals. However, the estimated coefficient (−0.0716) was small in magnitude, suggesting that serial correlation is present but likely to have a limited impact on our estimates.

4) **Normality of residuals**: The Jarque-Bera test strongly rejected the null hypothesis of normally distributed residuals ($p < 0.001$ for both skewness and kurtosis). While this indicates non-normality in the residuals, the large sample size ($n = 3,058$) allows us to rely on the Central Limit Theorem. This ensures that our OLS estimators retain their desirable large-sample properties, including asymptotic normality.

Table 18. Cross-Sectional Regressions Using Piecewise Linear Regression: Robustness to the Use of 10Y DDM and Composite Models

This table reports the results from cross-sectional regressions examining the relationship between default risk and the ERP using a piecewise linear specification. The sample is segmented at the 85th percentile of default risk to allow for a change in slope among firms in the top 15% of the distribution. This threshold is motivated by earlier findings suggesting that the turning point in the relationship between default risk and ERP lies around the top 15% of the default risk distribution. The dependent variable is the ERP, estimated using the 10-year DDM and composite valuation models to test the robustness of the results to alternative ICC specifications. The key independent variable is the raw annual default probability, $P(Fail)_{Raw}$, calculated using the Skogsvik (1987) model. Control variables include firm size (log market capitalization), B/M ratio, and one-month lagged returns. All regressions are estimated using pooled OLS with heteroskedasticity-robust standard errors. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. The coefficient on $P(Fail)_{Low}$ captures the slope of the relationship between default risk and ERP below the specified threshold (e.g., up to the top 10%), while the coefficient on $P(Fail)_{High}$ captures the change in slope above that threshold, i.e., how the relationship between default risk and ERP differs among firms in the top x% of the default risk distribution, relative to the baseline slope below the cutoff.

	DDM	Composite
$P(Fail)_{Low}$	-1.9460** (-2.22)	-2.1763*** (-3.07)
$P(Fail)_{High}$	2.7917*** (3.65)	2.2763*** (3.83)
$Size_t$	-0.0106*** (-10.14)	-0.0016* (-1.70)
B/M_t	0.0182*** (4.26)	0.0289*** (6.53)
$ret_{t-1,t}$	-0.0340 (-1.23)	-0.0455* (-1.93)
$intercept$	0.1850*** (16.69)	0.0995*** (9.98)
N	*3,058*	*3,058*
R^2	*0.0729*	*0.0564*

Appendix 5. Statement on the Use of Generative AI Tools

Generative AI, specifically ChatGPT, was not used to generate any content in this thesis. However, we did use it in two specific ways.

First, ChatGPT was used as a grammar and tense-checking tool. After manual revisions of the literature review and method sections, selected portions of the text were reviewed to confirm consistent use of the present tense. This served as a secondary check to ensure grammatical consistency, not as a means of producing or rewriting content. The following is an example of a prompt and answer in this process:

Prompt:

Review the text to ensure that the present tense is used correctly in all sentences, and highlight any instances where past or other tenses are used.

Answer from ChatGPT:

"Fama and French (2006) supported these findings by showing that default risk remained negatively associated with realized returns also in a multifactor framework." → This sentence combines a mix of tenses: "supported" and "remained" are in the past tense, while "showing" functions as a participle linked to the past action.

Second, ChatGPT was used as a digital discussion partner when conducting regressions in Stata, specifically to troubleshoot error messages. It provided guidance on possible causes of specific errors, which helped improve the efficiency of the debugging process. At no point was ChatGPT used to perform data analysis or interpret empirical results. The following is an example of a prompt and answer in this process:

Prompt:

Why does the following Stata code: “reg ERP10Y_RIV_w Skogsvik~3decile ln_marketcap_w BM_w monthlaggedstockreturns_w , robust” return the error message “no observations, r(2000)”, when we do in fact have observations?

Answer from ChatGPT:

This typically occurs when no complete rows exist that contain valid (non-missing) values for all variables used in the regression. Common causes:

1. Missing values: If any of the variables contain missing values (.) for all or most observations, Stata drops those rows. If no rows remain after listwise deletion, the regression will fail.

2. Incorrect or truncated variable names: If a variable like Skogsvik~3decile appears due to name truncation in the output but is miswritten in the code, it may refer to a non-existent variable, which results in all missing values.

3. String values: If one or more of the variables are stored as strings, they must be converted to numeric using the destring command before being used in a regression.
4. All observations filtered out: If a prior command or script applies a condition (e.g., if or in) that excludes all observations, the dataset passed to the regression is empty.
5. Constant variables or insufficient variation: If one or more independent variables are constant (or nearly so), and others are missing, Stata cannot estimate the model.

Using generative AI in the above way thus indirectly supported the quality of the thesis; not as a tool to produce content itself, but rather to assist us in making timely troubleshooting processes more effective.