BANKRUPTCY RISK AND MARKET RATIONALITY DURING COVID-19: SWEDISH EVIDENCE

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Bankruptcy Risk and Market Rationality During Covid-19: Swedish Evidence

Abstract:

Purpose: To examine the changes in bankruptcy risk that occurred during the beginning of the Covid-19 pandemic for companies listed on Nasdaq Stockholm, and to test market rationality regarding i) the changes in bankruptcy risk, ii) the equity risk premium associated with bankruptcy risk in the 1-year period after the market trough.

Method: Bankruptcy risk is estimated with the Skogsvik (1990) model and a bankruptcy risk calibrated Residual Income Valuation model. To test market rationality, three tests are conducted: i) a comparison of changes in bankruptcy risk among three groups of firms: winners, neutrals and losers, classified based on the expected Covid-19 impact, ii) a comparison of the 1-year returns for groups of firms with different bankruptcy risk, and iii) a regression analysis between 1-year returns and bankruptcy risk.

Key findings: The bankruptcy risk increased significantly for companies across all sectors, and it increased significantly more for the Covid-19 losers compared to the winners (average difference of 1.2pp.), indicating that the changes in bankruptcy risk were rational. Furthermore, as expected in a rational market, there was a substantial equity risk premium associated with bankruptcy risk in the 1-year period after the 23rd of March 2020 (14 pp. for each pp. of failure probability).

Keywords:

Bankruptcy risk, market rationality, Covid-19, residual income valuation, accounting based bankruptcy prediction

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Contents

1. Introduction

1.1 Background, research questions and methodology

The Covid-19 pandemic has led to one of the most significant shocks that the global economy has experienced during the last century, with the US GDP falling almost 32%[1] during the second quarter of 2020 (Bureau of Economic Analysis, 2020). Similarly, the GDP in UK contracted by more than 20% during the first half of 2020 (Office for National Statistics, 2020). Lockdowns and other restrictions caused disruptions in demand and supply chains, which in turn led to an unprecedented decline in revenue and a liquidity crunch for many firms (Cella, 2020). In Sweden, an abnormally large number of firms filed for bankruptcy already in March, even though the government and the Swedish Central Bank had started announcing the first support packages then (ibid).

The stock market reaction to the Covid-19 pandemic was dramatic. In the matter of around four weeks in February and March, the Swedish equity indices OMXS30 and OMXSPI lost more than 30% of their values (Nasdaq, 2021). What caused this decline? As shown in e.g. Skogsvik (2006), the theoretically correct equity prices are determined by a combination of three variables:

i) the expected profits, dividends, or cash-flows conditioned on company survival
ii) the expected rate of return
iii) the bankruptcy risk

The Covid-19 outbreak was expected to lead to temporary reductions in i) for many firms, as imposed restrictions had a negative short term impact not least on demand. The restrictions affected particularly consumer reliant sectors such as travel, hotels, restaurants, and retail, with the Purchasing Managers' Index (PMI) for the services sector in April 2020 declining to levels not seen since the global financial crisis (Swedbank, 2020a). Similarly, many manufacturing firms witnessed a significant decline in demand, with the period February to March 2020 representing the largest monthly decline ever in PMI for manufacturing firms (Swedbank, 2020b). Although the pandemic was expected to cause severe economic disruption, the value of a firm is determined by the profits or dividends it is expected to generate in *perpetuity*, while lockdowns and other restriction initially only were expected to last for a few months. Since the economy was expected to rebound once societies reopened and restrictions were relieved, i) alone is unlikely to explain the significant decline in equity prices.

Similarly, an increase in required rates of return appears to be unable to explain the significant market decline. In Sharpe's (1964) Capital Asset Pricing Model (CAPM), the required rate of

[1] Annualized.

return of a security is determined by the risk-free rate, market risk premium and covariance between the security's return and the market's return (Beta). The interest rate of Swedish government bonds with a 10-year maturity – which commonly is used as a proxy for the risk-free rate (PWC, 2020a) – decreased during Q1 2020 (Dagens Industri, 2021a), indicating a *lower* required rate of return for equities. Contrary, the market risk premium for Swedish equities increased by 0.9 percentage points to 7.7% year over year during 2020 (PWC, 2020a). However, such increase should not be enough to cause more than a 30% drop in equity prices.[2] Finally, there is no reason to believe that the market decline was preceded by a significant change in return-covariances, as these typically are estimated during a number of years and therefore tend to be quite stable over time. Thus, it is improbable that an increase in cost of equity caused the market decline.

Since the reduction in profits were expected to be temporary and the cost of equity appears to have been relatively unaffected, a credible hypothesis is that the dramatic fall in equity prices can be explained by iii), a significant increase in bankruptcy risk. Considering this, our first hypothesis is:

> ***Hypothesis 1: Companies listed in Sweden experienced a significant increase in bankruptcy risk during the beginning of the Covid-19 pandemic.***

Furthermore, we attempt to test if the presumed changes in bankruptcy risk were motivated; and, using the estimated bankruptcy risks and the realized returns in the 1-year period following the Covid-19 stock market trough, we investigate if there is an equity risk premium associated with bankruptcy risk. More formally, the present study attempts to answer two research questions:

> ***Research Question 1: How was the bankruptcy risk of companies listed in Sweden affected during the beginning of the Covid-19 pandemic?***

> ***Research Question 2: Were i) the changes in bankruptcy risk that occurred during the beginning of the Covid-19 pandemic, and ii) the equity risk premium associated with bankruptcy risk in the 1-year period after the market trough, rational?***

To operationalize the first question, bankruptcy risk is estimated on the 1st of January 2020 and the 23rd of March 2020 for 191 companies listed on Nasdaq Stockholm. To estimate bankruptcy risk in the beginning of the year, the Skogsvik (1990) bankruptcy prediction model is used. To estimate bankruptcy risk in March, a "bankruptcy calibrated" Residual Income Valuation (RIV) model is used.

[2] Moreover, the PWC study was conducted in May 2020, i.e. after the market collapse, so the increase cannot have *caused* the declining prices. Rather, it appears to be a reaction to the reminder that equity prices can be very volatile.

The second research question relates to market rationality and can be viewed as an extension of the first, as it builds on the estimated bankruptcy risks from the first research question. To answer the second question, three tests are conducted:

- In the first test, the sample companies are divided into three groups: winners, neutrals and losers, on the basis of the Covid-19 impact that was expected during the pandemic. We test if there were differences in how the bankruptcy risk changed among the groups.
- Second, using the bankruptcy risks found while answering the first research question, we divide our sample into quintiles based on bankruptcy risk and investigate the 1-year returns that the different quintiles generate after the Covid-19 market-trough in March.
- Finally, we perform a regression analysis on the 1-year returns in which the impact of bankruptcy risk on returns is isolated by considering additional, potentially skewing factors: price-to-book, size, Beta and one "surprise factor" (which is supposed to capture some of the return that occurred due to company specific events, in this case positive earnings surprises).

The first test is conducted to see if bankruptcy risk increased more for Covid-19 losers compared to the winners (which would indicate rationality). The second and third tests are conducted to see if there is an equity risk premium associated with bankruptcy risk. There should be such a premium in a rational market, as investors all else equal should demand a higher return for holding equities with high bankruptcy risk (cf. Skogsvik, 2006).

1.2 Key findings

We find that Covid-19 initially caused a significant increase in bankruptcy risk among Swedish companies, with the median bankruptcy risk in our sample increasing from 0.13% to 2.36%. With regard to the second research question, none of the rationality tests indicate that the market acted irrationally; bankrutpcy risk increased significantly more for the losers compared to the winners (average difference of 1.2pp.), and there was a significant equity risk premium associated with bankruptcy risk in the 1-year period following the Covid-19 market trough where an incremental increase in bankruptcy risk of 1pp. yielded a 14pp. increase in returns.

1.3 Contribution

The contribution of the present study is fourfold. First, similarly, to e.g. Cella (2020), it contributes to the knowledge regarding bankruptcy risk during Covid-19. To date, that body of research is scarce, not least in a Swedish context. Most prior studies focus on "ex-post" bankruptcy rates for various subsegments of firms (cf. Cella, 2020; Wang et al., 2020) or policy formulation (cf. Blanchard et al., 2020; Hodbod et al., 2020). Contrary, the present study examines the bankruptcy risk *implied* by the stock market during the peak of the crisis. In hindsight, it seems that Covid-19 has not led to the substantial wave of bankruptcies first anticipated, but nevertheless it is valuable to quantify the "perceived" bankruptcy risk during the crisis. This is crucial for comparisons between expected and actual bankruptcies, which in turn could be used to evaluate e.g. the outcome of policy interventions.

Furthermore, the study contributes to the field of stock-market rationality. It is a well-researched field, but most previous studies have focused on topics such as the performance of professional fund managers (cf. Malkiel, 2003), investor "overreactions" (cf. DeBondt and Thaler, 1985) or the performance of "value" stocks (cf. Fama and French, 1993). On the contrary, the present study is more of an event study that investigates market rationality regarding bankruptcy risk during one of the most significant market turmoils during the last century.

Third, the study contributes to the field of equity pricing and bankruptcy risk, a field in which the current body of research is scarce compared to e.g. bankruptcy risk in bond valuation. It is not obvious that the stock market incorporates bankruptcy risk into equity prices, as it is seemingly ignored by many professionals and scholars. Increased knowledge of equity pricing and bankruptcy risk is not only of academic importance[3], it is also important for participants in the capital markets for which equity pricing is crucial, i.e. investment banking divisions, equity analysts and fund managers.

Finally, the study contributes to the bankruptcy prediction model literature. Previous studies in this field typically estimate bankruptcy risk either with statistical accounting based prediction models that rely on "fundamental" historical accounting information, or with "market models" that rely capital markets data[4], e.g. using option pricing theory. To the authors knowledge, the present study is the first that employs a RIV-model to empirically estimate bankruptcy risk. The RIV-model functions in the intersect between "accounting" and "market based" bankruptcy prediction, as it utilizes both financial information and capital markets data to predict bankruptcy. Theoretically, bankruptcy risk estimation with a RIV-model should have a great potential as it avoids many of the common problems that most statistical accounting based bankruptcy prediction models face (see Chapter 2 and 3 for further discussion on this topic). But the RIV-model in the context of bankruptcy prediction is yet to be empirically tested, and the present study contributes to that.

[3] E.g. for testing theoretical relationships, for instance that increased bankruptcy risk ought to increase the demanded return, which in turn should depress prices.
[4] For instance return volatility and market prices.

2. Previous research and theoretical background

2.1 Bankruptcy risk in equity valuation textbooks and among investment professionals

Contrary to the considerable body of research regarding default risk for the purpose of valuation of corporate debt and derivatives on corporate debt (cf. Madan and Unal, 1998; Duffie and Singleton, 1999; Jarrow and Turnbull, 1995; Zhou, 1997), rather little is known about bankruptcy risk and equity valuation. Furthermore, bankruptcy risk appears to be ignored by many professionals and academics. In many corporate valuation textbooks (e.g. Penman, 2012; Koller et al., 2015), no attempt is made to explicitly quantify the impact of bankruptcy risk in equity valuation models. Considering that bankruptcies typically are significant negative events for equity holders, that is a cause for concern.[5] Skogsvik (2006) illustrates the importance of including bankruptcy risk in equity valuation modelling; assuming a company with a terminal growth of 5% and a cost of equity of 10%, an increase from 0% annual bankruptcy risk to 2% theoretically reduces the equity value of around 40% (ibid).

Bankruptcy risk is also often overlooked, or at least unpronounced, by many investment professionals. From casual observations of equity analysts' research reports, bankruptcy risk is rarely explicit in valuations and recommendations. Supporting that, Lindgren and Velander (2004) find that most analysts are unaware of the accounting-based valuation models that incorporate bankruptcy risk (cf. Skogsvik, 2006 for examples of such models). Furthermore, they find that analysts appear to make their valuations and recommendations contingent on corporate survival with the bankruptcy risk only incorporated in an arbitrary manner – if at all.

2.2 Statistical accounting based bankruptcy prediction models

Conversely, scholars have made much effort making models that predict bankruptcy and estimate bankruptcy risk. In a review of the existing literature on bankruptcy prediction models, Appiah et al. (2015) find that most are based on statistical techniques.[6] Pioneered by Beaver (1966) and Altman (1968), these models tend to use one or more accounting ratios in order to either discriminate between companies that risk bankruptcy and those that do not, or to estimate the probability of firm bankruptcy in a given time period (cf. Ohlson, 1980; Skogsvik, 1990). Among

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[5] Morellec et al. (2008) find that equity shareholders on average only recover around 20% of the asset value at the time of financial distress.

[6] Another type of model that sometimes is employed is theoretical/market based models. These typically use e.g. option pricing theory in order to estimate bankruptcy risk (cf. Aharony et al., 1980; Scott; 1981; Hillegeist et al., 2004; Agarwal and Taffler, 2008)

the statistical accounting based models, the former group of discriminant models is the most common in the published literature (Bellovary et al., 2007).

Although the statistical accounting based models have received critique, e.g. for bankruptcy bias in the sample, sample specific independent variables, neglect of non-financial information, ad hoc choice of variables and lack of theoretical foundation (cf. Appiah, 2015), many are still useful for bankruptcy prediction. In a review of the existing literature, Bellovary et al. (2007) observe that the most successful models have been able to predict bankruptcy several years prior to failure with an accuracy of 100%. However, the worst performing models have had a significantly lower accuracy (ibid). An accuracy in the range of 80 to 90%, such as in Altman (1968) and Skogsvik (1990), appear to be most common for the best performing models.[7]

Besides the good forecasting capabilities of these models, a strength is that the they are relatively simple to estimate and use. The principles for estimating and using most statistical accounting based models are fairly similar. First, historical financial data from annual reports for bankrupt and non-bankrupt firms are collected and compared in order to find the accounting ratios that best distinguish the two categories of firms from each other. Most models use fairly similar independent variables to predict bankruptcy (Bellovary et al., 2007); commonly, they use some measure of profitability (e.g. Return On Assets), short term liquidity (e.g. Current Ratio) and solvency (e.g. $\frac{Equity}{Total\ assets}\ or\ \frac{Equity}{Debt}$) – i.e. ratios that intuitively appear as reasonable indicators of the financial health of a firm. After the accounting ratios have been chosen, the coefficients for the ratios are estimated, often by choosing coefficients that minimize the combination of type I and II errors (i.e. misclassifying bankrupt firms as non-bankrupt or vice versa).[8] Finally, to use the model and estimate bankruptcy risk, the user inputs the financial information for the firm(s) under investigation.

2.2.1 The Skogsvik (1990) model

Among studies on Swedish firms, the perhaps most well-recognized statistical accounting based prediction model is the Skogsvik (1990) model. It was estimated using a sample of 51 bankrupt and 328 non-bankrupt Swedish manufacturing and mining companies. The estimation sample was limited to companies with assets exceeding SEK 20m or 200 employees during the period 1966-1971. Firms were classified as bankrupt if they filed for bankruptcy, shut down their

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[7] A common method of testing the validity of such models is the use of a hold-out sample (Bellovary et al., 2007), i.e. applying the model to a new set of observations and to test the predictive capability. Strong proponents of this method include Jones (1987). Another method of testing validity is "the jackknife", where one observation is withheld from the estimation sample and subsequently classified with the model. The process is then repeated for each observation in the sample (Bellovary et al., 2007).

[8] However, since the "cost" of misclassification not necessarily is equivalent for the two types of errors – type I errors are typically perceived as more costly – model optimization can be a dilemma.

primary production activity, or received substantial state subsidies. The model generates bankruptcy probabilities up to six years prior to failure and the one-year model is specified as follows (Skogsvik, 1990, p.145):

$$V = \beta_0 + \beta_1 * R_A + \beta_2 * R_L + \beta_3 * t(1) + \beta_4 * TIV + \beta_5 * LI_I + \beta_6 * ER + \beta_7 * E' + \beta_8 * diff(R_L) \quad (1)$$

Where R_A = Earnings before interest and taxes/Average total assets

R_L = Interest expense/Average total liabilities

t(1) = Income taxes/Profit before taxes

TIV = Average inventory/Revenues

LI_I = Cash/Current liabilities

ER = Owners' equity/Total assets

E' = Growth owners' equity/Owners' equity

diff(R_L)= $[R_L^{(n)} - \frac{\mu\left(R_L^{(n-1)}\right]}{\sigma R_L^{(n-1)}}$, where μ (…) = estimated mean of $R_L^{(n)}$ and σ (…) = estimated standard deviation of $R_L^{(n)}$

V = Overall index

According to Skogsvik (1990), the ratios could be viewed as descriptors of profitability, cost structure, capital turnover, liquidity, asset structure, financial structure, and growth, i.e. factors that commonly are included in statistical accounting based models and ought to provide a good overview of the financial health of a firm. The model generates an index value *V* for each forecast year. *V* is assumed to be normally distributed, and hence a normal distribution table can be used to estimate the probability of bankruptcy.

Note that the proportion of bankrupt firm in the sample (51 out of 379) is much higher than it would be in most real-world situations with random samples. This phenomenon is called the "choice based sample bias" and causes the estimated bankruptcy probabilities in statistical models to be biased (Skogsvik and Skogsvik, 2013). More specifically, the bankruptcy probabilities are biased upwards by a factor that is closely related to the relationship between the fraction of bankrupt firms in the population and the sample. Skogsvik and Skogsvik (2013) shows that this does not cause any concern as long as the estimated probabilities are used to classify firms as bankrupt or survival.[9] But for studies that are concerned with bankruptcy probabilities in the context of equity valuation, such as the present, *unbiased* probabilities are required. To

[9] As long as the cut-off value is empirically assessed.

estimate unbiased bankruptcy probabilities from biased bankruptcy probabilities, Skogsvik and Skogsvik (2013) shows that equation (2) can be used:

$$P_{fail}^{(adj)} = [1 + \frac{1-\pi}{\pi} * \frac{prop}{1-prop} * \frac{1-P_{fail}^{(prop)}}{P_{fail}^{(prop)}}]^{-1} \quad (2)$$

Where $P_{fail}^{(adj)}$ = The unbiased bankruptcy probability

π = Fraction of bankrupt firms in the population

$prop$ = Fraction of bankrupt firms in the sample

$P_{fail}^{(prop)}$ = The biased bankruptcy probability

2.3 Bankruptcy prediction using fundamental valuation methods

For reasons further elaborated on in section 3.1.1, it is sometimes problematic to use statistical accounting based bankruptcy prediction models. Fortunately, there are other options. Skogsvik (2006) shows how bankruptcy risk can be incorporated into accounting based fundamental valuation models, where the most common are the Dividend Discount Model (DDM) and the Residual Income Valuation (RIV) model.

2.3.1 Introduction to the DDM

The background to the DDM is that "*a stock is worth the present value of all dividends ever to be paid upon it*" (William, 1938), and in its most simple version, it can be formulated like below (cf. Gordon and Shapiro, 1956):

$$V_0 = \sum_{t=1}^{\infty} \frac{D_t - N_t}{(1+\rho)^t} \quad (3)$$

Where: V_0 = The value of equity at t = 0

D_t = The dividend expected at time t

N_t = Owners' contribution at time t

ρ = The cost of equity

Over time, various more sophisticated versions of the DDM have been formulated. For instance, Gordon and Shapiro (1956) made the impact of dividend growth more explicit, and Molodovsky et al. (1965) integrated earnings growth in the model. Similarly, Fuller and Hsia (1984) proposed a model including growth but with a non-constant growth rate.

Although the model is simple and intuitive, the DDM has some flaws. It is obviously problematic to apply to non-dividend paying firms. On the other end of the spectrum, there are firms that pay more in dividends than they can sustain with their operational cash flow, which is problematic since they then have to raise new debt or equity in order to continue paying that level of dividends (Damodaran, 2006). Similarly, Miller & Modigliani (1961) argue that dividend decisions shouldn't impact the market value of equity, considering that a dividend payout theoretically should reduce the equity value of a firm by an amount that is equally large to the dividend.[10]

2.3.2 Introduction to the RIV-model

Another fundamental valuation model is the Residual Income Valuation (RIV). Under certain assumptions[11], the RIV can be derived from the DDM, and theoretically the two models should yield consistent valuations.[12] Below is the old RIV-model (cf. Preinreich, 1938; Edwards and Bell, 1961):

$$V_0 = BV_0 + \sum_{t=1}^{T} \frac{NI_t - \rho * BV_{t-1}}{(1+\rho)^t} + \frac{V_T - BV_T}{(1+\rho)^T} \tag{4}$$

Where: BV_t = The book value of equity in t

NI_t = The net profit in t

$V_T =$ The equity value in the end of the forecast period

The model is constituted of three parts:

i) the book value at the point of valuation
ii) the sum of the discounted residual income in each period, defined as the net income in *t* less the "demanded" net profit given the book value of owners' equity and the cost of equity
iii) the terminal value, defined as the discounted difference between the theoretical value of owners' equity and book value of owners' equity in the end of the forecast period.

Letting $ROE_t = \frac{NI_t}{BV_{t-1}}$ and $q_t = \frac{V_T}{BV_T} - 1$, equation (4) can be rewritten slightly:

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[10] This is only true under the assumptions of no transaction costs, sufficient trading liquidity in the equity, rational behavior (investor preference of more wealth than less, and an indifference to if the returns are generated via capital gains or dividends), and perfect certainty regarding investment program and future profits. It can certainly be questioned whether these assumptions are realistic.
[11] E.g. that the clean surplus relationship holds. Other requirements for theoretical consistency are elaborated on in Chapter 3.
[12] See Skogsvik (2002) pp. 1-14 for more in-depth tutorial on the RIV-model.

(4’) $$V_0 = BV_0 + \sum_{t=1}^{T} \frac{(ROE_t - \rho) * BV_{t-1}}{(1+\rho)^t} + \frac{q_T * BV_T}{(1+\rho)^T}$$

Where $q_T =$ The accounting measurement bias of owners’ equity at t = T.

The rewritten RIV-model in equation (4’) is less cumbersome to use than (4) since it can be difficult to estimate the future theoretical value of owners’ equity (V_T) (which is required for calculating the terminal value in equation 4). Meanwhile, there are readily available estimates of q_T (cf. Runsten, 1998). Whereas $V_t - BV_t$ can be thought of as a combination of “business goodwill” that exists due to investment opportunities for the company that will generate profitability in excess of the required return and accounting bias that exists due to conservative accounting, q_T represents only the accounting bias.[13] In a model with a long enough forecast period, companies are expected to be in a “competitive equilibrium” without business goodwill at the end of the forecast period. Therefore, the entire difference between V_T and BV_t should theoretically be explained by accounting measurement bias (q_T).

2.3.3 Empirical evidence regarding the accuracy of the RIV-model and the DDM – implications for the present study

There are several studies that examine the accuracy of the RIV and DDM. Regarding the DDM, Shiller (1981) shows empirically that stock prices are too volatile to be explained by changes in dividends. Although Shiller’s study received certain critique – e.g. for small sample bias (Flavin, 1983) and for his “variance bound methodology” (Marsh and Merton, 1986) – later studies (that were absent of those flaws) confirmed that equity prices in fact are too volatile to be explained by dividends (Campbell and Shiller, 1987: West, 1988).

Similarly, Bernard (1995) tests empirically to what extent different fundamental valuation methods can explain stock price variation. While the DDM only was able to explain 28% of the price variation, the RIV-model could explain as much as 68%. Similar results were latter obtained in Penman and Sougiannis (1998). Also comparing different fundamental equity valuation models, Francis et al. (2000) test the respective models’ pricing accuracy, defined as the difference between the observed market price and the “intrinsic” price obtained from the models. In line with previous studies comparing the two models, the RIV performed better than the DDM, with a mean pricing error of 30% (69%) for the RIV (DDM).

[13] Conservative accounting refers to e.g. the fact that certain investments, such as investments in marketing or other intangible assets, typically are expensed instead of capitalized due to accounting prudence.

Courteau et al. (2001) also test the accuracy of different fundamental valuation models, but contrary to previous studies, they introduce models specified using "ideal" terminal values.[14] They find that ideal terminal values could significantly improve the pricing accuracy across all models, including RIV. In a similar manner, Jorgensen et al. (2011) examined the impact of adjusting the forecast horizons on model accuracy. The authors found that the RIV-model was relatively insensitive to variations in forecast horizons and praised the RIV-model's consistency and accuracy. Recently, Anesten et al. (2020) found that the RIV is more accurate than the DDM in a Scandinavian setting for most model specifications, including various complexity adjustments.[15] Considering the scarcity of previous studies conducted on samples of Scandinavian firms, those results are an important confirmation that the RIV-model also performs well in a Scandinavian setting. Furthermore, they found that the RIV is the model that performs best in a setting without analyst forecast – which partly is the case in the present study.

To conclude, most previous research indicates that the RIV is more accurate than the DDM for valuation purposes. For the present study, it is ideal to use a model that can "explain" the market prices of equity as accurately as possible, since the model will be used to calculate the implied bankruptcy risk given the market price and the company's forecasted earnings. Provided the strong empirical support in favor of the RIV relative to other models, it will be used in the present study.

2.3.4 Introducing bankruptcy risk to the RIV-model

To introduce bankruptcy risk to the RIV-model[16], it is assumed that the "failure loss recognition principle" (cf. Skogsvik, 2006) holds:

$$E_0(NI_t|fail_t) = -E_0(BV_{t-1}^*) \tag{5}$$

i.e. that the net income in period *t* equals the loss of the opening book value if the company enters bankruptcy. This can be viewed as an extention of the clean surplus relationship and needs to hold in order for the RIV-model to yield a valuation that is constistent with the DDM (Skogsvik, 2006). From (5) follows that the expected residual income $E_0(NI_t - \rho * BV_{t-1})$, i.e. the second part of the RIV-model, can have three outcomes in each period:

i) $E_0(NI_t^* - \rho * BV_{t-1}^*)$ i.e. a "regular" residual income if the company survives in period *t*

[14] The concept of ideal terminal values was first introduced by Penman (1997). The ideal terminal value can be expressed as $V - BV$, where *V* represents the theoretical fair value of the equity and *BV* represents the book value. $V_T - BV_T$ is thus the expected "fair value premium" of the book value of equity at the end of the forecast period T, and should represent a combination of net present value projects and accounting conservatism as discussed previously. Most models in prior research had relied on a terminal value estimated by e.g. a Gordon Growth.
[15] For instance, inclusion of bankruptcy risk and removal of transitory items.
[16] See Skogsvik (2006) for a more in-depth tutorial.

ii) $(-1-\rho) * E_0(BV_{t-1}^*)$ i.e. a loss of the entire opening book value (in addition to the "cost" of the book value)
iii) or 0 if the bankrupcy occurred in any prior period

Similarly, the expected terminal value $E_0(q_T * BV_T)$ will be 0 if bankruptcy occured in any prior period, and $E_0(q_T^* * BV_T^*)$ if the company has survived until the end of the forecast period. Following this and adding the probability of failure $P(fail_t)$ in each period, the RIV in equation (4') can be rewritten to handle bankruptcy risk:

$$V_0 = BV_0 + \sum_{t=1}^{T} \frac{(1-Pfail)^t * E_0[(ROE_t^* - \rho) * BV_{t-1}^*]}{(1+\rho)^t} + \sum_{t=1}^{T} \frac{(1-Pfail)^{t-1} * Pfail * (-1-\rho) * E_0(BV_{t-1}^*)}{(1+\rho)^t} + \frac{(1-Pfail)^T * E_0(q_T^* * BV_T^*)}{(1+\rho)^T} \quad (6)$$

Similar to the RIV without bankruptcy, the first term is the book value of owners' equity at the time of valuation. The second and third terms are the present values of the expected future residual incomes, where the former is the "survival" scenario and the latter is the bankruptcy scenario. The final term is the expected residual value conditioned on company survival. The equation in (6) is somewhat cumbersome to work with and can be further simplified by introducing the following assumptions:

i) $Pfail$ is constant over time, and
ii) the "recovery" value to equity holders if a firm enters bankruptcy = 0.

If these assumptions hold, ρ can be "calibrated" to handle the bankruptcy risk in the regular RIV-model (see Skogsvik, 2006, p.21):

$$\rho^* = \frac{\rho + Pfail}{1 - Pfail} = failure\ adjusted\ cost\ of\ capital \quad (7)$$

Following this, the RIV-model including bankruptcy risk in equation (6) can be re-written as:

$$V_0 = BV_0 + \sum_{t=1}^{T} \frac{(ROE_t^* - \rho^*) * BV_{t-1}^*}{(1+\rho^*)^t} + \frac{q_T * BV_T^*}{(1+\rho^*)^T} \quad (6')$$

Equation (6'), which is the RIV including bankruptcy risk, is very similar to (4') – i.e. the RIV without bankruptcy risk – and is also composed of three major parts. What distinguishes this model is that the cost of equity is failure adjusted to incorporate the probability of bankruptcy and that all terms are conditioned on company survival. Although the model typically is used to estimate the equity value of a firm, it can also be used to "solve" for the failure adjusted cost of equity given a market value and estimates of the other variables. After that, equation (7) can be used to infer the probability of failure.

2.4 Market rationality

2.4.1 Background

Early during the crisis, it became evident that certain industries and firms would be worse impacted than others given the government restrictions that were imposed. For instance, travel restrictions were expected to have a severe impact on the transportation sector. Similarly, recommendations to stay at home as much as possible in combination with restrictions on how many people that could be in a certain area were negative for stores, nightclubs, and restaurants. However, the restrictions were on the other hand expected to have a positive impact for other companies, e.g. those focusing on in-home entertainment, since people were expected to spend more time at home. In a rational market, this should be reflected in changes in bankruptcy risk that varied strongly among "winning" and "losing" firms. Since the present study estimates the bankruptcy risk *implied* by the stock market, we are able to test if the market acted rational with regard to how bankruptcy risk changed for different firms during the Covid-19 crisis. In Chapter 3, it is further elaborated on how these tests are conducted.

With regard to market rationality, a common definition is that *the price of a security reflects all available information, and when new information arises, the price adjusts quickly to incorporate that new information* (cf. Fama, 1970). This is called the efficient market hypothesis. In an efficient market, the only way to increase expected returns is to increase the level of risk, and following that, even uninformed investors will earn as generous returns as the professionals if they buy a diversified enough portfolio (Malkiel, 2003). Such a reasoning is the foundation for Sharpe's (1964) Capital Asset Pricing Model (CAPM).

Proponents of the efficient market hypothesis have suggested that stock market prices follow a "random walk" (cf. Harry, 1959; Godfrey et al., 1964; Malkiel, 1973), implying that future stock prices cannot be predicted. This challenges conventional techniques for price prediction such as fundamental and technical analysis (Fama, 1965). In support of the random walk hypothesis, Jensen (1968) evaluated the performance of mutual funds and found that these on average did not generate excess returns high enough to recoup trading expenses; if it were possible to exploit market inefficiencies to generate excess returns, one could believe that investment professionals are best equipped to do so. However, it has been confirmed in many later studies that fund managers on average underperform the market (cf. Malkiel, 1995). In line with this, fund managers that overperform in a certain period tend to underperform in the next (Malkiel, 2003).

Although the view that markets are efficient was widely accepted by academic financial economists during the 60s and 70s, it has since then endured substantial criticism (Malkiel, 2003). For instance, Lo and MacKinlay (1999) find that prices in the short term have a serial correlation in excess of zero and that prices tend to have too many consecutive movements in the same direction for them to be random, which causes them to reject the random walk hypothesis. This is called the "momentum anomaly", and the behavioral school of economists has explained it by a tendency of investors to underreact to new information (Malkiel, 2003); if the full impact of new information is grasped over time rather than instantly, stock prices will also adjust over time, causing serial correlation. Another explanation offered is the "bandwagon effect", where investors see the stock market rise and are lured into buying stocks as they expect the market to continue rising. This creates a feedback loop where the new demand drives prices even higher. According to Shiller (2000), that type of irrational exuberance has been proposed to explain market booms and busts.

However, the momentum anomaly has been contested. Odean (1999) finds that the transaction costs are too high to realize excess returns from a momentum strategy. Building upon that, Malkiel (2003) argues that it is important to distinguish between statistical and economic significance when evaluating market (in)efficiency and urges to caution with interpreting results that merely show statistical significance as evidence of inefficiency. Finally, Fama (1998) finds that overreactions are as common as underreactions in events such as earnings surprises, mergers and dividend actions, and that post-event abnormal returns are as frequent as reversals.

Another common critique against efficient markets is that investors are subject to waves of optimism and pessimism, and therefore tend to "overreact", causing prices to deviate systematically from their fundamental values (DeBondt and Thaler, 1985). Many studies have indeed found evidence of substantial mean reversal in returns over longer holding periods (e.g. Fama and French, 1988; Poterba and Summers, 1988), which could be interpreted as an indication of overreactions that subsequently are followed by "corrections". Proponents of the efficient market hypothesis have responded to this critique by claiming that the results aren't robust across different time periods and that mean reversals are consistent with an efficient market due to fluctuations in bond prices (Malkiel, 2003). They have also, like the response to the momentum critique, claimed that the results aren't economically significant (Fluck et al., 1997).

Moreover, there are numerous studies which claim that firms with certain characteristics generate excess returns. For instance, it has been shown that stocks with a low market capitalization as a group ("small-cap stocks") significantly outperform the stock market (cf. Keim, 1983; Fama and French, 1993). Similarly, stocks with a low price-to-earnings ratio (Nicholson, 1960; Ball, 1978; Basu, 1983) or a low price-to-book ratio (Fama and French; 1993; 1998) on average generate a significantly higher return compared to stocks with high ratios on the same metrics. A common response by proponents of the efficient market hypothesis is that these ratios capture some risk factor that the traditional CAPM doesn't (Lakonishok et al., 1994). For example, Fama and French (1993) argue that firms in financial distress are more likely to trade at a lower price in relation to their book value, and that a low price-to-book ratio therefore reflects the increased bankruptcy risk.

2.4.2 Market rationality, bankruptcy risk and investment returns

Relating back to Fama's (1970) definition of efficient markets, the key question is how much of the publicly available information that is reflected in equity prices. As bankruptcy risk is devoted relatively limited attention from scholars and professionals, it is possible that bankruptcy risk is a more common source of mispricing than factors such as Beta, momentum, or value. However, the previous research regarding bankruptcy risk and investment returns is rather limited. Table 1 shows a summary of the most important literature in this field.

As bankruptcies often lead to a significant loss of capital, equity investors should – all else equal – demand a higher return for a security with higher bankruptcy risk, as shown by Skogsvik (2006). Otherwise the investor isn't compensated for the probability that the firm defaults, in which the investment return is close to zero.

Some studies have found that firms with a substantial deterioration in financial health generate excess negative returns in the period after the deterioration has occurred[17] (e.g. Altman & Brenner; 1981; Katz et al., 1985; Burgstahler. 1989). This appears rational as the company value, all else equal, should decrease when bankruptcy risk increases. Similarly, Katz et al. (1985) find that firms with a deteriorating financial position generates excess negative returns in the 15-month period before the shift in bankruptcy status, implying that investors – rationally – proactively price in increasing bankruptcy risk in distressed firms.

Meanwhile, Dichev (1998) and Campbell et al. (2008) find that firms with high bankruptcy risk generate below average returns, contrary to what is expected from valuation theory. Similarly, Piotroski (2000) as well as Griffin and Lemon (2002) find a negative relationship between default probabilities and returns. The latter study finds that the underperformance largely is driven by the subsegment of distressed firms that have a high market price compared to the book value of owners' equity.[18]

[17] That is, companies shifting from being healthy to distressed, according to the bankruptcy prediction model.
[18] Firms with high market-to-book have been found to generate excess negative returns in other studies (e.g. Fama and French, 1996), which obfuscates the results somewhat.

Contrary to these findings, Vassalou and Xing (2004) find that firms with high bankruptcy risk generate higher returns compared to firms with low bankruptcy risk. However, the higher returns only persist to the extent that the firms are small and have a low market price compared to the book value of equity – characteristics that other studies have observed to generate excess returns (cf. Fama and French, 1996). In a recent study that includes over two decades of data from 38 countries, Gao et al. (2018) conclude that the counterintuitive "anomaly" with distressed firms generating below average returns indeed appears to exist, and to be most prevalent among smaller firms in developed markets. They suggest that temporary overvaluations of distressed firms can explain their results. Considering the unambiguous findings in the previous research we formulate the following hypothesis[19]:

> ***Hypothesis 2: No equity risk premium was associated with bankruptcy risk in the 1-year period following the 23rd of March 2020.***

[19] Even though it is difficult to reconcile with valuation theory, and implies an irrational market and stock mispricing.

Table 1. Summary of previous research regarding bankruptcy risk and investment returns

Author(s)	Year of publication	Sample - market and period	Model	Key findings
Altman & Brenner	1981	American manufacturing firms, 1960-1963	Altman Z-score	Firms that surpass the Z-score threshold (indicating a shift from going concern to a potential bankruptcy) generate excess negative returns for at least 12 months following the shift
Katz et al.	1985	American industrial firms, 1968-76	Altman Z-score, Wilcox X value model	Firms classified by the Altman model as recovering from distress (deteriorating) displayed significant abnormal positive (negative) returns during the 15-months period prior to the issuance of the annual report that triggered a shift in state, and nine months following the announcement date
Burgstahler	1989	NYSE, 1976-1986	Ohlson O-score	Firms with high bankruptcy risk that has a positive (negative) unexpected change in bankruptcy risk generates excess positive (negative) returns, even after controlling for the impact of earnings surprises
Dichev	1998	American industrial firms, 1981-1995	Altman Z-score, Ohlson O-score	Distressed firms generate abnormal negative returns
Piotroski	2000	American firms, 1976-1996	Proprietary accounting-based MDA ("F_SCORE")	A portfolio of financially strong high book-to-market firms generates a substantially higher return than a portfolio that includes distressed high book-to-market firms
Griffin & Lemmon	2002	American firms, 1965-1996	Ohlson O-score	Among the most distressed firms, the difference between returns for high BM and low BM firms is more than twice as large as that in other firms
Vassalou & Xing	2004	American firms, 1971-1999	Merton's 1974 option pricing model	Within the highest default risk quintile, the return difference between value (high BM) and growth (low BM) stocks is around 30 percent p.a.
Campbell et al.	2008	American firms, 1963-2003	Proprietary accounting based logit	Financially distressed stocks generate anomalously low returns, and have much higher return-standard deviations and market betas
Gao et al.	2018	38 different developed and emerging markets, 1992-2013	Moody's KMW model	Distressed firms generate abnormal negative returns

Note: The table displays a summary of the previous research regarding the relation between bankruptcy risk and investment returns, i.e. previous research that relates to market rationality in the context of bankruptcy risk and returns. Thus, previous literature that has been mentioned which is unrelated to that topic is not included in the table.

3. Method

In this chapter, we explain how we measure the change in bankruptcy risk during the Covid-19 market decline (sections 3.1-3.3) and our approach to testing market rationality (section 3.4). To estimate bankruptcy risk, we use the Skogsvik (1990) model per the 1st of January 2020 and a bankruptcy calibrated RIV-model per the 23rd of March 2020. To investigate market rationality, we conduct three different tests: one regarding how the bankruptcy risks developed among Covid-19 winners versus losers, and two regarding the relationship between estimated bankruptcy risk and realized returns in the 1-year period following the Covid-19 trough.

3.1 Choice of estimation dates and bankruptcy prediction models

The first aim of the present study is to measure the change in bankruptcy risk that occurred due to Covid-19. To fulfill that, we must select one date when the "pre-crisis" bankruptcy risk can be estimated, and another date for the "crisis" ditto. For the pre-crisis date, we use the 1st of January because it ensures that most companies were unaffected by Covid-19 and simplifies discounting procedures. For the crisis date, we choose 23rd of March because it was the trough date of the OMXS30 and OMXSPI indices, and thus represents the peak of the crisis from the stock market's point of view. In order to avoid that the results are skewed by the significant price volatility that was present in March, we use the average of the closing price on 23rd of March ± 1 trading day to calculate equity values.

3.1.1 The Skogsvik (1990) model is appropriate to use on a Swedish sample prior to the Covid-19 outbreak

To estimate bankruptcy risk the 1st of January, we use the Skogsvik (1990) model previously shown in equation (1). In a study of Swedish companies such as the present, it is appropriate to use a model with accounting ratios which previously have worked well for Swedish firms, such as Skogsvik's, since it is well known that independent variables tend to have some degree of sample specificity[20] in statistical accounting based models (cf. Appiah, 2015). However, it should be noted that the Skogsvik model is specified to be used on industrial firms, whereas the present study uses the model to estimate bankruptcy risk for firms in a variety of industries. This could impact the accuracy negatively.

[20] i.e. that the independent variables to some degree are specific to Swedish firms.

3.1.2 The problems with using statistical accounting based bankruptcy prediction models during Covid-19 – the bankruptcy calibrated RIV-model is a good alternative

The reliance on historical accounting data – that only is reported quarterly at best – makes a model such as Skogsvik's unapplicable when an event leads to a sudden spike in bankruptcy risk. Taking the Covid-19 pandemic as an example, the lockdowns of many societies started during March of 2020. This led to an unprecedented decline in revenues and a liquidity crunch for many firms (Cella, 2020), which in turn could have led to a substantial increase in bankruptcy risk. However, a statistical accounting based bankruptcy model would not have been useful for estimating bankruptcy risk in late March or early April, because the only financial information that was available at that point in time was the Q4 reports for 2019, i.e. reports that do not capture the financial impact of the crisis.

Neither would the subsequent Q1 reports have been useful since i) they are not published until the end of April (i.e. they were unavailable amid the peak of the crisis), and ii) only a few weeks of the impact caused by the lockdowns are included. The Q2 reports would include the financial effect of the pandemic, but these reports are not published until the latter part of the summer. Long before that, the equity markets had both collapsed and recovered, which possibly implies a large increase and a succeeding decrease in bankruptcy risk that one wouldn't have been able to measure using a statistical accounting based prediction model. Therefore, to estimate bankruptcy risk in March, we use a bankruptcy calibrated RIV-model as shown in equation (6'). As highlighted in the literature review, several fundamental accounting based valuation methods exist that could be used to estimate bankruptcy risk. But in the context of valuation, the RIV has in many previous studies proved to be the most accurate and reliable model, and hence we favor that over e.g. the DDM in the present study.

One strength of using the RIV-model is that we are able to capture the market's view of bankruptcy risk at a specific point in time, without relying solely on historical financial statements like in a statistical accounting based model. Instead, market prices, estimated cost of equities and forward-looking analysts' estimates are used. Since analysts regularly make revisions of their earnings estimates and the cost of equity is estimated per the valuation date, the RIV-model should be able to isolate the impact of increased bankruptcy risk on equity values; future depressed earnings caused by the pandemic ought to be captured by lower earnings estimates, and a higher market risk ought to be captured in the cost of equity.

Furthermore, the RIV-model avoids much of the critique that commonly is raised against statistical accounting based models. First, it avoids the critique that the prediction model isn't well established in economic theory, since the RIV-model is well anchored in equity valuation theory. Second, the model does not use any arbitrary sample specific independent variables to predict bankruptcy, so a generic RIV-model should be applicable in all bankruptcy prediction contexts. Third, since the model does not require any firm-matching, it avoids the ad hoc process that often is present in statistical accounting based models. Finally, since the RIV-model uses market prices, it can be argued that it also incorporates relevant non-financial information, as opposed to the statistical accounting based models that rely solely on historical financial information.[21]

3.2 Bankruptcy prediction the 1st of January 2020 with the Skogsvik (1990) model

To use the Skogsvik-model, balance sheet and income statement data is collected for the fiscal years 2018 and 2019[22] for each company from the database FACTSET, after which bankruptcy probabilities are estimated 1, 3, and 5 years in the future. As mentioned in the Chapter 2, the bankruptcy probabilities obtained by the Skogsvik-model are “biased” due to the large proportion of bankrupt companies in Skogsvik’s sample relative to the bankruptcies that occur in the entire population of firms. Therefore, equation (2) is subsequently used to estimate the unbiased bankruptcy probabilities. The equation requires three input variables:

i) the biased bankruptcy probabilities, which are obtained for each company from the Skogsvik model
ii) the proportion of bankrupt companies in the original sample
iii) the bankruptcy probability in the relevant population of firms

Whereas i) is known from our use of the Skogsvik model and ii) is known from Skogsvik’s study, an estimate of iii) is required. Ideally, the actual bankruptcy probability of all stocks listed in Sweden that meet the inclusion criteria of the study would be used. However, due to the unavailability of that data, the proportion of bankrupt companies in relation to all active companies in Sweden is used instead. During 2019 that proportion amounted to 1% and it has been on a relatively stable level during the past years (Creditsafe, 2020). Consequently, in the present study it is assumed that the bankruptcy probability in the population is 1%.

[21] Initially, the intention was to use a RIV-model to estimate bankruptcy risk in January as well, in order to be consistent with the use of models. However, this was not possible and in section 3.3.4 we elaborate on why. However, we doubt that the use of two different bankruptcy prediction models will cause significant problems with the study; similarly (low) bankruptcy probabilities in January would likely have been obtained irrespective of which bankruptcy prediction model that would have been used.

[22] The financial statements for Q4 2019 would not be available the 1st of January 2020, but we use Skogsvik’s model as if they were. Other options considered were i) to use the “rolling twelve months” financials as of Q3 2019 or ii) to use analysts estimates for FY2019 as of 1st of January 2020. The authors believe that all options would yield similar results in terms of bankruptcy probabilities. Three quarters of financial statements are available to the equity analysts, so the analyst estimates should be close to the actual numbers. Similarly, a naïve prediction is that Q4 2019 = Q4 2018, so the rolling twelve months numbers should also be close to the actual numbers.

After obtaining unbiased bankruptcy probabilities, the *constant* unbiased bankruptcy probability is estimated by taking an average of the 1-, 3-, and 5-year unbiased bankruptcy risks. Although it would be ideal to estimate bankruptcy probabilities for each individual future year, these probabilities would not be comparable to the ones obtained in March with the RIV-model, since the bankruptcy calibrated RIV rests on the assumption that the probability of bankruptcy is constant.

3.3 Bankruptcy prediction the 23rd of March 2020 with the RIV-model

Section 3.3 is devoted to explaining our approach for estimating bankruptcy risk in March in depth with a RIV-model, and the approach can be summarized as follows:

- First, we use the RIV per the 1st of January 2020 to estimate q-values and steady state profitability for the sample companies.
    - To do this, we obtain analyst estimates (regarding e.g. expected net profits, dividends, and book values from FACTSET), cost of equities (with CAPM), and bankruptcy risks (with Skogsvik, 1990) per the 1st of January. For the forecast years that does not have any analyst estimates, the required input is estimated by linearly interpolating ROE from the last available estimate year to the forecasted steady state profitability.
- Then, under the assumption that the q-values and steady state profitability obtained per the 1st of January are unchanged, we use the RIV per the 23rd of March 2020 to infer the probability of failure. This is done by first solving for the bankruptcy adjusted cost of equity, and then using equation (7) to solve for the probability of failure.
    - To do this, costs of equities are re-estimated per the 23rd of March and analyst estimates are obtained per the 1st of May. For the forecast years that does not have any analyst estimates, the required input is estimated using the process described above.

3.3.1 The market values of equity as a starting point

The RIV-model is typically used to calculate the intrinsic equity value of a firm given estimates for ROE, ρ^*, BV and q. However, as the present study is concerned with estimating bankruptcy risk, the starting point is instead that the equity value is known such as that: $V_0 = the\ market\ value\ of\ owners' equity$. In order to avoid skewing from the significant volatility that was present in March of 2020, we use average market value of equity at the valuation date (23rd of March) ± one trading day. To estimate the probability of bankruptcy in March, we first solve for ρ^* with the bankruptcy calibrated RIV-model in equation (6'). After that, equation (7) is used to solve for the probability of failure. Apart from the market value of equity, the inputs that are needed to solve for p^* with the RIV-model are the following:

i) Forecasts of future net profits, dividends, and book values for the period 2020-2029, as well as the most recent closing book value per the valuation date
ii) Estimates of the cost of equity
iii) Estimates of the permanent measurement bias q_T and steady state return on equity

The following sections are devoted to explaining how these inputs are obtained.

3.3.2 Forecasts of future net profits, dividends, and book values

By using the database FACTSET, analyst estimates of net profits and book values for the period 2020-2024 are obtained.[23] Using the same database, we also obtain the closing book values for 2019 (i.e. BV_0).[24] For most companies in the sample, no analysts' estimates are available after 2021. When no estimates are available, future net profits and book values are estimated. Similarly, the present study assumes that steady state occurs in 2030, and therefore all values for the period 2025-2029 are also estimated.[25] The starting point to estimate book values, net profit, and dividends is the "equilibrium formula" for steady state profitability (cf. Skogsvik, 2006):

$$ROE_T^* = \rho^* + q_T^* * (\rho^* - g_{ss}^*) \quad (8)$$

where ROE_T^* is the steady state return on owners' equity contingent on company survival and g_{ss}^* is the steady state growth ditto. The logic behind the formula is that in steady state in a competitive equilibrium, the net present value of all future investment opportunities are zero, and therefore the long-term sustainable profitability is a function of the cost of equity, the permanent measurement bias, and the growth. Section 3.3.4 describes further how ROE_T^* was estimated in the present study, but for the sake of the argument we here assume that it is known.

After obtaining estimates of the steady state ROE, the next step is to estimate ROE for each year until steady state for the period that are missing analyst estimates (i.e. 2022-2029). That is done

[23] It is assumed that the analysts' data is conditional on company survival.
[24] Even though it is most intuitive to collect the analyst estimates as of the valuation date (23rd of March), estimates are collected per the 1st of May instead. This is because the analysts typically update their earnings estimates in conjunction with the publication of quarterly reports, and most Q1 reports are released during the latter part of April. Most earnings estimates therefore weren't updated to incorporate the "Covid-19 effect" on earnings per the 23rd of March, even though it at that point in time was obvious that many companies would be significantly negatively impacted by the pandemic. However, on the 1st of May, most of that effect ought to be incorporated.
[25] The reason for such a long explicit forecast horizon is that only the permanent measurement bias q_T should impact the difference between the terminal value V_T and the terminal book value BV_T. Our long explicit forecast horizon should ensure that any excess profitability due to an abundance of profitable investment opportunities have sufficient time to be competed away, thus avoiding inflated terminal values; e.g. Penman (1991) finds that ROE is mean reverting, and that most of the excess profitability is competed away within five years. This should theoretically increase the model accuracy, and recently Anesten et al. (2020) empirically found some support in favor of long forecast horizons increasing accuracy.

by a linear interpolation with ROE^*_{2021} as the starting point and ROE^*_{2030} as the end point.[26] The linear change in ROE (ROE_Δ) each year from 2021 to 2030 is:

$$ROE_\Delta = \frac{ROE^*_{2030} - ROE^*_{2021}}{T + 1} \tag{9}$$

Where T represents the number of periods left until steady state from 2021.[27] ROE for any estimation year after 2021 can then be described as:

$$ROE^*_{2021+t} = ROE^*_{2021} + t * ROE_\Delta \tag{10}$$

Where t represents the number of years after 2021. The above equations can be used to estimate ROE for each year in the period 2022-2029. Having ROE estimates makes it easy to also obtain estimates of net profits and book values for each year, as $ROE^*_t = \frac{NI^*_t}{BV^*_{t-1}}$. Having analyst estimates of BV^*_{2021} , and ROE^*_{2022} estimates from equation (9) and (10), the net profit for 2022 can be estimated with equation (11):

$$NI^*_{2022} = BV^*_{2021} * ROE^*_{2022} \tag{11}$$

The next step is to estimate the closing book value of 2022. Under the assumptions that the clean surplus relationship holds, and no new issues are made, the closing book value for 2022 will be the opening book value plus the net profit minus any dividend payouts:

$$BV^*_{2022} = BV^*_{2021} + NI^*_{2022} - D^*_{2022} \tag{12}$$

Where D^*_{2022} represents dividends paid out during the year. To estimate future dividend payouts, historical dividend payouts and opening book values are collected for each company for the fiscal years 2016-2018. The payout share (*PS*) for each year fiscal year in the period 2016-2018 can be described as:

$$PS_t = \frac{D_t}{BV_{t-1}} \tag{13}$$

From that, the average payout share for the period can be calculated:

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[26] For companies without any estimates available after 2021. Whenever estimates are available after 2021, those re used.

[27] Although not particularly intuitive, the denominator is *T* (the number of years left until steady state) *+ 1*, as a denominator with only *T* would cause the steady state profitability to be reached one year before entering steady state.

(14) $$PS_{avg} = \frac{PS_{2016} + PS_{2017} + PS_{2018}}{3}$$

Under the assumption that the future payout share will be equivalent to the average historical payout share, the average payout share can be multiplied with the opening book value of a particular year to estimate the dividend payout.[28] Using the year 2022 as an example again, the estimated dividend payout is:

(15) $$D^*_{2022} = BV^*_{2021} * PS_{avg}$$

Thus, since an estimate of the dividend payout is obtained with equation (15) and an estimate of the net profit is obtained with equation (11), the closing book value for the year 2022 shown in equation (12) can be estimated. The above process is then repeated for all subsequent years until steady state, i.e. the last estimated value is the closing book value for 2029.

3.3.3 Estimating cost of equity with CAPM

To estimate the firm specific cost of equity capital, the present study employs Sharpe's (1964) Capital Asset Pricing Model (CAPM):

(16) $$\rho = r_f + \beta_j * [E(r_m) - r_f]$$

Where r_f denotes the risk-free interest rate which theoretically should represent the interest that can be earned without any probability of loss of capital. The present study uses the Swedish 10-year government bond yield at the valuation date as a proxy for the risk-free rate. B_j represents the covariance in returns between a specific firm and its market index over a certain period. We estimate B_j by regressing the last five years of monthly total return data for each firm against OMXSGI.[29] $E(r_m) - r_f$ represents the market risk premium, i.e. the return that is expected to be

[28] Approximately one fifth of the companies in the sample did not pay any dividends for the fiscal years 2016-2018. The future dividend payouts of these companies could be estimated by calculating steady state payout ratios (proportion of dividend in relation to net profit) as: $PR = 1 - \frac{g^*_{ss}}{ROE^*_{ss}}$. However, that requires known values of q_T and ROE^*_{ss}, and in the present study those are also estimated, and that estimation relies on known dividend payout shares. Thus, estimating dividends the above way would create circularity as there would be too many unknown variables. Instead, dividends for non-dividend paying companies are estimated by assuming that their steady state payout share is the average PS_{avg} for the dividend paying companies. The payout share for the former group is assumed to increase linearly from 0 during fiscal year 2019 to the average of the dividend paying companies when steady state is reached.

[29] The total return index (including dividends) for all shares listed on Nasdaq Stockholm.

earned in excess of the risk-free rate for holding a diversified portfolio of equities. We use the results found in PWC's (2020a) yearly study as an estimate of the market risk premium. The participants in PWC's study on average responded that the market risk premium amounted to 7,7% during 2020.[30] It is assumed that the cost of equity obtained by CAPM is constant, and it is furthermore truncated to 1% as a lower bound.[31]

Using CAPM to estimate the cost of equity, we consciously neglect other methods (e.g. multi-factor models such as Fama and French, 1993). There are two main reasons for that. First, prior studies that test the pricing accuracy of the RIV-model in a Scandinavian context (cf. Anesten et al., 2020) use CAPM to estimate the cost of equity, and we want to be coherent with their method. Second, it is beyond the scope of this study to investigate the precision of different cost of equity models, and CAPM is one of the most widely used methods.

3.3.4 Estimating the permanent measurement bias (q) and steady state return on equity

The q-value is needed to estimate the terminal value in the RIV in equation (6') and the steady state profitability in equation (8). Since most of the ROEs in the period 2022-2029 are estimated by a linear interpolation with the steady state ROE as the end point, the q-value and steady state ROE have a large impact on the "value drivers" of the model.[32] We use the bankruptcy adjusted RIV-model per the 1st of January together with the average unbiased average bankruptcy probabilities estimated with the Skogsvik (1990) model to simultaneously[33] solve for the q-values and the steady state ROE[34], and then we assume that these values were unchanged in March; it is a reasonable assumption as the Covid-19 was expected to be limited mostly to 2020 and 2021, thus not impacting the long-term profitability.[35]

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[30] The participants in the study responded in May, so any Covid-19 related increase in the perceived market risk premium ought to be captured in this estimate.
[31] Six companies in the sample had estimated cost of equity below 1%.
[32] A simple solution is to use q-values obtained in previous studies, e.g. Runsten (1998), and the intention was initially to do so in the present study. However, using the q-values from Runsten (1998) at the valuation date 1st of January, we are unable to find values of ρ^* that yields a RIV value equal to the market capitalization for most companies. Almost exclusively, the problem lies in the market value exceeding the RIV value for all values of ρ^*. The issue is the following: considering that we use a linear interpolation approach (with the steady state ROE as the end point) to estimate ROEs, a lower value of ρ^* not only decreases the discounting rate and the "charge" on book value of owners' equity (thereby increasing the equity value), it also reduces the estimated steady state ROE. In turn, this reduces the estimated ROEs in the period 2022-2029, which decreases the equity value. Thus, using exogenously generated q-values that are "too" low makes the RIV-model unable to find any non-negative ρ^* to justify the market valuation. This issue is especially prominent for companies with high market values in relation to book values and expected residual incomes.
[33] Since the q-value impacts the steady state ROE as shown in equation (8), they were solved for simultaneously.
[34] This means that we repeated the previously described forecasting process of book values, net profits, and dividends (see section 3.3.2), but with analyst estimates and cost of equities per the 1st of January.
[35] Initially, the steady state ROEs were re-estimated per the 23rd of March, but that led to problems similar to the ones described previously in this section (i.e. we were unable to find any solutions where the RIV equity value was equal to the market equity value in around 10% of the cases, due to model circularity).

To solve for q and the steady state ROE requires an estimate of the steady state growth rate. Previous studies (e.g. Francis et al., 2000; Courteau et al., 2001; Jorgensen et al., 2011; Anesten et al., 2020) have typically assumed a steady state growth rate between 0% and 4%. Some studies have found that a higher steady state growth increases model accuracy, especially of cash flow models such as the DCF and DDM. Although it is favorable to increase model accuracy, we believe that it is aggressive so assume a steady state growth of 4% in the current environment of low inflation and low interest rates. We therefore assume that the steady state growth rate is 3%.

3.3.5 Additional discounting procedures and the cum-dividend adjustment

In order to maintain theoretical consistency between the RIV-model and DDM in our study, two particular adjustments are needed to the RIV-model. First, theoretical equivalence is only obtained when the RIV-model is used to estimate the equity value at the date of the dividend payoff in a particular year. This means that the RIV-model always generates equity values as of the dividend payout date. In the present study, the valuation dates are the 1st of January (for estimation of q-values and steady state ROE) and the 23rd of March (for estimation of bankruptcy risk). Dividends are on the other hand typically paid after the Annual General Meeting in the end of April or beginning of May. This means that our valuation dates occur prior to the dividend payout, and consequently also prior to the valuation date given in a RIV-model. The simple solution to this problem is to discount the value generated from the RIV-model with the fraction of the year that remains from the valuation date until the upcoming dividend date. To facilitate that procedure, it is assumed that all dividends are paid out 1st of May.

Second, the market prices observed at the valuation dates are “cum-dividend”, i.e. including the expected upcoming dividend payments for the previous fiscal year, while the values obtained by the RIV-model are “ex-dividend”. To make the ex-dividend equity values cum-dividend, we add the upcoming expected dividend payments for the last fiscal year discounted by the fraction of the year that remains from the valuation date to the dividend payment to the value obtained by the RIV-model. Thus, in the RIV-model per the 1st of January, we add the expected dividend payment for fiscal year 2019 and discount it by four months, as it is expected to be paid four months from the valuation date. For the valuation made in March, such an adjustment is not made as most dividend proposals for fiscal year 2019 were canceled due to the Covid-19 outbreak. In extension, this means that for the RIV-model per the 23rd of March, no dividend is expected to be paid out until 1st of May 2021, and therefore the equity values obtained with that version of the RIV-model were discounted an additional ~13 months in total (in line with the first adjustment explained in this section).

3.4 Testing market rationality

In this section, it is explained how the three rationality tests that we conduct in order to answer the second research question are performed.

3.4.1 Bankruptcy risk for Covid-19 winners versus losers

Early during the pandemic, it became evident that some firms would be worse impacted than others due to the imposed restrictions and lockdowns.[36] For instance, it became clear that travel restrictions would have a negative impact on transportation, hotels, and tourism (Bain, 2020; Forbes, 2020). This was in turn expected to impact the demand for oil and gas negatively (Forbes, 2020). Similarly, traditional retailers, shopping malls, restaurants and nightclubs were expected to be some of the biggest losers as severe restrictions regarding e.g. opening hours and maximum visitors were imposed (BCG, 2020; Bain, 2020). Moreover, commercial construction and real estate were expected to be impacted negatively due to the many lessees in the retail sector that struggled, and due to reduced demand for office space as people were working more from home (Bain, 2020; Forbes, 2020). Also, like in many previous economic downturns, the automotive industry and the business services sector were expected to be losers due to their pro-cyclical nature (Bain, 2020; Swedbank, 2020a). On the contrary, the pandemic was expected to increase the demand for e.g. hygiene products, durable foods, household care products, certain pharmaceutical products, takeaway food, video conferencing tools, "home improvement products" (e.g. computer accessories, furniture, televisions), e-commerce, grocery stores, cable television and other in-home entertainment – i.e. product categories benefitting from people spending more time in their homes (Bain, 2020; BCG, 2020; Forbes; 2020; PWC, 2020b).

These expert predictions are used as the basis for classifying each firm in the sample as a winner, loser or neutral from the Covid-19 impact. However, the expert list is not comprehensive for all firms in our sample. In order to make systematic classifications in spite of that, we used the logic of a decision-tree (see figure 1 for an illustration of the thought process). The basis for the decision tree is the expert opinions. In the first step, firms that fit into one of the "expert categories" are classified as winners or losers. Firms that we were unable to classify were moved along to the next step. The manufacturing sector is an important and illustrative example, as a large part of the sample is manufacturers of some type, and the category contains a broad range of firms. Some manufacturing firms are clear losers according to the experts, e.g. those within automotive and transportation. But the category also contains companies that are suppliers to non-losing sectors such as grocery stores and medical technology firms, and for those firms the Covid-19 impact is more ambiguous.

Therefore, in the second step, the customer base of each firm that we were unable to classify is examined. Firms with a significant part of their customer base in winning or losing sectors are

[36] An important remark is that this analysis is built upon the knowledge that was available *early* during the pandemic, and the sources regarding winning and losing sectors that we use were available between March and May. Appendix 9.1 contains a summary of all expected winning and losing sectors and services according to the experts.

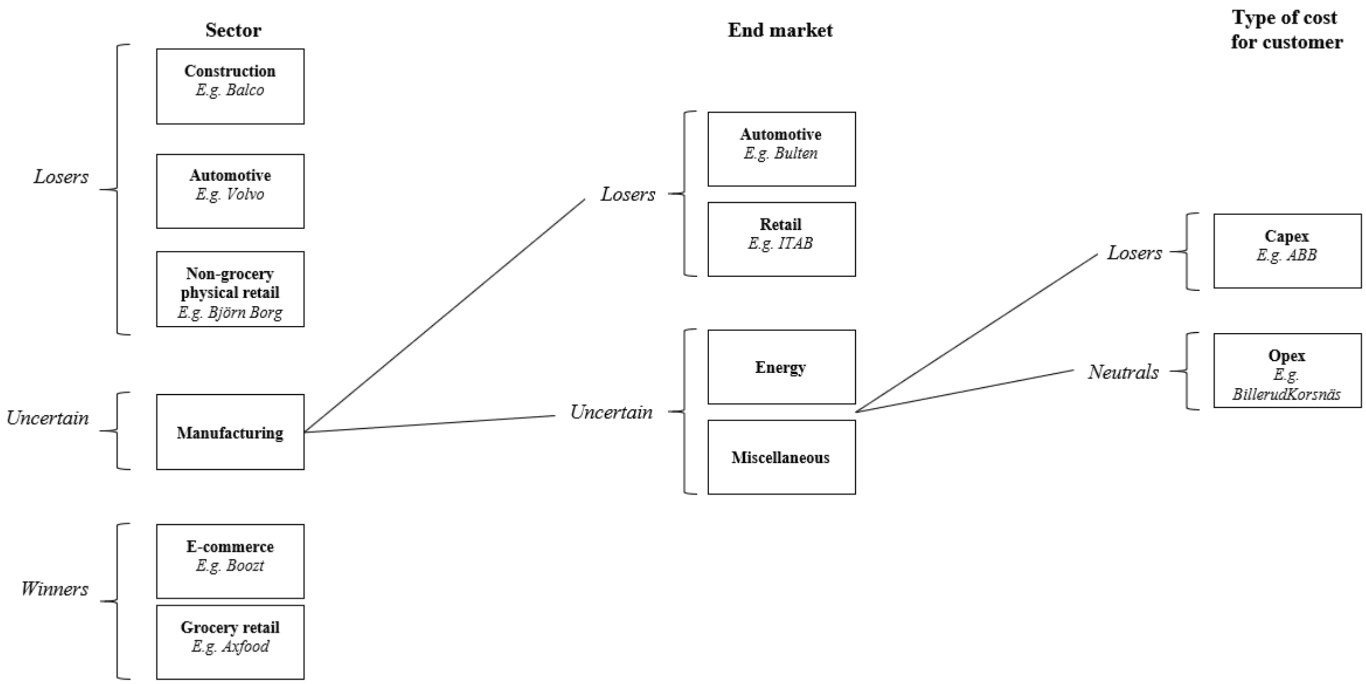
classified accordingly, so manufacturing firms with a significant part of the customer base in e.g. automotive are classified as losers. Firms that we were unable to classify based on the customer base are moved along to the third and final step. Here, we examine what type of products they produce, and we distinguish between “capital expenditures-type products” and “operating expenditures-type products”. The former category are long-term investments that are more costly and easier to defer during a crisis; manufacturers of such products are therefore more likely to experience decreasing demand and are hence classified as losers.

It should be noted that parts of the classification procedure are difficult to illustrate in the decision tree, as seemingly similar companies (on a sector level) were impacted very differently from Covid-19, and this is why the decision tree in figure 1 merely is to illustrate our thought process. As an example, the companies Better Collective and Catena Media both operate lead-generation websites in the online gambling industry – i.e. a sector that was expected to benefit from people spending more time at home. As suppliers to that sector, both Better Collective and Catena Media would according to the decision tree be classified as winners. However, the former company generates almost all revenue from sports wagering while the latter focuses on online casino. Early during the pandemic, most professional sport leagues announced that they would cancel their matches for an indefinite time. This was catastrophic for sports betting companies and their suppliers, such as Better Collective. It would hence be incorrect to classify Better Collective as a winner, even though the company technically is a supplier to a winner sector, and thus it was classified as a loser instead. A similar example is the clothing retailers, where some companies (e.g. H&M) were expected to be large losers due to the temporary closure of physical stores, while pure e-commerce players were expected to be winners due to a shift in distribution channels, even though both operate within the clothing industry, and all these caveats are difficult to illustrate comprehensively in a decision tree.

After classifying each firm, we compare how bankruptcy risk have changed among the three groups. In a rational market, we would expect larger increases in bankruptcy risk for the Covid-19 losers compared to the firms with neutral or positive impact. Therefore, the following hypothesis is formulated:

> ***Hypothesis 3: The bankruptcy risk increased significantly more for the group of losers compared to the group of winners during the beginning of the Covid-19 pandemic.***

Figure 1. Decision tree to illustrate the classification process



Note: The purpose of figure 1 is to illustrate our process of classifying firms as winners, neutrals, or losers according to the expected impact of Covid-19. The classifications are primarily based on research reports regarding expected Covid-19 impact on different industries that five expert sources published early during the pandemic. When a firm did not fit into one of the industries that was mentioned in the expert sources, we instead analyzed the industries in which the customers of the firm belongs, or what type of cost the firm's product is for the customers. The decision tree in figure 1 is not comprehensive, but for illustrative purposes only.

3.4.2 Equity returns and bankruptcy risk. Test 1: returns among different bankruptcy risk quintiles

As discussed in Chapter 2, in a rational market, firms with higher bankruptcy risk should, all else equal, have a higher cost of equity and therefore generate higher returns. However, many previous studies have found that there is a negative correlation between bankruptcy risk and returns, which is confounding. Using the bankruptcy risk estimates from the RIV-model per the 23rd of March, we divide the sample into quintiles based on bankruptcy risk, and then we measure the returns that the quintiles generate in the following 1-year period. We do this to answer our second research question and to test hypothesis 2.

3.4.3 Equity returns and bankruptcy risk. Test 2: regression analysis

In order to answer the second research question and to test hypothesis 2, we also conduct a regression analysis on the sample companies 1-year equity returns from the 23rd of March 2020, where the regression is specified as follows:

$$Y = \beta_0 + \beta_1 * Size_{Mar} + \beta_2 * Beta_{Mar} + \beta_3 * P/B_{Mar} + \beta_4 * SURP_1 + \beta_5 * Pfail_{Mar} \tag{17}$$

Where Y = 1-year equity return from the 23rd of March 2020

$Size_{Mar}$ = Average market value of equity 22nd-24th of March 2020

$Beta_{Mar}$ = Company Beta per the 23rd of March 2020

$P/B_{Mar} = \frac{Market\ value\ of\ equity}{Book\ value\ of\ owners'equity}$ per the 23rd of March 2020

$SURP_1 = \frac{Net\ profit\ 2021E\ per\ 23rd\ of\ March\ 2021}{Net\ profit\ 2021E\ per\ 1st\ of\ May\ 2020}$

$Pfail_{Mar}$ = Estimated yearly probability of failure per the 23rd of March 2020

The point of the regression is to test if there is a significant association between the estimated bankruptcy risk per the 23rd of March of 2020 and the subsequent 1-year equity returns (i.e. to test if there is an equity risk premium associated with bankruptcy risk), controlled for other factors that might influence the returns. It is well established that the first three independent variables (Size, Beta and P/B) impact equity returns (cf. Fama and French, 1996), and they are therefore included to control for that. In addition, one “surprise” factor has been included to control for surprises in the earnings revisions.

3.5 Reiteration of the initial hypotheses

We have formulated three hypotheses, which we reiterate below.

> ***Hypothesis 1: Companies listed in Sweden experienced a significant increase in bankruptcy risk during the beginning of the Covid-19 pandemic.***

The basis for hypothesis 1 is that the stock market experienced a significant price decline early during the pandemic, despite that the long term profitability of most companies weren't expected to be impacted negatively (as lockdowns were expected to be temporary) and cost of equity more or less ought to be unchanged. This hypothesis is tested by measuring changes in bankruptcy risk between the 1^{st} of January 2020 and the 23^{rd} of March 2020.

> ***Hypothesis 2: No equity risk premium was associated with bankruptcy risk in the 1-year period following the 23^{rd} of March 2020.***

The basis for hypothesis 2 is that the previous research empirically has found an unambiguous negative association between bankruptcy risk and returns (even though the negative relationship is irrational from a theoretical valuation standpoint). To test this hypothesis, we examine the association between 1-year returns after the Covid-19 trough and the estimated bankruptcy risks.

> ***Hypothesis 3: The bankruptcy risk increased significantly more for the group of losers compared to the group of winners during the beginning of the Covid-19 pandemic.***

The basis for hypothesis 3 is that the pandemic had a heterogenous impact on companies – most were expected to be impacted negatively, while a few were expected to benefit from it. If the market was rational, the heterogenous impact should be reflected in heterogenous changes in bankruptcy risks, where the bankruptcy risk for the losers increased significantly more than for the winners.

4. Data

4.1 Sample and exclusion criteria

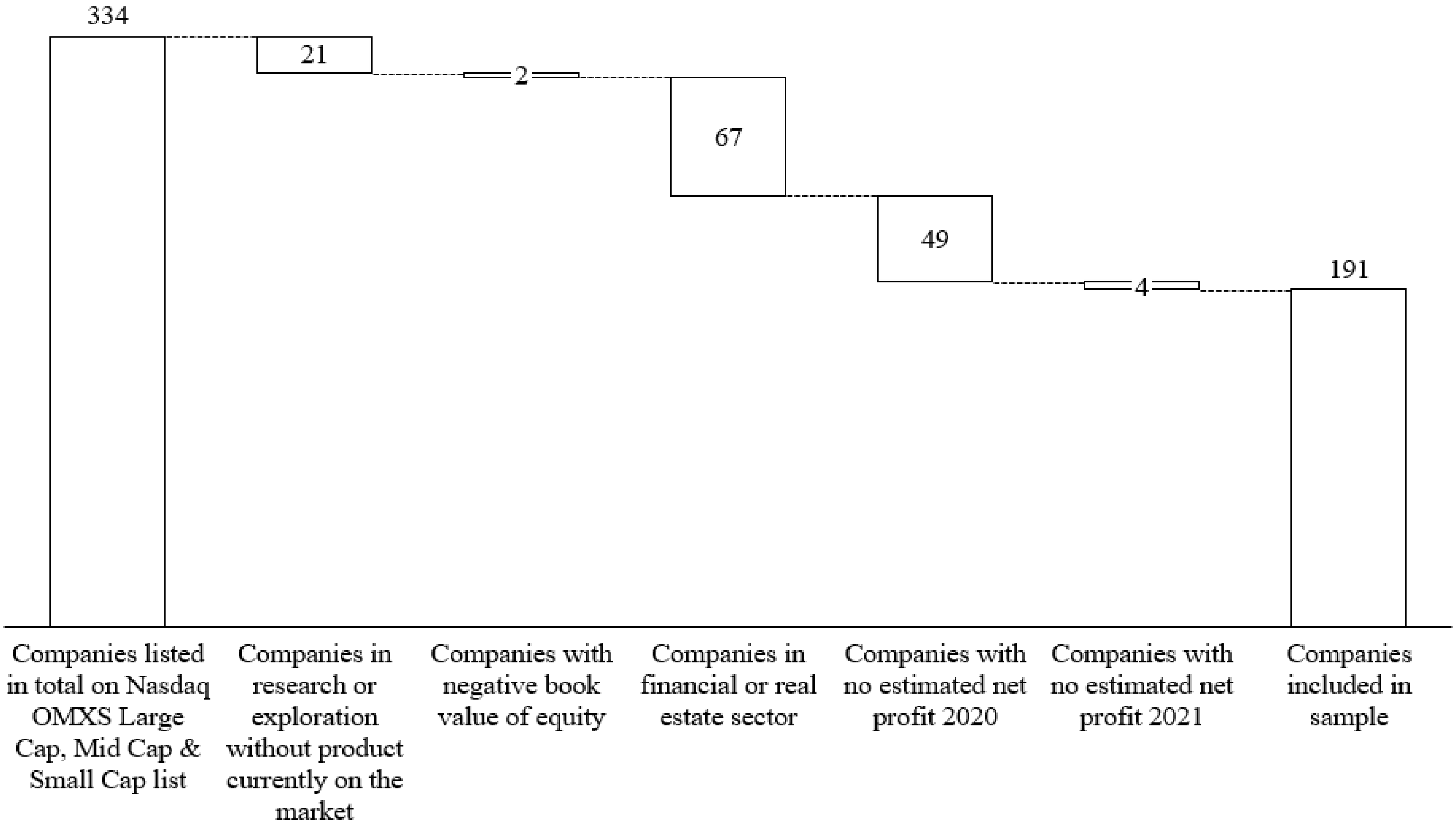
The sample consists of 191 companies listed on Nasdaq Stockholm Large-, Mid-, and Small-cap the 1st of January 2020. The total population of companies listed on Nasdaq Stockholm amounted to 334 per that date. Companies listed on e.g. First North or Spotlight are hence omitted. The other exclusion criteria are:

- **Companies with negative book value of equity.** This occurs in companies with large historical losses or generous share buy-back policies (e.g. Swedish Match). These companies were omitted as the RIV-model is not well equipped to value such firms, as the opening book value is the foundation of the RIV-valuation.
- **Companies operating within real estate or finance (including insurance and investment companies).[37]** The accounting for these firms differ substantially from firms within other sectors.[38] Hence, the accounting based valuation- and bankruptcy prediction models that we use are not specified to work for these types of companies; therefore they are typically excluded from studies using such models, including ours.
- **Research and exploration companies within e.g. pharmaceuticals or biotechnology without significant revenue.** The success of these companies is typically of binary nature which is difficult to capture in a RIV-model, and hence they are omitted.
- **Companies without analyst estimates at least two years forward.** Two years ensures that most of the population can be retained in the sample – conversely, only a relatively small proportion of the firms had earnings estimates beyond two years. Furthermore, since the last year of analyst forecasted earnings is used as the starting point for the linear interpolation in our own estimates (as described in Chapter 3), it would be problematic to include firms with only one year of estimates; the earnings were expected to be depressed during 2020 and consequently all the future estimated earnings would also be depressed.

Figure 2 is a waterfall that depicts the exclusions.

[37] In addition, forest owning companies with only minor industrial operations (e.g. Holmen) were omitted.
[38] For instance, the focus on fair value accounting of assets and liabilities is much higher.

Figure 2. Waterfall illustrating the number of exclusions per exclusion criteria



Note: Figure 2 illustrates the number of companies that have been excluded from the sample per exclusion criteria. Of the total potential sample of 334 listed companies per 1st of January, 191 companies were included in the final sample. The most common reasons for exclusion were lack of analyst estimates for 2020-2021 (53 companies) and companies belonging to the financial or real-estate sector (67 companies).

4.2 Descriptive statistics

Table 2 below shows a summary of the key variables in the sample. The median market capitalization in the sample was approximately 5.8 SEKbn in the beginning of 2020, which corresponds to the mid-cap segment of the Nasdaq Stockholm. As expected, the sample companies on average witnessed a substantial decrease in market capitalization between the 1st of January and the 23rd of March, with the median market capitalization declining around 35%.

Table 2. Sample statistics of key variables

Firm characteristics	**01/01/2020**	**23/03/2020**	**Comments**
Number of firms	191	191	
Market capitalization (SEKm)	5,802	3,760	
Steady state growth rate (g^*_{ss})	3.0%	3.0%	Assumed unchanged
Permanent measurement bias (q)	0.84	0.84	Assumed unchanged
Steady state ROE (ROE^*_{ss})	10.7%	10.7%	Assumed unchanged
Estimated ROE 2020 (ROE^*_{2020})	17.1%	11.4%	
Estimated ROE 2021 (ROE^*_{2021})	17.5%	14.8%	
Estimated ROE 2022 (ROE*2022)	17.0%	17.0%	

Cost of equity	**01/01/2020**	**23/03/2020**	**Comments**
Risk-free rate	0.01%	-0.01%	Gvt. 10-year yield
Market risk premium	6.80%	7.70%	From PWC
Beta	0.98	0.98	
Cost of equity (non-bankruptcy adjusted)	6.60%	7.50%	

Note: The table illustrates statistics for the key variables for the 191 sample companies. The cells in the table are the median values of the sample.

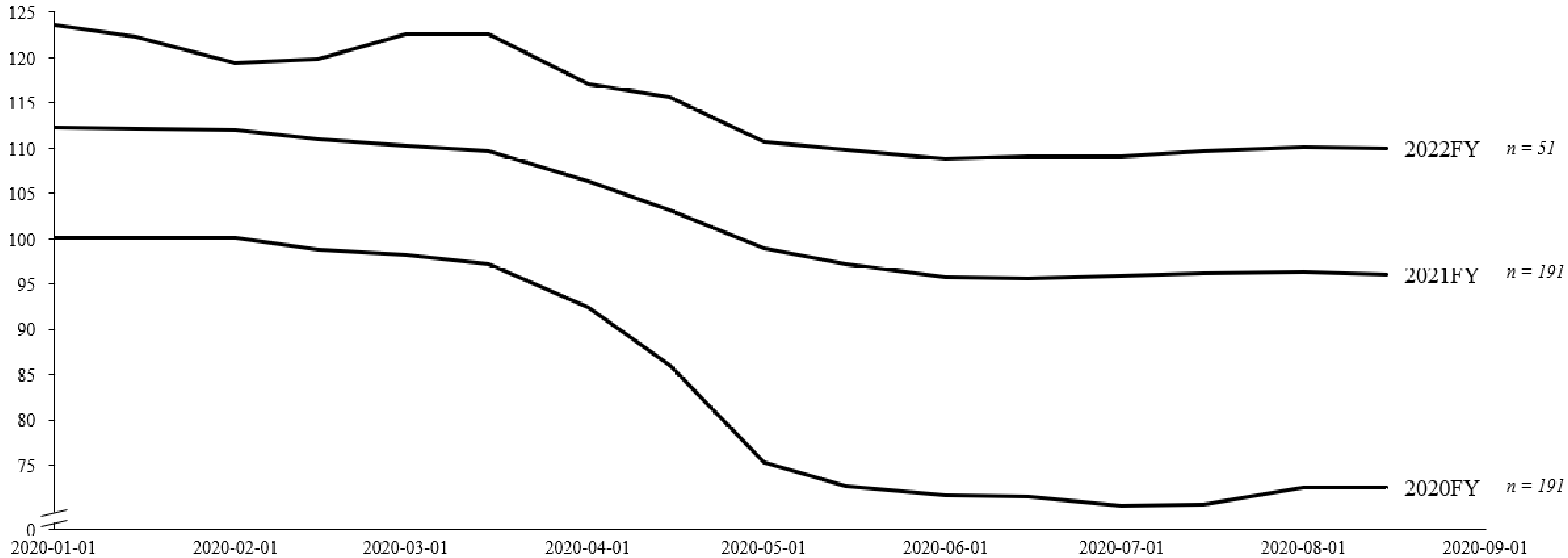
The median cost of equity (non-bankruptcy calibrated) increased slightly, from 6.6% in January to 7.5% in March. The increase is primarily driven by a higher market risk premium (from 6.8% to 7.7%) since the risk-free rate and Beta only witnessed modest changes.

The median estimated permanent measurement biases in the sample amounts to 0.84, which is substantially higher than in e.g. Runsten (1998). This illustrates the magnitude of the problem with using q-values from much older studies, that was elaborated on in Chapter 3. The median steady state ROE conditional on company survival is estimated to be 10.7%, which is significantly lower than the estimated ROE in the period 2020-2022. This is reasonable, as the investment opportunities in steady state are expected to be $NPV = 0$.

The estimated ROE for 2020 and 2021 changes significantly between the two estimation dates, from 17.1% to 11.4% for 2020, and from 17.5% to 14.8% for 2021. The downward revisions in profitability estimates are likely a consequence of the imposed restrictions and lockdowns. Interestingly, the estimated ROE for 2022 is unchanged between the estimation dates. It therefore seems as if the analysts expected the negative impact caused by the pandemic to have ceased by then.

Figure 3, which displays the development of earnings estimates for our sample companies, supports the above reasoning. The graph illustrates that in May 2020, the analysts expected a significant decline in 2020 earnings but only a slight decline in 2021 and 2022 earnings. This illustrates that the majority of the negative economic effects of the pandemic were expected to be gone after 2020, in line with our preliminary hypothesis. Moreover, it appears as if most estimate revisions took place in May, i.e. after the Q1 reports, as hypothesized in Chapter 3. This supports our decision to use analyst estimates per the 1st of May even though it differs from the bankruptcy risk estimation date.

Figure 3. Development of earnings estimates for sample companies



Note: The graph shows the development of earnings estimates from 1st of January 2020 to 1st of September 2020 for the Fiscal Years (FY) 2020-2022 for the sample companies as a group. The earnings estimates for each individual company have been indexed by its 2020E net profit per the 1st of January, i.e. net profit 2020E per the 1st of January = 100. Median values are displayed.

5. Results

5.1 Significant increase in bankruptcy risk across all sectors

In table 3, the key results are summarized on a sector level where the companies have been classified according to FACTSET's sector specifications.

Companies within all sectors experienced a significant increase in bankruptcy risk. This was expected given the significant decline in equity prices that occurred despite the relatively small changes in cost of equity and longer term earnings estimates. The median (average) bankruptcy risk increased with 2.23pp. (2.45pp.***). The largest increases occurred in Consumer Services as well as Commercial and Industrial Services. This is reasonable as these sectors were impacted significantly by the pandemic, and they experienced some of the largest declines in equity prices. The Minerals sector experienced a median increase in bankruptcy risk rougly in line with the rest of the sample (+2.44pp.), even though the equity prices dropped most sharply (-46.4%). This can be explained by the fact that the declining equity prices were accompanied by a significant decline in earnings estimates; the sector consists of many companies exposed to oil, gas and other commodities, and the prices of many commodities dropped sharply during the beginning of the year.

The Health sector experienced the smallest median (average) increase in bankruptcy risk, +1.06pp. (+1.66pp.***), and a relatively modest decline in equity prices compared to the rest of the sample, -29.4%. This sector contains companies within e.g. pharmaceuticals and medical technology that perhaps were not expected to be impacted by the pandemic as severely as companies within other sectors, illustrated by the fact that the downward revision in earnings estimates were not as drastic as for most other sectors. Similarly, the "Other" group saw a median increase in bankruptcy risk of only 1.34pp. This is interesting considering that it contains companies within some of the worst affected sectors, such as Retail (n=9) and Transportation (n=3). However, as the group also includes companies within relatively unaffected sectors such as Utilities and Communication, the losers are likely counterbalanced by relatively unaffected companies. This is supported by the fact that the earnings estimates only were revised downward slightly.

Although the changes in bankruptcy risk on a sector level are interesting, for a discussion about changes in bankruptcy risk and market rationality, an even more interesting analysis is that of the winners versus losers; the sector classifications are not very granular, and most sectors therefore contain a combination of firms that have benefitted and been impacted negatively by Covid-19. Thus, it is difficult to discuss changes in bankrutpcy risk and market rationality on a sector level.

Table 3. Results per sector

Sector	No. of firms	Median p-fail Jan	Median P-fail Mar	Change in median p-fail	Avg. change in p-fail	Market cap Jan (SEKm)	Returns 01/01/2020 - 23/03/2020	Returns 23/03/2020 - 23/03/2021	Change in 2020 est. earnings	Change in 2021 est. earnings	Change in 2022 est. earnings	COE Jan	COE Mar
A. Consumer (Consumer Non-Durables + Consumer Durables)	17	0.16%	2.36%	2.21pp.	2.36pp.***	12,918	-36.0%	124.7%	-19.7%	-12.0%	-16.0%	7.0%	8.3%
B. Minerals (Non-Energy Minerals + Energy Minerals)	13	0.07%	2.51%	2.44pp.	2.17pp.***	4,179	-46.4%	121.9%	-38.5%	-13.6%	-30.7%	9.7%	11.0%
C. Health (Health Services + Health Technology)	24	0.12%	1.18%	1.06pp.	1.66pp.***	5,224	-29.4%	115.8%	-23.7%	-9.3%	3.3%	5.9%	7.0%
D. Manufacturing (Producer Manufacturing + Process Industries)	41	0.10%	2.64%	2.54pp.	2.48pp.***	9,386	-40.6%	112.6%	-36.4%	-16.7%	-11.9%	7.7%	9.5%
E. Commercial Services + Industrial Services	25	0.18%	3.07%	2.89pp.	3.18pp.***	4,395	-41.2%	121.1%	-22.5%	-11.9%	-8.8%	6.1%	7.0%
F. Consumer Services	13	0.24%	3.35%	3.11pp.	3.02pp.***	5,336	-41.6%	255.6%	-16.1%	-9.3%	-29.3%	4.1%	5.0%
G. Technology Services	14	0.03%	2.41%	2.37pp.	3.19pp.***	3,827	-33.7%	127.5%	-19.4%	-9.3%	10.4%	7.3%	6.9%
H. Electronic Technology	18	0.17%	1.95%	1.78pp.	2.40pp.***	2,236	-35.7%	110.7%	-17.9%	-7.8%	-5.3%	6.3%	7.3%
I. Other (Utilities + Distribution Services + Retail Trade + Transportation + Communications)	26	0.16%	1.50%	1.34pp.	1.95pp.***	6,056	-28.5%	111.7%	-8.9%	-6.4%	-12.9%	4.6%	6.2%
Total	191	0.13%	2.36%	2.23pp.	2.45pp.***	5,802	-36.7%	126.4%	-24.7%	-11.9%	-10.4%	6.6%	7.7%

Note: The table displays the main results on a sector level. The firms have been classified according to FACTSET's sector classification, but in order to obtain large enough groups to e.g. perform statistical tests, some sectors have been merged. The FACTSET sector names are displayed in brackets in the column "Sector". P-fail has been truncated to 0% as a lower bound in March for individual firms. All values are medians, except for returns which are averages and average change in p-fail. *** indicates significance at the 99% level.

5.2 The losers experienced a significantly higher increase in bankruptcy risk compared to the winners

In tables 4 and 5 below, the results for the analysis on changes in bankruptcy risk for winners, neutrals and losers are summarized.

We find that the median (average) bankruptcy risk increased significantly more for the group of losers +2.79pp. (+2.76pp.***) compared to the winners +0.54pp. (+1.57pp.**). The average bankruptcy risk increased by 1.2pp.** more for the winners compared to the losers, and we therefore confirm hypothesis 3 – that the bankruptcy risk should have increased significantly more for the losers compared to the winners.

Interestingly, all groups had similar bankruptcy risks in January,[39] but the losers experienced a steeper decline in equity prices (-36.7%) compared to the winners (-24.7%), and much larger downward earnings revisions. The earnings projections of the winners were relatively unchanged in May compared to the beginning of the year, which can be interpreted as a testimonial to our method of classifying firms among the different groups. The argument can be made that the winners should have experienced increased earnings estimates. However, we believe that most analysts were conservative considering the significant turmoil and uncertainty at that point in time. Interestingly, the winners generated a much higher return than the losers in the 1-year period after the Covid-trough despite having lower estimated cost of equities (non-bankruptcy adjusted), which could be interpreted as if the positive Covid-impact for the winners initially was underestimated.

[39] Could this be an indication that the Skogsvik (1990) model is outdated and generates poor predictions? We find that unlikely; a recent study (Haglund and Olufsen, 2021) has found that the model still is reasonable accurate. Thus, we rather view the small differences as an indication that the three groups had similar bankruptcy risk characteristics in the beginning of the year.

Table 4. Results for Covid-19 losers, neutrals, and winners

Covid impact	No. of firms	Median p-fail Jan	Median p-fail Mar	Change in median p-fail	Avg. change in p-fail	Market cap Jan (SEKm)	Returns 01/01/2020 - 23/03/2020	Returns 23/03/2020 - 23/03/2021	Change in 2020 est. earnings	Change in 2021 est. earnings	Change in 2022 est. earnings	CoE Jan	CoE Mar
Loser	103	0.13%	2.92%	2.79pp.	2.76pp.***	7,560	-36.7%	126.4%	-31.7%	-15.0%	-12.5%	7.1%	8.6%
Neutral	71	0.11%	2.04%	1.93pp.	2.20pp.***	3,912	-29.8%	112.9%	-18.5%	-9.4%	-12.4%	5.8%	6.6%
Winner	17	0.16%	0.69%	0.54pp.	1.57pp.**	6,270	-24.7%	196.3%	-2.5%	2.4%	0.3%	5.6%	5.5%
Total	191	0.13%	2.36%	2.23pp.	2.45pp.***	5,802	-36.7%	126.4%	-24.7%	-11.9%	-10.4%	6.6%	7.7%

Note: The table displays key results for three groups of companies (winners, neutrals and losers), where each company has been classified to a group according to the expected Covid-19 impact (see Section 3.4.1 for further information regarding the classification process). All values shown in the table are medians, except for average change in p-fail and returns which are averages. **, *** indicates significance at the 95% and 99% level, respectively.

Table 5. Bankruptcy risk changes for Covid-19 losers versus Covid-19 winners

Comparison	No. of firms	Difference in changed average p-fail
Losers vs winner	17 winners, 103 losers	1.2pp.**

Note: The table displays the difference in average changed bankruptcy risks for the group of losers versus the group of winners, from January 1st, 2020 to March 23rd, 2020. ** indicates significance at the 95% level.

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5.3 Equity returns and bankruptcy risk

5.3.1 Firms with high bankruptcy risk generated significantly higher returns than firms with low bankruptcy risk in the post-trough period – indication of an equity risk premium associated with bankruptcy risk

In this section, the sample companies have been sorted according to bankruptcy risk and divided into five quintiles. In table 6 and 7 below, the results are summarized

In the quintile with the highest bankruptcy risk (quintile 1), the median bankruptcy risk was 5.84%, compared to 0% in the lowest quintile (quintile 5).[40] The quintile with highest bankruptcy risk generated a return of astonishing 176.8% in the 1-year period following the Covid-trough on the 23rd of March, compared to 90.2% for the quintile with lowest bankruptcy risk, for a total outperformance of 86.6pp.***. This indicates that there is an equity risk premium associated with bankruptcy risk.

However, the strong post-trough returns for the companies with the largest bankruptcy risk should be seen in the light of their substantial decline in share price between the 1st of January 2020 and the 23rd of March. So the steep increase in the following period can be viewed as sort of a reversal of the preceding decline. Furthermore, the strong returns might have been driven by other factors than an equity risk premium associated with bankruptcy risk. Hence, in the next section, we display the results from the regression analysis where some of the potentially skewing factors have been controlled for.

[40] The probability of failure in March was truncated to 0% as a lower bound.

Table 6. Returns across different bankruptcy risk quintiles

Quintile	No. of firms	P-fail Mar	Market value 23 Mar (SEKm)	CoE Mar	Returns 01/01/2020 - 23/03/2020	Returns 23/03/2020 - 23/03/2021
1	38	5.84%	2,735	8.3%	-49.9%	176.8%
2	38	3.45%	2,549	8.5%	-42.0%	128.4%
3	38	2.36%	4,240	7.1%	-36.3%	118.7%
4	38	1.03%	4,936	7.5%	-31.5%	118.6%
5	39	0.00%	3,307	6.6%	-24.0%	90.2%

Note: The table illustrates key results for five groups of companies, where the companies have been assigned to a group on the basis of estimated bankruptcy risk per the 23rd of March 2020. The 20% companies with the highest bankruptcy risk have been assigned to quintile 1, the following 20% of companies to quintile 2 etc. All values shown in the table are medians except for returns which are averages.

Table 7. 1-year returns, Quintile 1 compared to Quintile 5

Comparison	Difference in average returns 23/03/2020 - 23/03/2021
Quintile 1 vs Quintile 5	86.6pp.***

Note: The table displays the difference in average returns, from January 1st, 2020 to March 23rd, 2020, for the companies with the highest bankruptcy risk (quintile 1) versus the companies with the lowest bankruptcy risk (quintile 5). *** indicates significance at the 99% level.

5.3.2 The regression analysis indicate that the equity risk premium persists after other factors have been controlled for

The regression analysis (table 8) displays that the estimated bankruptcy risk in March is significant ($p<0.01$) for explaining the equity returns that was generated in the subsequent 1-year period. This indicates that there is an equity risk premium associated with bankruptcy risk which persists after other factors, such as size, price-to-book, Beta, and “surprises” in earnings have been controlled for. The regression indicates that a one percentage point increase in bankruptcy risk leads to an increase in returns of approximately 14% in the subsequent one year period. In total, the regression has a r^2 of around 9%, which means that the independent variables in the model are unable to explain the largest part of the 1-year returns. That is likely due to company specific events that the independent variables are unable to account for.

Table 8. Regression analysis

Intercept	1.072
	(0.261)
Change in 2021 est. earnings (%)	0.217*
	(0.118)
Market beta	-0.264
	(0.191)
Avg market cap 22-24 March 2020	0.000
	(0.000)
Price-to-Book ratio	0.034
	(0.024)
Estimated bankruptcy risk 23 March 2020 (%)	14.033***
	(3.886)
R-squared	0.088
No. Observations	191

Note: The table displays the results from the regression analysis performed on the 1-year returns that the sample companies generated in the period following the 23rd of March 2020. The coefficients and standard errors for each variable is displayed, where the standard errors are reported in parentheses. See equation (17) on p.34 for a further description of the included variables. The returns (i.e. the dependent variable) are expressed in percent meaning that an increase in the price-to-book ratio of 1 lead to a return increase of 3.4%. *, **, *** indicates significance at the 90%, 95% and 99% level, respectively.

6. Discussion

6.1 Significant increase in bankruptcy risk during Covid-19 – an indication that bankruptcy risk is incorporated into equity prices

In confirmation of hypothesis 1, the bankruptcy increased significantly during the first months of 2020 – neither the downward revisions in future expected earnings nor the increase in cost of equity were large enough to explain the significant decline in market prices independent of increased bankruptcy risk. As we hypothesized, the analysts expected significant negative impact on earnings during 2020 and 2021 due to Covid-19, but the earnings were expected to normalize during 2022 (as displayed previously in figure 3). Similarly, the cost of equity only increased slightly in the beginning of 2020, meaning that increased bankruptcy risk must have been an important factor in the price decline.

Interestingly, our results are similar to the Skogsvik (2006) example of the hypothetical company that experienced an increase in bankruptcy risk from 0 to 2%, with the consequence that its equity value declined by 40%. On an aggregated level, our sample companies experienced similar increases in bankruptcy risk and declines in equity values. Relating these results to the Lindgren and Velander (2004) study of investment professionals and bankruptcy risk, it is interesting that the market appears to price securities similar to Skogsvik's theoretical example, despite the fact that individual analysts seemingly have such a reserved attitude towards bankruptcy risk.

More generally, our results indicate that bankruptcy risk, at least to some extent, is incorporated into equity prices. The results are similar to the group of previous studies which have found that the market "prices in" bankruptcy risk in firms that experience a significant deterioration in the financial position (cf. Altman and Brenner, 1981; Katz et al., 1985; Burgstahler, 1989), in the regard that all these results, including those of the present study, indicate that the market is cognizant to changes in bankruptcy risk. These results have important implications for equity analysts and fund managers as valuation is one of their foremost tasks, and the findings should be particularly valuable to those professionals engaged in the valuation of equities with a substantial bankruptcy risk. A reasonable inference from our results is that bankruptcy risk also affects equity valuations in IPO-situations (although this has to be confirmed in future studies), and the results then have important implications e.g. private equity firms that are looking to IPO their holding companies. Considering the recent all-time-high activity on the Swedish IPO-market, this is an important topic.

6.2 Market rationality

Interestingly, none of the tests indicate that the market acted irrationally. Hypothesis 2 – that there is no equity risk premium associated with bankruptcy risk – can be refuted, as a high bankruptcy risk clearly was associated with high returns in the post-trough period. This effect persisted in our regression analysis when we controlled for other factors that could have influenced the returns. Furthermore, hypothesis 3 – that the bankruptcy risk would increase more for Covid-19 losers than winners – can be confirmed.

6.2.1 The change in bankruptcy risk for Covid-19 winners compared to losers appear rational

While the Covid-19 winners and losers had similar bankruptcy risk in the beginning of the year, the bankruptcy risk increased substantially more for the latter group amid the crisis. The group of winners experienced median increase in bankruptcy risk of only around +0.5pp., while the increase for the losers was around +3pp. This indicates that the stock market incorporated the information that was available during the beginning of the crisis to distinguish between winners and losers. We interpret these results as indicative of rational market behavior during the crisis.

However, is it rational that the bankruptcy risk for the winners increased *at all*, considering that these companies were expected to benefit from the crisis? We argue that it can be rational. In March, the uncertainty regarding the health- and economic impact of the pandemic was very large. For the health aspects, there was still much uncertainty regarding the rate of infection, mortality, immunity, and long term health impact of the disease. Regarding the economic aspects, the pandemic could have led to mass unemployment and permanent economic damages, had the central banks and governments not initiated the unprecedented fiscal- and financial stimulus packages. Given the uncertainty regarding the health- and economic aspects together, the impact of the pandemic *could* have been much worse if some of these variables would have been different, and that *could* have led to a negative impact even for the companies that initially were believed to be winners. For instance, if the global economy would have entered into a long term recession, even the winners within e.g. in-home entertainment could have experienced permanently depressed future prospects. Or, there could have been a significant liquidity crisis similar to that during the Global Financial Crisis, which could have caused otherwise healthy firms to enter distress. Even though none of these pessimistic scenarios played out, we propose that the increase in bankruptcy risk for winners could be attributed to this “systematic” tail-risk that had a low probability of occurrence but would have caused a large negative impact. The message is that we should distinguish between potential and materialized outcomes, and the former are more important when assessing if the implied bankruptcy risks were reasonable or not.

Another interesting result is that the winners generated much higher returns in the 1-year period following the trough, even though they had much lower cost of equity (non-bankruptcy adjusted) and bankruptcy risk. Thus, it would be fair to assume that they would generate lower returns.[41] Furthermore, much of the government support that was announced after the 23rd of March 2020 has supported the losers rather than the winners. A likely explanation for the differences in returns is that the market underestimated the length of the pandemic; initially, the consensus was that the restrictions would be fairly short-term, and now, more than a year later, many restrictions are still enforced. This has likely supported the winners and punished the losers even further, so it cannot be ruled out that the market pricing was "correct" provided the information that was available in March 2020.

6.2.2 The results from the return-tests indicate that there is an equity risk premium associated with bankruptcy risk, which also is rational

The return-outperformance of the quintile with highest bankruptcy risk is fully in line with equity valuation theory[42], as discussed in previous chapters. The positive association between bankruptcy risk and equity returns also persisted in the regression analysis, where we controlled for other factors that could have obscured the results. Thus, we can quite comfortably conclude that there was an equity risk premium associated with bankruptcy risk in our measurement period. These results are in conflict to most of the previous empirical studies that have been conducted on the relationship between bankruptcy risk and equity returns, which is intriguing.

The most likely explanation is that the companies with the highest bankruptcy risk were helped most by the government support packages. Another possible explanation is that the present study used a different bankruptcy prediction model compared to all previous studies. After all, the RIV-model is good in the sense that it uses forward looking and "up to date" information while most other models mainly use historical information. Perhaps the results in prior studies are a result of poor estimates of bankruptcy risk? We doubt that, as the models that have been used in prior studies have shown to be accurate (while the accuracy of the RIV-model is yet to be tested), and the existence of the negative relationship between bankruptcy risk and returns has been confirmed in numerous studies. Furthermore, the results in the present study were generated during an exceptional time period and would need to be replicated under more normal conditions.

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[41] Assuming that there is an equity risk premium associated with bankruptcy risk, contrary to the results in most prior studies.

[42] An observation is that both the winners, which as a group had the lowest bankruptcy risk, and the quintile with the highest bankruptcy risk generated very high returns. This obviously seems contradictory. The explanation is that the returns for the companies in the fifth quintile was rather heterogenous (with some firms generating very high returns, and other very low), and the group of winners only consist of 17 firms; many of these were among the strong performers of the fifth quintile.

6.2.3 Potential limitations with the market rationality tests

One potential issue relates to the process of classifying firms into the three groups. Although we tried to be as systematic as possible as described in section 3.4, parts of the classification process relied on our own judgement regarding e.g. the definition of *significant* exposure to customers within a losing industry. Furthermore, the sample consists of almost 200 firms and it is difficult to have detailed knowledge of all of them, and hence it cannot be excluded that e.g. some losers ought to be classified as neutrals, or vice versa. On the other hand, we believe that our classification process yields more relevant results compared to relying on e.g. SNI-codes or FACTSET's sector classification to group firms, considering that companies within the same sector can be winners and losers (as illustrated by e.g. Better Collective and Catena Media). We also acknowledge that the classification process might lead to issues with replicability.

Furthermore, although the *changes* in bankruptcy risk among the three groups seem rational (with the largest increase in the group of losers, and the smallest in the group of winners), our results does not give any insights to if the *magnitude* of the bankruptcy rates implied by the market were rational; is it obvious that the median implied bankruptcy rate of around 2.5% for the sample is correct? In hindsight, and compared to materialized bankruptcies among listed companies, 2.5% appears very high. Internationally, bankruptcies have remained low thanks to massive policy support (Banerjee et al., 2020). Similarly, Cella (2020) finds that the bankruptcy rate for the entire population of Swedish firms was 0.4% between March and June 2020 (or around 1.2% annualized, ignoring seasonality). Considering that bankruptcy rates for all companies was around 1% during 2019 (Creditsafe, 2020), it appears like materialized bankruptcies in the entire population of firms did not increase significantly. Meanwhile, the implied bankruptcy risk increased by a factor of over 10 in our sample, while the materialized bankruptcies have remained low thus far.[43]

There are two main factors that obfuscates the comparability between the implied bankruptcy risk found in our study with the ex-post materialized bankruptcy rates. First, and most importantly, it is possible that the government interventions were much more powerful compared to what the market had anticipated in the end of March, allowing firms that otherwise would have been insolvent to survive. In a recent publication, IMF (2021) indeed confirms that the massive policy support has been crucial for maintaining the flow of credit, which have kept financial risks and bankruptcies at bay. Second, there is typically a substantial lag between declines in GDP and insolvencies (Banerjee et al., 2020), so it cannot be ruled out that there will be a future large wave

[43] We have only come across one listed potential bankruptcy in the one-year period following the 23rd of March 2020: Retail and Brands, a clothing retailer that went into reconstruction during the spring of 2020. The company completed its reconstruction during the fall and is as of present still listed on the Nasdaq small-cap list.

of bankruptcies.[44] To conclude, it is difficult to preclude that an implied bankruptcy risk of around 2.5% was not rational considering the information that was available in the end of March.

Regarding the tests of the relationship between bankruptcy risk and equity returns, two limitations are that the tests were conducted in a single 1-year period and that there may be factors positively influencing the returns for companies with high bankruptcy risk that we were unable to control for, which wouldn't be present in other periods. The most obvious one is all the government support packages; the companies with high bankruptcy risk likely benefitted the most from these, which may have influenced their returns. This creates the impression of a positive relationship between bankruptcy risk and returns that in fact could have been a positive relationship between how much a company benefit from support packages and their returns.

Furthermore, in the regression analysis, it would have been preferable to control for more "surprise factors" that could have impacted the returns. For instance, we could have re-estimated the bankruptcy risks on the 23rd of March 2021 to include that as an independent variable; this would ensure that the returns weren't skewed by changes in bankruptcy risk during the measurement period. If we would have had time, such a controls variable would have been included, but it is a time-consuming exercise to re-estimate the bankruptcy risks.

Finally, we acknowledge that all firms in the sample, even in the quintile with the highest bankruptcy risk, survived during the measurement period. This obviously has a big impact on the results; if only a few firms within the riskier quintiles would have entered bankruptcy – which on average, without government support packages likely would have happened – the returns would have been substantially worse, and perhaps we wouldn't have found any return premium associated with bankruptcy risk then.

6.3 Bankruptcy risk estimation with the RIV-model – reflections

6.3.1 Promising first signs

The RIV-model implies that there was a substantial increase in bankruptcy risk during the first months of 2020, in line with our preliminary hypothesis. These results make much sense considering the dusk economic prospects in March 2020. Furthermore, the results regarding 1-year equity returns indicate that there is a significant equity risk premium associated with bankruptcy risk, and this is more coherent with valuation theory compared to the results in prior studies that use different bankruptcy models. Therefore, we consider that our results are a promising indication that the RIV-model can be used empirically to estimate bankruptcy risk.

[44] Recently, the credit analysis institute Creditsafe has commented that it is too early to rule out a wave of future bankruptcies, primarily alluding to the fact that the Swedish Tax Agency have granted payment respites that in the upcoming years will have to be paid, which can cause a liquidity crunch (Dagens Industri, 2021b).

The RIV-model has two clear advantages over statistical accounting based prediction models that we want to highlight:

- It should be applicable to all geographies and more or less all industries, as it avoids the problem with sample specific independent variables and coefficients that is known to be prevalent in statistical accounting based prediction models. Instead of having to re-estimate the model to fit each sample, one relatively simple and standardized model can be used to estimate bankruptcy risk in virtually all contexts.
- It should yield more accurate results in situations where the future prospects of firms change quickly, such as during the pandemic, as it incorporates market prices in combination with historical and forward-looking information. [45] Contrary, the statistical accounting based models rely only on historical information that can be outdated if the conditions change quickly.

6.3.2 The limitations of the bankruptcy risk estimates, considerations for future studies and discussion of q-values

When determining how good a bankruptcy prediction model is, the probably most important criteria is accuracy. The present study has made no effort in testing how accurate the implied bankruptcy rates are. Such an investigation is in itself no small task. As discussed previously in this chapter, we observe that our estimated bankruptcy risks appear to be much higher than the materialized bankruptcies among listed firms. However, our estimates might have been good considering the information that was available at that point in time, even though it appears as if the outcome of the estimates were poor.

Furthermore, we acknowledge that the estimation of bankruptcy risk rests on multiple assumptions. Although we believe that we were careful with choosing the most realistic ones, it would have been preferable to perform some robustness analysis of the more crucial assumptions. However, considering that our method requires us to manually solve for each firm's implied bankruptcy risk, it is a fairly time-consuming exercise to perform such tests, and we didn't have the time to do that.

For future studies that try to test the accuracy of the RIV-model, a suggestion is to estimate bankruptcy risk and materialized bankruptcies over multiple years (considering that 2020 in particular was a year of extreme uncertainty it would be interesting to see how well it works in normal conditions). Furthermore, future studies ought to have large samples; assuming that the implied bankruptcy rates for a RIV during "normal" times are similar to that we found with the

[45] Under the assumption that the market incorporates new information somewhat efficiently.

Skogsvik (1990) model, only around $\frac{1}{1000}$ of listed firms are expected to go bankrupt, so firm specific events can have a large impact on the estimated accuracy if the sample is too small.

Moreover, the q-values are a very important part of the model; they are used to estimate the terminal value, and even more importantly the steady state ROE which in turn is used to estimate the value drivers for the period when no analyst estimates are available. In our study, the q-values were estimated with the RIV-model in January and assumed to be constant. However, such a method relies on the assumption that the market is rational and makes the q-values very sensitive to the prevailing market conditions when they are estimated; had we estimated the q-values in March instead of January, we would on average have obtained significantly lower values. Provided that the q-values have such a large impact on the model, future studies should try to obtain them as of the "valuation date" of the RIV-model and perhaps using a more thorough method, e.g. in line with Runsten (1998).

Initially, we intended to use Runsten's (1998) q-values, but as described in Chapter 3, it did not work, and we have three suggestions as to why. First, the accounting regime has changed in Sweden since Runsten conducted his study. In 2005, companies listed in Sweden had to adopt International Financial Reporting Standards (IFRS) as opposed to the previous local accounting regime (Nobes and Parker, 2006). However, IFRS typically involves *more* fair value accounting (ibid) which theoretically should reduce the accounting measurement bias that exists due to accounting conservatism (i.e. q-values). Previous studies have indeed concluded that the introduction of IFRS is unlikely to have had a significant impact on the q-values for at least Large-cap companies in Sweden (Bergman and Tegnér, 2008). However, it is our opinion that more research is needed – especially regarding small- and mid-sized firms – to fully rule out this hypothesis.

Second, as the economy has become increasingly technology dependent, a substantial and increasing part of corporate assets are intangible, many of which are absent from the balance sheets (Lim et al., 2020). For instance, it has been estimated that today's firms only capitalize 19% of their intangible assets (Peters and Taylor, 2017) whereas the rest is expensed due to accounting prudence and thereby are absent from the balance sheets. The increasing importance of technology firms suggests that the q-values related to intangible assets could have increased substantially compared to in Runsten (1998), which mostly included companies from the "old-economy".

A final hypothesis is that the equity market per the 1st of January 2020 was overvalued. We observe that the Swedish stock market per that date had increased more than three-fold in the last ten years or so, which is much higher than the long-term average return. Similarly, observing the

American stock market, the Shiller PE[46], which commonly is used to test the valuation of the entire stock market, reached levels not seen since before the burst of the IT-bubble (Yale, 2021). See Appendix 9.2 for Shiller PE development over time. If the market prices diverge too much from the expected "fundamental" development of the company (i.e. book values and expected residual incomes), it will be difficult to reconcile the RIV-model valuation with the market valuation using predetermined q-values.

7. Conclusion

The present study has attempted to answer the following two research questions:

> ***Research Question 1: How was the bankruptcy risk of companies listed in Sweden affected during the beginning of the Covid-19 pandemic?***
>
> ***Research Question 2: Were i) the changes in bankruptcy risk that occurred during the beginning of the Covid-19 pandemic, and ii) the equity risk premium associated with bankruptcy risk in the 1-year period after the market trough, rational?***

We found that the implied bankruptcy risk increased significantly across all sectors in our sample during the beginning of the pandemic. The explanation is that market prices declined significantly even though long-term profitability and cost of equities experienced relatively small changes, which means that the decline must have been caused by increased bankruptcy risk. Furthermore, we can conclude that the market was rational in regard to the topics that the study investigated; the bankruptcy risk increased significantly more for the group of Covid-19 losers compared to the winners (average difference of 1.2pp), and there was a significant equity risk premium associated with bankruptcy risk in the period following the Covid-19 trough (14pp. return premium for each percentage point of bankruptcy risk).

[46] The market value of the entire stock market divided by the stock market's average profits during the last 10 years.

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9. Appendix

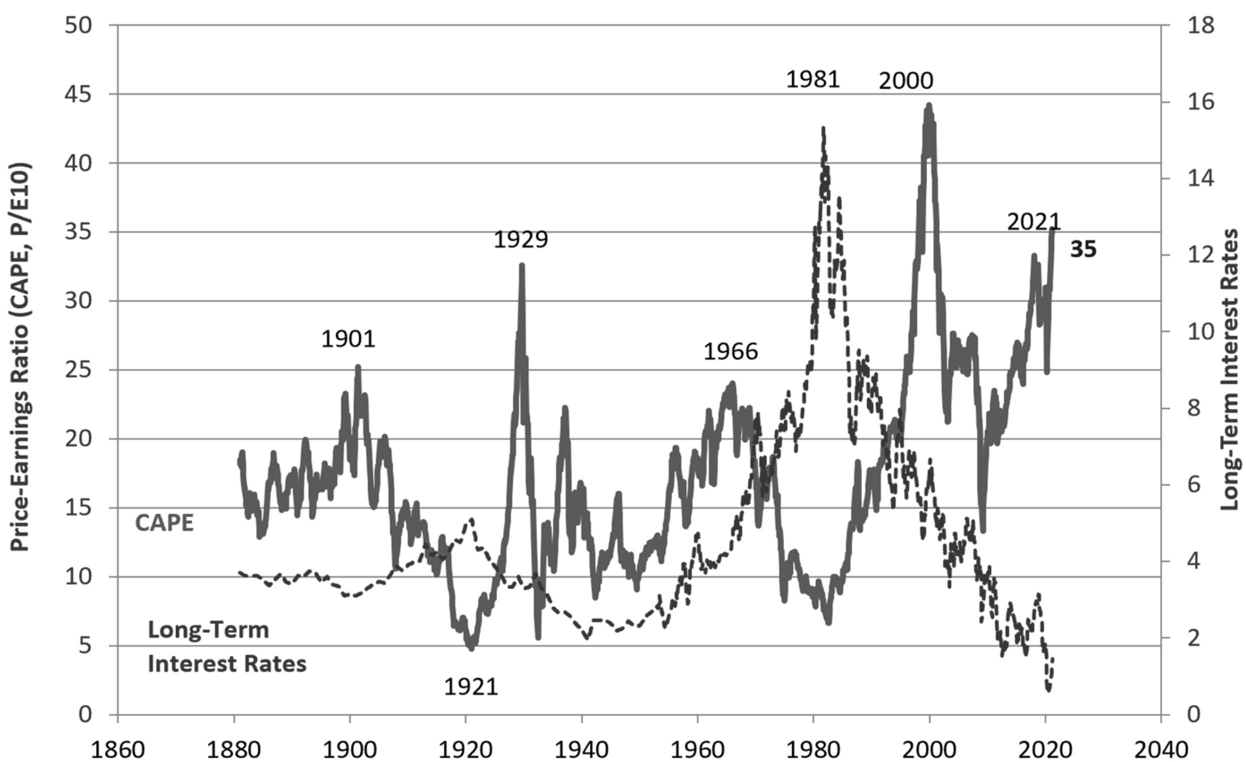
9.1 Winning and losing sectors

Industry/sector/service	**Impact**
E-shopping for food	Winner
Hygiene products (sanitizers, masks)	Winner
Takeaway food	Winner
Covid tests	Winner
Video conferencing tools	Winner
Delivery companies	Winner
E-commerce	Winner
Personal computer gear	Winner
Grocery stores	Winner
Cable television/streaming entertainment	Winner
Video conferencing tools	Winner
Home improvement products (furniture, computer products etc.)	Winner
Healthcare and Pharma	Winner
Telemedicine	Winner
Household care products	Winner
Packaged food and beverage / Durable foods	Winner
In-home entertainment	Winner
Non-grocery retailers and shopping malls	Loser
Tourism	Loser
Construction	Loser
Restaurants and food service	Loser
Automotive	Loser
Luxury goods	Loser
Select retail health (dentists)	Loser
Pharmaceutical trials	Loser
Transportation	Loser
Oil and gas	Loser

Industry/sector/service	Impact
Restaurants and nightclubs	Loser
Hotels	Loser
Real estate	Loser
Public transportation	Loser
Clothing/outerwear	Loser
Out-of-home entertainment	Loser
Certain manufacturing firms (e.g. with automotive exposure)	Loser

Sources: Bain (2020), BCG (2020), Forbes (2020), PWC (2020), Swedbank (2020)
Note: The list is our best effort on winning and losing sectors given our readings of all the articles. The list is not exhaustive, i.e. it does not cover every industry and it does not cover industries with neutral or only somewhat negative/positive Covid-impact. Furthermore, many sectors, such as manufacturing, are difficult to classify on a sector level, as it includes winners, losers, and neutral firms (see section 3.4.1 for further discussion on this topic).

9.2 Shiller P/E Ratio, S&P 500



Source: Yale (2021)
Note: The Shiller P/E Ratio for S&P 500 (solid line) displays the sum of the market value of all equities included in S&P 500 divided by their average profits in the previous 10-year period, where a higher ratio can be an indication of overvaluation of the stock market.