FINANCIAL STATEMENT INFORMATION AND ABNORMAL STOCK RETURNS

A TEST OF INCREASED MARKET EFFICIENCY OVER TIME IN THE SWEDISH STOCK MARKET

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Abstract:

This study revisits the question of whether publicly available financial statement information can be used to generate abnormal returns. The study tests the hypothesis that the Swedish stock market has become increasingly efficient over time with respect to publicly available financial statement information, suggested by Skogsvik and Skogsvik (2010), by applying their investment strategy, combining the estimated probability of an increase in mid-term ROE with the implied market expectations for future mid-term ROE estimated from a RIV-model. The sample consists of listed Swedish manufacturing companies between 2008-2019. No evidence of the investment strategy yielding any abnormal return during the sample period is found, supporting the notion of increasing market efficiency over time. These results are robust and consistent even after (i) introducing the risk of bankruptcy to the RIV-valuation framework, (ii) considering an alternative statistical method for estimating the ROE prediction model, and (iii) evaluating the abnormal returns using the Fama-French-Carhart model. By applying the Fama-French-Carhart model, this study also addresses the concerns raised by previous scholars regarding that the predicted probability of an increase in some key value driver is a proxy for systematic risk factors, where we find support to this notion, concluding that the estimated probability of an increase in ROE has significant covariance with the size factor.

Keywords:

Financial statement analysis, Fundamental valuation, Abnormal returns, Market mispricing.

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1. Introduction

In contrast to the widely accepted efficient market hypothesis, fundamental analysis based on publicly available historical financial information has consistently been proven to generate abnormal returns (see for example Ou and Penman, 1989; Holthausen et al., 1992; Stober, 1992; and Setiono and Strong, 1998). These results have large implications for both market efficiency and the understanding of how accounting data can be or are used in valuation. Recent results, using Swedish data, are found in Skogsvik and Skogsvik (2010) where a self-financing, fully implementable, trading strategy yields an average 36-month abnormal return of over 40% in the period 1983-2003. The trading strategy implemented, the "*indicator variable strategy*" is based on predicting the change in future mid-term[1] return on owners' equity **(**ROE**)** and positions are taken when this prediction differs from the implied market expectations, which are estimated through the residual income valuation (RIV) model. Despite achieving significant abnormal returns during this period, Skogsvik and Skogsvik (2010) does not reach the conclusion that the Swedish stock market is inefficient. They instead conclude that information and data processing costs have prevented investors from taking advantage of the apparent mispricing up to around 1995, but that the mispricing vanished by the mid-1990s, which is believed to be due to *investor learning*, where investors have gained more knowledge about the predictability of medium-term ROE and have become more sophisticated in their valuation modelling over time. Indeed, the investment strategy yields no abnormal returns in the period 1995-2003. The conclusion from Skogsvik and Skogsvik (2010) stands out compared to previous literature that has shown that historical financial information can, through fundamental analysis, yield abnormal returns. This paper re-examines the usefulness of historical financial information to achieve abnormal returns by applying the test design from Skogsvik and Skogsvik (2010) to a more recent time period (2008-2019), testing the hypothesis that the stock market has become more efficient over time which, if true, would imply that the market anomaly observed in previous papers (Ou and Penman, 1989; Holthausen et al., 1992; Stober, 1992; and Setiono and Strong, 1998) would no longer be valid. Furthermore, this study adds robustness to the results by sophisticating the test design by (i) controlling the realistic return metric for known risk factors, (ii) introducing the risk of bankruptcy to the RIV-framework applied, and (iii) considering an alternative method for estimating the ROE prediction model using a fixed effects logistic regression.

[1] Mid-term refers to the three-year average.

The results can be summarised as the following: The investment strategies show no signs of generating abnormal returns, with the realistic 36-month market-adjusted buy-and-hold return to a self-financing hedge portfolio using the *indicator variable strategy* amounting to between -34% to -41%, supporting the hypothesis that the Swedish stock market has become increasingly efficient over time, presumably due to investor learning and lower costs for obtaining and processing information. The results are not sensitive to the inclusion of bankruptcy risk in the RIV-model nor to the ROE prediction model being estimated through fixed effect logistic regression. Furthermore, when controlling for systematic risk factors, we conclude that both the realistic and the statistical return measures have systematic differences between the long and short portfolios for exposure to the size factor, resulting in the constructed self-financing hedge portfolios having a net exposure to the size factor. This supports previous conclusions from Greig (1992), stating that the predicted probability of an increase in some key value driver constitutes a proxy for size.

1.1 Background

All listed[2] companies must regularly disclose financial information to the public. In the EU, consolidated financial statements must be prepared in accordance with a single set of international standards called IFRS[3]. IFRS is used in more than 100 countries which is crucial for the analysis of securities since it enables comparisons between firms within different industries and geographies. Previous research has investigated the relevance of financial information for shareholders when valuing a company's securities. Some key ratios that have been found to have a strong impact on the price of a company's publicly traded shares, i.e., have strong value relevance, including for example unexpected changes in earnings (see for example Beaver 1968, Ball and Brown 1968, Forsgårdh and Hertzen 1975). This evidence has inspired scholars to leverage the established causality between financial information and firm by testing the hypothesis that financial information can be used to predict future stock returns. Such a hypothesis would imply that current share prices do not, at all times, reflect all available public information and, at times, can deviate from a firm's fundamental value. Hence, a test of this hypothesis equals a test of the efficient market hypothesis in its semi-strong form. The claim that stock prices reflect all relevant publicly available information and always correspond to the intrinsic value of the firm is supported by several papers and summarised by Fama in

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[2] Companies with one or more securities traded on a regulated market.

[3] International financial reporting standards.

1970. In short, he concludes in this paper (as well as in several preceding papers), that all value relevant publicly available information is reflected in the share price at any given point in time and that is it impossible to consistently achieve abnormal returns[4] over time using only publicly available information. This conclusion has later been supported in several papers, with Jensen (1978) stating: " *I believe there is no other proposition in economics which has more solid empirical evidence supporting it than the efficient market hypothesis".* However, the acceptance of the efficient market hypothesis did also spark a new area of research within finance, where so-called "market anomalies" are investigated. Researchers have over the years explored a wide range of possible methods for achieving abnormal returns, with every significant result questioning the efficient market hypothesis. See Feng et al. (2019) for a comprehensive list of anomalies that have been discovered in the past 50 years. One recurring market anomaly is implementing trading strategies based on fundamental analysis. In short, fundamental analysis entails that the true value of a security can differ from the observed share price at some point in time and instead of equalling the share price, the fundamental value of a firm and its securities can be derived from information in financial statements (Ou and Penman, 1989). Hence, this implies that not all information in historical financial statements is reflected in the share price, which would enable abnormal returns given the assumption that market prices tend to revert to the security's fundamental values. Examples of trading strategies based on fundamental analysis include Ou and Penman (1989) and Skogsvik (2008), with the first taking positions based on the predicted probability of a positive change in next year's earnings per share, and the latter taking positions based on the predicted probability of a positive change in future mid-term return on owner's equity. In both these papers, significant abnormal returns[5] are achieved. These types of investment strategies rely not only on the ability to predict the future change in some key value driving variable from the financial statements, but also on that the variable in question has a causal effect on firm value. The impact on firm value from the chosen variable can be tested *ex post* using the perfect foresight strategy put forth in Ball and Brown (1968), where one assumes perfect foresight of the future development of the selected value driver and evaluates a trading strategy based on this perfect foresight. Using these types of test designs, both earnings per share and ROE has been shown to have a causal effect on the share price (Ball and Brown, 1968; Skogsvik; 2008).

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[4] Returns after adjusting for appropriate risk measures.

[5] Using market-adjusted returns as abnormal return metric.

This type of fundamental trading strategy is further sophisticated in the paper from Skogsvik and Skogsvik (2010), testing the trading strategy which is not only based on the predicted change in return on equity but also based on the estimated market expectations of the future change in return on equity, yielding, in theory, a more accurate trading strategy since one could argue that it would be when one has more information than the market regarding the future development of some value driver that abnormal returns would be achieved. When the trading strategy is implemented, an average 36-month abnormal return of over 40% is achieved between 1983-2003, with high statistical significance. However, due to (i) possibly overstated significance levels due to overlapping data, (ii) a positive sentiment bias[6] during the period, and (iii) the majority of the abnormal returns being achieved in the first third of the investment period, with no abnormal return being achieved in the last third of the period (1995-2003) presumably due to investor learning[7], they argue that the stock market has become more efficient over time and that the anomaly observed in previous research has vanished. Furthermore, several scholars (for example Greig, 1992; and Ball, 1992) argues that the usefulness of historical financial statements for achieving abnormal returns has been overstated from the beginning, stating that the observed abnormal returns obtained using financial statement analysis are not actually abnormal returns, but rather compensation for systematic risk factors. These conclusions call for a re-examination of the usefulness of historical financial information for achieving abnormal returns in the stock market in a recent time period, using contemporary methods for measuring abnormal returns.

2. Overview of the prevailing literature

In this section, we briefly present an overview of some of the key papers testing the usefulness of financial statements for achieving abnormal returns. In all papers covered, a trading strategy that is based on predictions of the change in some key value driver has been implemented.

2.1 Financial statement analysis and abnormal returns

When examining the literature covering relationships between historical publicly available financial information and stock prices, one must anchor with the paper *"An Empirical Evaluation of Accounting Income Numbers"* by Ball and Brown in 1968, which turned out to

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[6] Larger positive stock price reactions on unexpected increases in medium-term ROE than negative stock price reactions on unexpected decreases in medium-term ROE.

[7] Research-based insights required for the implementation of accounting-based investment strategies was not publicly available until around the mid-1990s (Skogsvik and Skogsvik, 2010).

be one of the most influential papers within accounting and finance from its time. The study compares abnormal returns for companies delivering positive[8] earnings announcements versus companies delivering negative earnings announcements. The strategy is implemented on an *ex post* basis where. the companies are divided into portfolios based on the type of earnings announcement at time $t = 0$, and abnormal returns are measured from $t = -12$ (months) to $t = 0$. The results are clear and show that companies delivering positive earnings announcements experience positive abnormal returns during the year preceding the announcement, and vice versa for companies delivering negative earnings announcements. Although this is not an implementable trading strategy, it establishes the important premises that public financial information has a strong effect on share prices and that one could potentially achieve abnormal returns if one was able to predict the direction of change in some key value driving variable.

One of the first studies examining the possibility to use the established relationship between public financial information and share prices to construct a trading strategy was conducted by Ou and Penman in 1989. They define earnings per share (EPS) as the value driving variable and estimate a predictive model for predicting the change in EPS one year in the future. They subsequently take long or short positions depending on the sign of the predicted change in EPS, where a long position is taken if the predicted probability for an increase in EPS is above 60% and a short position taken if the probability of an increase in EPS is below 40%. The probability of an increase in EPS is estimated through a logistic regression using a set of accounting ratios as independent variables. The data sample includes approximately 20 thousand company-year observations for listed companies in the US between 1973-1983. Using this strategy, a market-adjusted return of 12.6% is earned from a realistic trading strategy that only requires information known at the investment dates. After adjusting for size (which is a commonly accepted proxy for systematic risk[9]), the yearly abnormal return amounts to 7.4%. These returns could not be explained by any at the time nominated risk factors including estimated market beta, return variance, earnings yield, market premium over book value or leverage.

[8] "Positive earnings announcement" means that the change in EPS exceeded the market expected change, with the market expectations proxied with average earnings per share for other companies.

[9] See Fama and French (1992) for an elaboration of the size factor.

Understandably, it did not take long for other researchers to question the results from Ou and Penman (1989) and conduct replicating studies as well as similar studies with altered test designs.

The first study re-examining the results by Ou and Penman (1989) was conducted by Holthausen et al. (1992) and examines the performance of a fundamental trading strategy which is based on the same 68 accounting ratios. However, a key difference in the test design is that they estimate a predictive model where the sign of twelve-month excess returns is used directly as the independent variable instead of the change in EPS as in Ou and Penman (1989), with the main argument that since the success of a trading strategy is determined by its association to excess returns, it's reasonable to predict this measure directly. The method of directly predicting excess returns was discarded by Ou and Penman (1989) with the main reason being that such a model would suffer a higher probability of simply detecting misspecifications in the measurement of excess returns. Holthausen et al. (1992) mitigate this issue by examining multiple metrics of excess returns, more precisely market-adjusted returns, excess return according to CAPM[10] as well as size-adjusted returns. The dataset covers firms listed on NYSE[11], ASE[12] as well as OTC[13] firms between 1978-1988. They deploy a realistic trading strategy requiring no *ex post* information and obtain 12-month market-adjusted returns of 7.3%, 12-months Jensen's alpha of 9.5% and 12-month size-adjusted returns of 7.9%. They also replicate the trading strategy used by Ou and Penman (1989) but find significantly lower abnormal returns amounting to between -0.1% and 1.6% on a yearly basis, depending on the measure used for excess returns. The main reason for these different results is believed to be due to the different time periods applied, where Holthausen et al.'s later time period is coupled with poor performance after 1983 (the last year for Ou and Penman's study), and that the period 1973-1977 was coupled with a strong performance for Ou and Penman's trading strategy, which is a time period not included in Holthausenet et al.'s study. To conclude, Holthausen et al. (i) question the choice to predict the performance of some key value driver, preferring instead to directly predict excess returns, (ii) find the results of Ou and Penman to lack

[10] The Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965).

[11] New York Stock Exchange.

[12] American Stock Exchange.

[13] Firms which securities traded over the counter.

robustness and (iii) find indications of increasing market efficiency (lower abnormal returns) over time.

In the same year, Greig (1992) also re-examines the Ou and Penman (1989) paper, to which he is quite critical. He starts by declaring some reasons for applying some caution to the results, by concluding that although it is established that the accounting ratios deployed by Ou and Penman (1989) do vary as a function of the change in future earnings, they also vary cross-sectionally as a function of risk, size, and other previously identified determents of expected return, hence, he argues that additional tests of abnormal returns are called for. Firstly, he performs a pure replication of the trading strategy, yielding similar results. He then implements additional robustness tests to see if the abnormal returns persist. He controls for market risk by regressing monthly returns for the hedge portfolio to the market risk premium. Advantages with this approach include that beta and abnormal returns are calculated simultaneously, mitigating the issue with potential time-varying betas. He concludes that the hedge portfolio has a net-positive beta in all sub-periods and that the abnormal return decreases when controlling for this, but do not vanish. He continues to control for size by performing the same regressions but with the sample divided into size-deciles with regressions performed for each decile. Using this approach, he finds that abnormal returns become insignificant, and argues that the estimated probability of the change in EPS actually is a proxy for the size factor. Lastly, he conducts cross-sectional regression analysis using firm-year observations instead of performing the analysis on portfolio level, with advantages including (i) the possibility to measure the relation between the predicted probability of an increase in EPS (from now on called ***Pr***) and stock returns independent of portfolios, (ii) the possibility to control for size as a continuous variable instead of dividing the portfolio into size deciles and (iii) results being less affected by potentially arbitrary decisions when creating the portfolios such as the cut-off point for *Pr* to include some security in the portfolio. The *Pr* measure is included as an independent variable along with lagged *Pr* values and size, and the results show that the *Pr* measure becomes insignificant while the size factor is strongly significant. This further strengthens Greig's hypothesis that the *Pr* measure is a proxy for the size factor. To conclude, Greig (1992) extends the control for risk factors to the results from Ou and Penman (1989) and finds that when changing the method for controlling for size, the abnormal returns vanish, entailing that the *Pr* measure is merely a proxy for the size effect.

Also in 1992, Stober has a paper published in which he includes the market expectations of the direction of the one-year change in EPS in the form of consensus estimates from stock market analysts. Since the *Pr* variable is a measure of the predicted probability of an increase in EPS, it can be compared to the forecasts for the change in EPS from stock market analysts. Interestingly, Stober finds that "*much of the information in Pr is in the public domain*", with the prediction agreeing with those from analysts about 75% of the time. Stober proceeds to test a trading strategy based on *Pr* in two samples, one in which *Pr* agrees with analysts' forecasts, and one in which *Pr* disagrees with analysts' forecasts. It turns out that abnormal returns are only obtained for the strategy trading on *Pr* signals disagreeing with analyst forecasts, which has two broad applications. Firstly, it seems as *Pr* does include some additional information not captured in the analyst's forecasts. Secondly, one should not only consider the probability of an increase in EPS when designing a trading strategy but also benchmark this against the market expectations which one can assume are reflected in the current share price. Furthermore, Stober touches upon the critique put forth by Greig (1992) and provides some arguments for the *Pr* variable to be a proxy for some systematic risk factor. He notices that the abnormal returns using the trading strategy from Ou and Penman (1989) persist well beyond the 2-3 years holding periods considered in the study, where abnormal returns seem to persist for up to 6 years. This observation implies that *Pr* is a proxy for cross-sectional differences in expected returns since if it was not, the abnormal returns shouldn't be as persistent.

The results from Ou and Penman (1989) are further put to the test when Setiono and Strong (1998) publish their contribution to the growing body of re-examinations. They consider the critique that has been put forth by previous research and end up using two approaches to investigate fundamental analysis' ability to generate abnormal returns. Firstly, they replicate the test design from Ou and Penman (1989), where predictions of the future change in EPS constitute the basis for the trading strategy. Secondly, they adopt the approach from Holthausen et al. (1992) by directly predicting the abnormal returns. They also acknowledge the corners raised by Greig (1992) regarding omitted risk factors and provide comments on the two different approaches of controlling for risk used by Ou and Penman (1989) and Greig (1992). Lastly, they consider alternative metrics for measuring abnormal returns. The dataset includes 13,517 company-year observations from the UK stock market between 1971-1992. When replicating the method from Ou and Penman (1989) they find highly significant abnormal returns. When adjusting for size, they split the sample into size deciles and calculate a size-adjusted returns measure. In line with Ou and Penman (1989), this reduces abnormal returns, but they are still positive and significant. Using the method for adjusting for size suggested by Greig (1992), which is based on regressing market-adjusted returns on market cap, *Pr* and lagged *Pr*, the regression shows the significance for the *Pr* coefficient vanishes when the size factor is introduced. The lack of significance for the *Pr* variables is consistent also when using binary variables for *Pr*. However, Setiono and Strong (1998) argues that since the regression analysis does not correspond to an implementable trading strategy (all positions are equally weighted, which requires *ex-post* knowledge of the number of positions over the whole investment period), larger emphasis should be put on the portfolio results from the implementable trading strategy, which show persisting significant abnormal returns even after adjusting for size. As for the direct prediction of abnormal returns, using the method from Holthausen et al. (1992), they find the results less robust, with poor predictive power for abnormal returns (around 50% for the logistic estimation models) and subsequently non-significant values for abnormal returns. The authors argue that the prediction of abnormal returns directly is disturbed by too much noise compared to the separate prediction of future change in EPS and the subsequent causality test of changes in EPS' effect on abnormal returns.

2.2 Financial statement analysis and abnormal returns on Swedish data

In 2008, Skogsvik tests if abnormal returns can be achieved using Swedish data between 1973-1983. The method put forth by Ou and Penman (1989) is used as the base, with some changes implemented. Firstly, the key value driver, *Pr*, which in Ou and Penman (1989) refers to the probability of an increase in one-year EPS, is changed to the probability of an increase in the three-year future average of return on owners' equity (ROE) compared to the last three years historical average. The choice of ROE as the key value driver instead of EPS is elegantly derived from the RIV model (specified in Skogsvik 1998). Furthermore, the mid-term changes in a company's profitability are argued to (i) be more value relevant than one-year-ahead changes and (ii) be less distorted by transitory items. Furthermore, Skogsvik limits the sample to only manufacturing companies arguing that a heterogenous sample might negatively affect the predictive power for the change in ROE since accounting ratios tend to differ among industries. The predictive model is re-estimated every third year[14], allowing for changes in the relationship between the changes in medium-term ROE and financial statement information over time to be captured. In addition to using several accounting ratios to predict the change in

[14] As opposed to every 5 years in Ou and Penman (1989).

mid-term ROE, Skogsvik also tests a predictive model which only uses historical three-year average ROE as predictor. Interestingly, in the out of sample validation periods, the model with only three-year historical ROE as the predictor showed the best predictive power, with an accuracy[15] of c. 70%. Despite previous research (Greig, 1992; Ball, 1992) arguing that the, from financial statements, predicted probability of an increase in some key value driver, the size factor is not controlled for in Skogsvik, only Jensen's alpha and market-adjusted BHAR[16] are used to measure abnormal returns. The main investment strategy, which is a realistic hedge strategy requiring no *ex post* knowledge, using only three-year average ROE as the predictor for change in medium-term ROE, yields a significant 36-month BHAR of 29% but a non-significant Jensen's alpha. Skogsvik concludes that financial statement information appears to be helpful in generating abnormal returns, although the results are sensitive to the choice of abnormal return metric.

Two years later, in 2010, Skogsvik and Skogsvik published a new paper that can be viewed as an extension to the paper published by Skogsvik in 2008, using data from the Swedish market from 1983 to 2003. The tests design performed by Skogsvik and Skogsvik (2010) is applied in this paper and hence analysed in detail in subsequent sections[17]. In short, the method from Skogsvik (2008) is applied with respect to the predictive model (where only historical medium-term ROE is used as the independent variable since it had the best accuracy in Skogsvik (2008). The main addition to Skogsvik (2008), and to the previous literature in general, is the inclusion of a measure for capturing the market expectations for the future change in medium-term ROE. This is made in the same spirit as in Setiono and Strong (2008), who uses analysts estimates as a proxy for the market expectations, but Skogsvik and Skogsvik takes a novel approach by using the RIV[18] valuation model. In short[19], a fundamental valuation of owner's equity using historical values of ROE is performed, with the output called the "historically motivated value of owners' equity". The difference between the historically motivated value of owner's equity and the current market capitalisation of a firm is then assumed to stem from different views of future medium-term ROE, where a market capitalisation above the historically motivated value

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[15] Number of correct predictions divided with the total number of predictions.

[16] Buy and hold abnormal return.

[17] Se section *3. Applying the test design from Skogsvik and Skogsvik (2010) to a later time period.*

[18] Residual income valuation.

[19] For further details, section *3.4 The residual income valuation (RIV) model and the indicator variable strategy.*

of equity implies that the market believes the future medium-term ROE to be higher than the historical average and *vice versa*. With this information, combined with the predicted changes in future medium-term ROE from the prediction model, a trading strategy is implemented in which positions are taken when the predicted change in future medium-term ROE differs from the implied market expectations (the *indicator variable strategy*). In addition, a trading strategy only considering the predicted change in mid-term ROE (the *base case strategy*) is also tested. The main results from the *indicator variable strategy* show that abnormal returns are significant for the whole period. For the realistic return measure, monthly Jensen's alpha amounts to a significant 0.8% and 36-month market-adjusted BHAR to significant >40%. As mentioned, the authors do not dismiss EMH, but rather conclude that abnormal returns at the beginning of the test period are achieved due to (i) positive sentiment bias and (ii) information and data processing costs preventing investors from taking advantage of the apparent mispricing, and the possibility to achieve abnormal after 1995 vanished due to (i) lower costs for information and data processing and (ii) investor learning.

2.3 Key takeaways from literature overview and our contribution

Increasing market efficiency over time

The conclusion from Skogsvik and Skogsvik (2010) stands out compared to previous literature. Although they do not achieve abnormal returns between 1995-2003, we argue that this is too short of a time frame to make certain conclusions. Furthermore, they argue that their sample period was affected by significant positive sentiment bias, casting doubt over the validity of the results in out-of-sample inferences. Hence, we apply the test design between 2008-2019 to test the hypothesis that the Swedish stock market has become more efficient over time with respect to publicly available financial information.

Measurement of abnormal returns

Critics have argued that the abnormal returns achieved by for example Ou and Penman (1989) do not indicate market inefficiency, but rather represent compensation for systematic risk factors such as market beta and size, suggesting that the fundamental analysis anomaly never have been valid (Greig, 1992; Ball, 1992). However, this question is still debated. Despite Greig (1992) reaching the conclusion that abnormal returns from the investment strategy in Ou and Penman (1989) are solely due to higher systematic risk exposure, Setiono and Strong (1998) argues that emphasis should not be put on these results since the OLS regression used by Greig (1992) pool all company-years, and by design assigning equal weights to all positions taken, only tests the statistical return measure, arguing that it is the realistic return measure that is relevant, and this measure has not been proven to only be compensation for systematic risk. Considering later studies such as Skogsvik and Skogsvik (2010), they also pool all company-years and controls for risk factors through OLS regressions. Hence, in this paper, we provide a new method for controlling the realistic return measure for systematic risk factors by applying the Fama-French-Carhart model[20] on monthly portfolio returns, adding to the robustness, and general acceptance, of the results.

Sophistication of the investment strategies

Ou and Penman's (1989) investment strategy of taking positions based on the predicted change in next year's EPS has been improved in several steps in more recent papers. Firstly, Stober (1992) introduced the idea of benchmarking the predictions to the market expectations which was proxied with analyst's forecasts. Skogsvik and Skogsvik (2010) further developed this notion arguing that analyst's forecasts include other input than solely historical financial statement information, hence negatively impacting its usefulness when testing hypotheses about historical financial information and abnormal returns. Instead, they developed a measure of implied market expectations derived from the RIV-valuation framework. In this paper, we further develop this method for estimating implied market expectations by introducing bankruptcy risk to the RIV-valuation framework. As elegantly described in Anesten et al. (2020), the RIV valuation model assumes non-conditional expected values of future ROE, hence the conditional values one gets from simply forecasting the future development will be systematically too high when ignoring the risk of bankruptcy, implying that the RIV model-based values of owners' equity calculated in Skogsvik & Skogsvik (2010) are systematically biased. Hence, one should take the risk of bankruptcy into account, in the expected values or in the discount rate[21]. Assuming that the market considers the risk of bankruptcy, our implied market expectations will be of higher accuracy than in Skogsvik and Skogsvik (2010).

This paper now proceeds as the following: In section 3, the test design from Skogsvik and Skogsvik (2010) is applied in a later time period to test the hypothesis that the Swedish stock market has become more efficient over time and that the fundamental analysis anomaly has

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[20] We acknowledge that there are even more contemporary frameworks for adjusting returns for systematic risk, such as the Fama and French five-factor model (Fama and French 2015), however, we are restricted to the factor data for the Swedish stock market available on the Swedish House of Finance's database, which only contains the four factors included in the Carhart-Fama-Franch four-factor model.

[21] For further details, section *5. Introducing bankruptcy risk.*

seized to exist. In section 4, we introduce the Fama-French-Carhart four-factor model to control the realistic return measure for systematic risk factors. In section 5, the investment strategies are re-evaluated as we include the risk of bankruptcy to the RIV model, to increase the accuracy of the investment strategies. In section 6, the investment strategies are again re-evaluated, using a fixed effect logistic regression to estimate the ROE prediction model, as opposed to the ordinary logistic regression model proposed in Skogsvik and Skogsvik (2010). In section 7, we compare the performance of the implemented investment strategies with a hypothetical strategy based on *ex post* knowledge of the change in the key value driver (the perfect foresight strategy). Lastly in section 8, we summarise our findings and elaborate on our conclusions.

3. Applying the test design from Skogsvik and Skogsvik (2010) to a later time period

To test the conclusion in Skogsvik and Skogsvik (2010), as well as to have a benchmark to isolate the effects from subsequent alterations to the test design, the methods of Skogsvik and Skogsvik (2010) is applied in the latter time period, 2008 to 2019. Keeping other parameters of the method constant, differences in our results compared to those from Skogsvik and Skogsvik (2010) can be isolated to the different time period considered.

To briefly summarise the test design, two investment strategies are implemented. The first strategy (the *base case strategy*) is constructed by taking a long position when the, from an estimated prediction model, predicted change in mid-term ROE, compared to historical mid-term ROE, is positive, and a short position is taken if the predicted change is negative. This strategy is similar to the strategy in Ou and Penman (1989). The second strategy (the *indicator variable strategy*) uses both the predicted change in mid-term ROE from the prediction model, as well as the implied market expectations of the change in mid-term ROE, which are estimated using the RIV-model. Long positions are taken when the prediction from the prediction model differs from the implied market expectations. The rationale is that in these cases, the predicted change in future ROE is not reflected by the current market price of the security, and hence there exists an information advantage over the market and abnormal returns can be achieved. To operationalise the markets expectations for the change in future ROE, a variable called the *Indicator variable* is defined, which represents the implied market expectations for the direction of the change in future ROE.

The disposition of this section proceeds as the following: Firstly, a brief description of the data sample is presented, followed by the derivation from which ROE is identified as the key value driving variable. Secondly, the estimation and performance of the ROE prediction model are illustrated and evaluated. Thirdly, the residual income method for estimating market expectations of the change in mid-term ROE as well as the operationalisation of the *indicator variable* are presented. Lastly, the investment strategies are formulated, and the returns are evaluated using the methods from Skogsvik and Skogsvik (2010).

3.1 Empirical data

This study has covered data between the years 2008-2019 and the sample consists, as in Skogsvik (2010), of manufacturing companies listed on the Stockholm Stock Exchange. Limiting the sample to one industry increases homogeneity which is believed to increase the predictive power of the ROE estimation models since accounting ratios tend to differ among industries. Skogsvik and Skogsvik (2010) used the industry classification from the Swedish business magazine "*Affärsvärlden*" to identify manufacturing companies. This industry classification is no longer available, and hence, we have relied on the Standard Industry Classification (SIC) code system[22], where SIC codes 20-39 represents manufacturing firms. In order to preserve the replicability of the study, no subjective judgement has been applied when defining the sample. All firm-specific data was collected from Capital IQ (CIQ)[23], while data for the market returns and returns for other risk factor portfolios were collected from the Swedish House of Finance (SHoF)[24].

TABLE 1 – DATA SAMPLE

	Estimation of ROE prediction models	Evaluation of investment strategies
Subperiod I	1997-04	2008-10
Subperiod II	2000-07	2011-13
Subperiod III	2003-10	2014-16
No. Of observations		
Subperiod I	605 (92)[i]	264
Subperiod II	632 (85)[i]	255
Subperiod III	648 (88)[i]	282

[23] https://www.capitaliq.com.

[24] https://www.hhs.se/en/houseoffinance/.

Table 1 presents the estimation periods for the ROE prediction model and the evaluation periods for the investment strategy, as well as the number of observations and the number of companies. For the ROE prediction model, the dependent variable $\Delta\overline{ROE}_{mt}$ *requires data for six consecutive years for each calendar year, that is data for years* $t-2$, $t-1$, $t+1$ t, $t+2$ *and* $t+3$[27]*.* [i] *Number of unique companies.*

The total period for which the investment strategies were tested is 2008-2019, with positions being taken every year from 2008 to 2016. We can conclude that the investment period ends just before the COVID-19 crisis. However, the beginning of our investment period is quite special since it includes the financial crisis in 2008. Performing the study in turbulent time periods adds a valuable contribution to the prevailing literature since it may place greater strains on the stability of the relationship between historical financial statement information and stock returns (Setiono and Strong, 1998). The total period has been divided into subperiods, with the same length as in Skogsvik and Skogsvik (2010), where the first period includes the investments made 2008-2010, the second 2011-2013, and the third 2014-2016. The positions were taken in the third month every year between 2008-2016 to ensure that year-end financial statements have become publicly available. All investment positions were held over a 36-month period to ensure sufficient time for the predicted change in ROE to actualize and potential market mispricing to correct. The total number of positions[25] taken in each period was 264, 255 and 282 in period I, II and III respectively, with the average number of investments per period amounting to 267. This can be compared to the average number of investments per period in Skogsvik and Skogsvik (2010) of 161. The larger number of yearly observations in our study is probably due to the larger number of listed firms during 2008-2016 compared to 1983-2000.

The ROE estimation model[26] was estimated in the beginning of each sub-period, i.e. in 2008, 2011 and 2014. The respective estimation periods for the prediction models were 1997-2004, 2000-2007 and 2003-2010. Estimating the ROE prediction models required historical data over six consecutive years[27] prior to the date for the model estimation. we have a larger set of company-year observations than Skogsvik and Skogsvik (2010), where we have an average of

[25] Refers to the *base case strategy*. For the *indicator variable* strategies, fewer positions were taken.

[26] The ROE estimation model refers to the predictive model estimated for predicting the probability of an increase in mid-term ROE, defined as the future three-year average less the historical three-year average.

[27] If historical ROE was not been available for six consecutive years, averages have been calculated based on the years that have been available. This affects a low share of the sample and is hence not estimated to have any material effects on the estimated coefficients.

628 observations per estimation period, while Skogsvik and Skogsvik (2010) has an average of 371 observations, which we attribute to a larger number of listed manufacturing firms and better data availability. The ROE prediction models were tested out-of-sample in holdout periods of three years; 2007-2009, 2010-2012 and 2013-2015 for the first, second and third prediction model respectively.

3.2 ROE as value driver of owners' equity

Skogsvik and Skogsvik (2010) uses ROE as the key value driver. This differs from previous research in which EPS has commonly been used (See for example Ou and Penman, 1989). A premise for an investment strategy based on predicting the direction of change in some key value driving variable is of course that the change in the selected key value driver has a causal effect on the value of the firm and subsequently the share price. Below we show the derivation from Skogsvik and Skogsvik (2008), proving that ROE has a direct effect on firm value, a relationship that has also been proven empirically in previous research (Skogsvik, 2008).

To deductively prove that ROE is a value driver of owners' equity, the residual income valuation model (RIV) is used, as specified in Skogsvik (1998)[28]. The value of owners' equity is derived from the present value of future expected net dividends. With the assumption of clean-surplus relation of accounting, the expected net dividends to shareholders can be stated as:

$$D_t - N_t = B_{t-1} + I_t - B_t = B_{t-1} * ROE_t - (B_t - B_{t-1}) \tag{1}$$

where $D_t =$ dividend paid to shareholders at time *t*,

$N_t =$ new issue of share capital at time *t*,

$B_t =$ ex-dividend book value of owners' equity, including new issue of share capital, at time *t*,

$I_t =$ accrued accounting net income in period *t*,

$ROE_t = \frac{I_t}{B_{t-1}} =$ accrued book return on owners' equity in period *t*.

The net dividend in (1) can be further rewritten as:

$$D_t - N_t = B_{t-1} * [\rho + (ROE_t - \rho)] - (B_t - B_{t-1}) \tag{2}$$

This implies that the residual income valuation model (RIV), assuming a finite time horizon T, can be stated as:

$$V_0 = B_0 + \sum_{t=1}^{T} \frac{B_{t-1}(ROE_t - \rho)}{(1+\rho)^t} + \frac{B_T(\frac{V_T}{B_T} - 1)}{(1+\rho)^T} \tag{3}$$

[28] The modelling framework was originally developed by Preinreich (1938), and further refined by Edwards and Bell (1961), and Ohlson (1995).

where V_0 = value of owners' equity (ex-dividend and including any new issues) at time $t = 0$, V_T = value of owners' equity (ex-dividend and including any new issues) at the horizon point in time $t = T$.

Hence, assuming that the assumptions for the RIV-model[29] hold, the above derivation from Skogsvik & Skogsvik (2010) proves that ROE is a value driver of owners' equity. According to the RIV model in (3), forecasts of ROE_t are required for each future period t. Instead of predicting ROE for every period, one can predict some medium-term value of ROE (Skogsvik and Skogsvik, 2010). The medium-term ROE is measured as the arithmetic average of the book return on owners' equity for years $t + 1$, $t + 2$ and $t + 3$. By focusing on the medium-term average of ROE, the prediction of transitory changes in company profitability is avoided.

3.3 The estimation and performance of the ROE prediction model

As in Skogsvik and Skogsvik (2010), the prediction model for changes in the average future ROE has been estimated through a univariate logistic regression model, with the historical three-year average ROE as the independent variable, which is shown to have higher accuracy than various multivariate logistic regression models (Skogsvik, 2008). The dependent variable, the change in medium-term ROE, has been defined as:

$$\Delta\overline{ROE}_{mt} = \overline{ROE}_f - \overline{ROE}_h = \frac{(ROE_{t+1}+ROE_{t+2}+ROE_{t+3})}{3} - \frac{(ROE_{t-2}+ROE_{t-1}+ROE_t)}{3} \tag{4}$$

where $\Delta\overline{ROE}_{mt}$ = change in average medium-term future ROE,

$\overline{ROE}_f$ = average future ROE for years $t + 1$, $t + 2$ and $t + 3$ for company *i*,

$\overline{ROE}_h$ = average historical ROE for years t, $t - 1$ and $t - 2$ for company *i*.

When estimating the logistic regression model, the independent variable is converted to a binary variable, with the value 1 if medium-term ROE increases and 0 if the medium-term ROE decreases. An unobservable variable Z_j is defined, which is larger than some threshold Z_j^* when a change in medium-term ROE is positive, and *vice versa.* Z_j follows a logistic distribution and is modelled as a univariate linear function of historical average ROE. Z_j is equal to the log-odds for a positive change in ROE. The logistic regression model is defined as:

$$Z_{j,t} = \log\left(\frac{p(Y=1)}{1-p(Y=1)}\right) = \beta_0 + \beta_1 * \overline{ROE}_h \tag{5}$$

[29] The assumptions are (i) the value of owner's equity equals the net present value of all future net dividends, (ii) the clean surplus relationship holds and (iii) market values are used in the accounting for net dividends.

where $Z_{j,t}$ = logistically distributed unobservable variable,

$\log\left(\frac{p(Y=1)}{1-p(Y=1)}\right)$ = log-odds of an increase in average future ROE, where $p(Y=1)$ = probability of an increase in average future ROE,

$\beta_{(*)}$ = coefficient for the ROE prediction model.

The probability of an increase in the average future ROE can be stated as:

$$P\left(Y(\Delta\overline{ROE}_{mt}) = 1 \middle| Z_{j,t}\right) = P(Z_{j,t} \geq Z^*_{j,t}) \tag{6}$$

where $Y(\Delta\overline{ROE}_{mt}) = 1$ if $\overline{ROE}_{mt} \geq 0$,

$Y(\Delta\overline{ROE}_{mt}) = 0$ if $\overline{ROE}_{mt} < 0$.

The probability that $Z_{j,t}$ exceeds the cut-off point is logistically distributed such that:

$$P\left(Y(\Delta\overline{ROE}_{mt}) = 1 \middle| Z_{j,t}\right) = \frac{1}{(1+e^{-Z_{j,t}})} \tag{7}$$

The coefficients β_0 and β_1 are estimated through the maximum-likelihood method, which entails finding the set of parameters for which the probability of the observed data is the greatest.

Since the proportion of increases in future mid-term ROE in the sample possibly differs from the *a priori* probability (π) of 50%, the predicted probabilities have been adjusted according to Skogsvik (2010)[30] as:

$$\hat{p}(\Delta(\overline{ROE}_{i,t+3}) \geq 0)^{adj} = \hat{p}\left(\Delta\left(\overline{ROE}_{i,t+3}\right) \geq 0\right) * \left[\frac{\pi*(1-prop)}{prop*(1-\pi)+\hat{p}\left(\Delta\left(\overline{ROE}_{i,t+3}\right)\geq 0\right)*(\pi-prop)}\right] \tag{8}$$

where π = *a priori* probability of an increase in the future medium-term ROE set to 0.5,

$prop$ = the proportion of increases in the medium-term ROE in the estimation sample,

$\hat{p}(\Delta(\overline{ROE}_{i,t+3}) \geq 0)^{adj}$ = the model-based predicted probability of an increase in the future medium-term ROE.

The logistic prediction model is re-estimated every third year, allowing for changes in the underlying relationship between changes in medium-term ROE and publicly available accounting information to be reflected. All prediction models are tested for out of sample performance in validation periods preceding the estimation period. The significance of the

[30] See also Skogsvik (2005).

prediction models is tested in $2 * 2$ contingency table tests where the test statistics is chi-square distributed.

Performance of the ROE prediction model

With a cut-off value of 0.5[31] for the adjusted model-based predicted probability of an increase in the medium-term ROE, the results from the predictive models are illustrated in Table 2. The accuracy of the models in the holdout periods ranges from 61% to 65%, with the highest accuracy being observed in the first holdout period. The chi-square values are strongly significant in all periods. Overall, the accuracy is lower than in Skogsvik and Skogsvik (2010), in which they had an overall accuracy of 73.7%. In all periods, in line with the results from Skogsvik and Skogsvik (2010), the model has higher accuracy when predicting decreases than when predicting increases, with correctly predicted decreases ranging from 69.4% to 78.4%, and correctly predicted increases ranging from 50.6% to 59.2%. The accuracy of predicted increases and decreases shows the opposite development over time, where the accuracy seems to get worse over time for predicting increases, with the opposite being the case for predicting decreases. We have a significantly larger sample size in each holdout period compared to Skogsvik and Skogsvik (2010), with an average of 255 firm-year observations, compared to an average of 119 in Skogsvik and Skogsvik (2010). This might explain the lower variance for the accuracy in our holdout periods compared to their paper.

TABLE 2 – PERFORMANCE OF ROE PREDICTION MODELS

	Holdout period I: 2007-2009	Holdout period II: 2010-2012	Holdout period III: 2013-2015
No. of firm-year observations	270	241	255
% overall correct predictions	63.7%	58.9%	51.8%
X^2-value	10.94	7.69	6.72
(p-value)	(0.001)	(0.006)	(0.010)
% increases correctly predicted	41.7%	42.7%	33.5%
% decreases correctly predicted	77.2%	74.2%	81.4%

Table 2 shows the validation results from the three estimated ROE prediction models. A probability cut-off value of 0.5 has been used. The probability of changes in the medium-term ROE have been predicted with the three different logistic regression models and calibrated with the calibration formula in equation (8) with the a priori probability, π, set to 0.5. The χ^2 values are from $2 * 2$ contingency table tests.

[31] The cut of value refers to the limit probability of an increase in mid-term ROE for which an investment position is taken. A cut off value of 0.5 means that long positions have been taken when the estimated probability of an increase in ROE is equal to or above 0.5, and a short position is taken if the probability is less than 0.5.

3.4 The residual income valuation (RIV) model and the *indicator variable strategy*

As in Skogsvik and Skogsvik (2010), the RIV-model has been used to estimate the market expectations for the direction of change in mid-term ROE. In this section, the method used in Skogsvik and Skogsvik (2010) for calculating the implied market expectations is illustrated, followed by a description of the investment strategies that are implemented.

RIV Model application

To estimate the market expectations of future ROE, the residual income valuation model (RIV) has been used, as specified in Skogsvik (2010)[32]. The RIV model is defined as:

$$V_0 = B_0 + \sum_{t=1}^{T} \frac{E_{(0)}[\tilde{B}_{t-1} * (\widetilde{ROE}_t - \rho_t)]}{(1+\rho)^t} + \frac{E_{(0)}[\tilde{q}(B_T) * \tilde{B}_T]}{(1+\rho)^T} \quad (9)$$

where $V_0 =$ book value of owners' equity at time *t*,

$\rho =$ required return on owners' equity,

$ROE_t = \frac{I_t}{B_{t-1}} =$ book return on owners' equity in time *t*, where $I_t =$ net income in time *t*,

$q(B_T) = \frac{(V_T - B_T)}{B_T} =$ measurement bias of owners' equity at time $t = T$, where $V_T =$ value of owners' equity at time $t = T$,

$E_{(0)}(*) =$ expected value operator conditioned on available information at time $t = 0$,

~ = (denotes) a random variable.

Given the specification of the RIV model and the assumption that the clean-surplus relation holds, the expected book value of owners' equity can be defined as $E_{(0)}(\tilde{B}_t) = E_{(0)}[\tilde{B}_{t-1} * (1 + \widetilde{ROE}_t - \widetilde{DS}_t)]$, where $\widetilde{DS}_t =$ dividend at time *t* divided by the book value of owners' equity at time *t*. In line with Skogsvik and Skogsvik (2010), the horizon point in time is assumed to $T = 3$, and that $E_0(\widetilde{DS}_t)$ and $E_0(\widetilde{ROE}_t)$ are constants and equal to $E_0(\widetilde{DS}_{mt})$ and $E_0(\widetilde{ROE}_{mt})$ in all periods. It is further assumed that $Cov(\widetilde{ROE}_{mt}, \widetilde{DS}_{mt}) = 0$,

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[32] The model was originally stated by Preinreich (1938), Edwards and Bell (1961) and Peasnell (1982), and further developed by Ohlson (1995) and Feltham and Ohlson (1995). The model relies on the assumptions that (i) the value of owners' equity equals the present value of future expected net dividends, (ii) that the clean-surplus relation of accounting holds, and (iii) that market values are used in the accounting for net dividends.

$Cov\left(\widetilde{ROE}_{mt},\ \tilde{q}(B_T)\right) = 0$ and $Cov\left(\widetilde{DS}_{mt},\ \tilde{q}(B_T)\right) = 0$ for simplification purposes of the modelling. Given these assumptions, (9) can be restated as:

$$V_0 = B_0 + \sum_{t=1}^{3} \frac{B_0 * E_{(0)}\left(1 + \widetilde{ROE}_{mt} - \widetilde{D}S_{mt}\right)^{t-1} * E_{(0)}\left(\widetilde{ROE}_{mt} - \rho_t\right)}{(1+\rho)^t} + \frac{B_0 * E_{(0)}\left(1 + \widetilde{ROE}_{mt} - \widetilde{D}S_{mt}\right)^{3} * E_{(0)}[\tilde{q}(B_3)]}{(1+\rho)^3} \tag{10}$$

where $\widetilde{ROE}_{mt}$ = medium-term return on owners' equity,
$\widetilde{D}S_{mt}$ = medium-term dividend payout share.

We assume that the RIV model in (10) is used by the market to determine stock prices. We further assume that all input values, i.e. B_0, $E_0\left(\widetilde{D}S_{mt}\right)$, $E_{(0)}[\tilde{q}(B_3)$ and ρ that we use are also used by the market, resulting in any differences between the value of owners' equity we get when applying the model and the stock price are solely attributable to different views for $E_0\left(\widetilde{ROE}_{mt}\right)$.

The *indicator variable*

As in Skogsvik and Skogsvik (2010), the *indicator variable* is defined as: $IND_0 = P_0 - V_0^{(h)}$ where, P_0 = the market price of owners' equity (i.e., the market capitalization), and $V_0^{(h)}$ = the *historically motivated* value of owners' equity. $V_0^{(h)}$ is calculated from the RIV model in (10) and is based on historical average values for $\widetilde{ROE}_{mt}$ ($\overline{ROE}_h$) and $\widetilde{D}S_{mt}$ ($\overline{DS}_h$), and with an exogenously determined valuation bias of owner's equity ($\bar{q}_h(B_3)$)[33], reflecting business goodwill and the effects of conservative accounting (Skogsvik, 1998). Hence, $V_0^{(h)}$ is calculated as:

[33] Using an exogenously determined ($\bar{q}_h(B_3)$) for calculating the terminal value of owners' equity is of great advantage for modelling purposes, since the alternative requires assumptions of several variables such as terminal growth and terminal ROE, which are coupled with high forecasting uncertainties. Thanks to the extensive work from Runsten (1998) on calculating $q(B_T)$ -values for Swedish companies, we can use these values given that the sample comprises only Swedish firms, making the RIV model highly effective.

$$V_0^{(h)} = B_0 + \sum_{t=1}^{3} \frac{B_0 * (1 + \overline{ROE}_h - \overline{DS}_h)^{t-1} * (\overline{ROE}_h - \rho_t)}{(1+\mathrm{\rho})^{\mathrm{t}}} + \frac{B_0 * (1 + \overline{ROE}_h - \overline{DS}_h)^{t-1} * (\overline{ROE}_h - \rho_t)}{(1+\rho)^3} \quad (11)$$

Assuming that the RIV model in (10) is also used by the market in valuing securities and that the market also expects $\widetilde{DS}_{mt}$ to equal the historical average ($\overline{DS}_h$), and the permanent valuation bias of owner's equity to equal ($\bar{q}_h(B_3)$), the market capitalization of a security can be represented by:

$$P_0 = B_0 + \sum_{t=1}^{3} \frac{B_0 * [1 + E_0^M(\widetilde{\overline{ROE}}_{mt}) - \overline{DS}_h)]^{t-1} * [E_0^M(\widetilde{\overline{ROE}}_{mt} - \rho_t)]}{(1+\rho)^t} + \frac{B_0 * [1 + E_0^M(\widetilde{\overline{ROE}}_{mt}) - \overline{DS}_h]^3 * \bar{q}_h(B_3)}{(1+\rho)^3} \quad (12)$$

With $E_0^M(\widetilde{\overline{ROE}}_{mt})$ representing the markets expectation for the future mid-term ROE. Given that the *indicator variable* (IND_0) equals the difference between the market price of owner's equity (P_0) and the *historically motivated* value of owners' equity ($V_0^{(h)}$), and that the only difference between (P_0, Equation 12) and ($V_0^{(h)}$, Equation 11) is the measure for $\widetilde{\overline{ROE}}_{mt}$, the *indicator variable* $IND_0 = P_0 - V_0^{(h)}$ represents the difference between $E_0^M(\widetilde{\overline{ROE}}_{mt})$ and ($\overline{ROE}_h$) we can conclude that the sign of the *indicator variable* tells us if the market believes the future mid-term roe to be higher or lower than the historical average. To ensure the interpretation of the *indicator variable* is clear, we have the following interpretations:

$Negative\ market\ outlook$: $IND_0 < 0$ if $E_{(0)}^{(M)}(\widetilde{\overline{ROE}}_{mt}) < \overline{ROE}_h$ (13a)

$Neutral\ market\ outlook$: $IND_0 = 0$ if $E_{(0)}^{(M)}(\widetilde{\overline{ROE}}_{mt}) = \overline{ROE}_h$ (13b)

$Positive\ market\ outlook$: $IND_0 > 0$ if $E_{(0)}^{(M)}(\widetilde{\overline{ROE}}_{mt}) > \overline{ROE}_h$ (13c)

Operationalisation of the *indicator variable*

To determine the value for $IND_0 = P_0 - V_0^{(h)}$ we need the values for P_0 and $V_0^{(h)}$. Since P_0 equals the market capitalization, we already have this value. Hence, we must determine the value of $V_0^{(h)}$ by determining the input variables to equation 11. B_0 is the book value of owner's equity at the valuation point in time. $\overline{ROE}_h$ and $\overline{DS}_h$ have been calculated as the arithmetic average of the last three years historical ROE and dividend payout share from the valuation point in time. The required return on owner's equity (ρ) has been calculated through the CAPM-model, where the market beta of owners' equity has been determined through an OLS regression of the last four years'[34] firm-specific monthly stock returns and market index returns. The market risk premium has been exogenously determined through the PWC annual risk premium study and the risk-free rate is observed on a yearly basis for the year of calculation. Finally, for $\bar{q}(B_3)$, we assume that the time for business goodwill to diminish is about 5-6 years[35] and that it diminishes linearly over this period. Given these assumptions, the $\bar{q}_h(B_3)$ at the horizon point in time ($T = 3$) is calculated as a weighted average of the current price-to-book ratio of owners' equity and an exogenously determined permanent measurement bias of owners' equity: $\bar{q}_h(B_3) = (1 - w) * \left(\frac{P_0}{B_0} - 1\right) + w * E_{(0)}(\frac{\tilde{V}_T}{\tilde{B}_T} - 1)$, with w set to 0.5 and $E_{(0)}(\frac{\tilde{V}_T}{\tilde{B}_T} - 1)$ retrieved from Runsten (1998). In his paper, he categorises five industries as manufacturing and, hence, as in Skogsvik and Skogsvik (2010), the arithmetic average of these industries[36] (0.49) has been used for all companies in the sample. The measurement bias of owners' equity at the horizon point in time $\bar{q}_h(B_3)$ has thus been calculated as: $q(B_T) = (1 - 0.5) * \left(\frac{P_0}{B_0} - 1\right) + 0.5 * 0.49$.

3.5 Investment strategies

In the following section, the investment strategies are explained. The two investment strategies from Skogsvik and Skogsvik (2010) have been considered; Firstly, a strategy solely based on the predicted change in mid-term ROE has been be evaluated (the *base case strategy*). Secondly, the signals from the *base case strategy* have been combined with the implied market expectations for the change mid-term ROE, and positions formed when these two differ (the *indicator variable strategy*). The *indicator variable strategy* has been divided into three sub-strategies with different cut-off values for the *indicator variable* in accordance with Skogsvik and Skogsvik (2010).

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[34] In cases where share price data for four years back were not available, the average beta for the sample was used.

[35] The assumption is supported by Penman (1991) for US firms.

[36] The industries classified as manufacturing in Runsten (1998) are (q-values in parentheses) consumer goods (0.72), pulp and paper (0.67), chemical industry (0.44), engineering (0.33), and other production (0.31).

3.5.1 The base case strategy

The positions taken in the *base case strategy* are solely determined by the ROE prediction model. A long position has been taken if the predicted probability of an increase in medium-term ROE is above 0.5, and a short position has been taken if the predicted probability of an increase in medium-term roe is below 0.5. The decision rule can be summarised as:

Long position if: $\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)^{adj} > 0.5$

Short position if: $\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)^{adj} < 0.5$

The predicted value of $\hat{p}(\Delta(\overline{ROE}_{mt})^{adj}$ was calculated using the most recent estimated logistic regression model.

3.5.2 The indicator variable strategy

The *indicator variable strategy* takes both the predicted change in future mid-term ROE and the implied market expectations into account when positions are taken. The investment rules are shown in figure 1 (from Skogsvik and Skogsvik, 2010).

FIGURE 1 – THE *INDICATOR VARIABLE STRATEGY*

		Accounting-based probability of change in medium-term ROE	
		$p(\overline{ROE_f} > \overline{ROE_h}) > 0.5$	$p(\overline{ROE_f} > \overline{ROE_h}) < 0.5$
Indicator variable	$IND_0 < 0$: $E_{(0)}^{(M)}(\widetilde{ROE_{mt}}) < \overline{ROE_h}$	Long position[i]	(-)
	$IND_0 = 0$: $E_{(0)}^{(M)}(\widetilde{ROE_{mt}}) = \overline{ROE_h}$	Long position	Short position
	$IND_0 > 0$: $E_{(0)}^{(M)}(\widetilde{ROE_{mt}}) > \overline{ROE_h}$	(-)	Short position[i]

Figure 1 illustrates the investments positions formed in the indicator variables strategy from the different combinations of the probability of change in medium-term ROE and the market expectations of ROE. [i]*Investment positions are also taken if* $p(\overline{ROE_f} > \overline{ROE_h}) = 0.5$. *Figure 1 is the same as in Skogsvik and Skogsvik (2010).*

The *indicator variable strategy* is based on the *base case strategy*, with the extension of including the market expectations of future ROE implied by the *indicator variable*. A negative value of IND_0 implies that the market value of owner's equity (market capitalization) is lower than the RIV model-based value of owner's equity, and thus, the market expectations of future ROE is lower than the average historical level of ROE. A value of IND_0 equal to 0 implies that the market value of owners' equity is in line with the RIV model-based value of owner's equity, and thus, market expectations of ROE are in line with historical levels of ROE. A positive value of IND_0 implies that the market value of owners' equity is higher than the RIV model-based value of owner's equity, and thus, the market expectations of future ROE is higher than the historical level of ROE.

The investment positions taken in the *indicator variable strategy* depends on the combination of the predicted change in future ROE and the market expectations of future ROE. Positions are taken when the two signals differ, i.e., when the expected change in future ROE from the prediction model differ from the *indicator variable*'s implied market expectations of future ROE. The positions are formed as:

If $IND_0 < 0$: **Long position** if $\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)^{adj} \geq 0.5$ in the ROE prediction model
If $IND_0 = 0$: **Long position** if $\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)^{adj} > 0.5$ in the ROE prediction model
If $IND_0 = 0$: **Short position** if $\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)^{adj} < 0.5$ in the ROE prediction model
If $IND_0 > 0$: **Short position** if $\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)^{adj} < 0.5$ in the ROE prediction model

Considering the inherent measurement problems associated with the *indicator variable*, Skogsvik and Skogsvik (2010) consider three different operationalizations of $IND_0 = 0$. The intervals are a) $IND_0 = 0$ if a) $-0.1 \leq \frac{IND_0}{B_0} \leq 0.1$, b) $-0.2 \leq \frac{IND_0}{B_0} \leq 0.2$, and c) $-0.4 \leq \frac{IND_0}{B_0} \leq 0.4$. Going forward, these intervals are referred to as a) *IND01*, b) *IND02*, and c) *IND04* respectively. These three operationalizations are tested in this study as well. The rationale is that the relative difference between the market expectations for mid-term ROE and the historical average is proportional to the absolute value of the *indicator variable*. Hence, the larger the interval for $IND_0 = 0$ is set, the stronger the signal from the market must be to conclude that the market has a positive or negative outlook for mid-term ROE.

3.6 Evaluation of investment returns

The investment positions were taken at the end of the third month every year between 2008-2016 to ensure that year-end financial statement information had been made publicly available, and subsequently for the trading strategy to be realistically implementable only using information available at the investment dates. As in Skogsvik and Skogsvik (2010), all positions are held over a 36-month period to ensure enough time for the predicted change in ROE to actualize and potential market mispricing to correct. At each investment date, an equally weighted long portfolio and an equally weighted short portfolio are constructed and subsequently combined, yielding a self-financing hedge portfolio. All three portfolios are evaluated, that is the long portfolio, the short portfolio, and the hedge portfolio.

A key distinction to make here is that both realistic and statistical return measures are evaluated. For the statistical return measure, all positions are equally weighted over the whole investment period. This requires *ex post* knowledge of the total number of investments; hence this method cannot be realistically implemented only using information available at the investment dates. Furthermore, for the statistical return measure, all securities that have been delisted during the investment period, regardless of reason, have been excluded from the sample, a method which of course also requires *ex post* knowledge of the securities that become delisted during the period. For the realistic return measure, the long and short portfolios have been equally weighted each year, and subsequently, each year has been equally weighted when calculating returns for the whole investment period. This requires no knowledge of the number of investments in future years. For the companies that have been delisted during the investment period, any proceeds have been reinvested in the market index, hence the realistic return measure represents the return that would have been achievable for an investor and mitigates the issue concerned with a survivorship bias. There are two reasons for including the statistical return measure; (i) results are easy to compare with previous studies, and (ii) it enables cross-sectional regression analysis on firm-year observations instead of on portfolio level, resulting in larger sample sizes as well as enabling more sophisticated risk adjustments with the possibility to include risk proxies as continuous variables on company level. It should be noted that, since the statistical return metric excludes all firms that for whatever reason has been delisted during the period, suffers from survivorship bias.

For ease of comparison, all returns are evaluated through the methods used in Skogsvik and Skogsvik (2010). First, abnormal CAPM returns are measured through Jensen's alpha. Secondly, abnormal returns are measured through a market-adjusted buy-and-hold return measure. Lastly, cross-sectional regressions on firm-year observations are performed to control for certain known risk factors. Some summary statistics for the sample are presented in Table 3.

TABLE 3 – SUMMARY STATISTICS FOR THE INVESTMENT PERIOD

Year	No. of firms	P_0/B_0		$V_0^{(h)}/B_0$		IND_0/B_0		$\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)^{adj}$	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median
2008	90	3.5242	2.1304	2.3656	1.7332	0.8549	0.1787	0.4895	0.4600
2009	88	2.1051	1.1131	2.0381	1.3503	0.2452	-0.3339	0.4858	0.4548
2010	86	4.3109	2.1591	2.3966	1.5711	0.9990	0.2519	0.4902	0.4608
2011	83	2.8613	2.2736	2.0101	1.5487	0.7776	0.2352	0.4991	0.4717
2012	85	2.0222	1.8884	1.8947	1.4056	0.3891	0.1434	0.5049	0.4711
2013	87	2.4636	2.1786	2.1197	1.5831	0.5784	0.1277	0.5038	0.4596
2014	87	3.0152	2.8176	1.6756	1.7983	1.0999	0.3509	0.5075	0.4651
2015	95	3.9448	3.1187	1.6116	2.0570	1.3236	0.5054	0.5061	0.4683
2016	100	4.0415	2.9677	2.8058	2.1089	0.9150	0.4760	0.4971	0.4645
All years		3.1687	2.2709	2.1100	1.6634	0.8056	0.2390	0.4982	0.4642

Table 3 shows the arithmetic average and median for the sample at the investment point in time in each year, that is at the end of the third month. P_0 is the stock price at the investment point in time. B_0 is the book value of owners' equity at the end of the previous year. IND_0 is the indicator variable defined as $P_0 - V_0^{(h)}$. $\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)^{adj}$ is the adjusted probability of an increase in the medium-term ROE.

For the whole period, the average price to book ratio amounted to 3.2, substantially higher than the 2.3 in Skogsvik and Skogsvik (2010). The average price-to-book ratio was also higher than the average historically motivated RIV model value-to-book ratio, implying a positive market outlook for mid-term ROE in general during the period. This is also shown by the average value for the *indicator variable* in relation to the book value of 0.8 for the whole period. This implies that the market, in general, has expected values of ROE to increase, as opposed to in Skogsvik and Skogsvik (2010) where the implied market outlook for future ROE, in general, was negative with IND_0/B_0 averaging -0.1 for the whole period. We also note that the median value for IND_0/B_0 is merely 0.24, implying a somewhat skewed distribution of if the *indicator variable*. As for the $\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)^{adj}$, we can conclude that the average estimated probability of an increase is close to 50%, and the median somewhat lower, implying a somewhat skewed distribution. This is quite different from the Skogsvik and Skogsvik (2010), where the average and median respectively for $\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)^{adj}$ amounted to 0.45 and 0.42. We can also conclude that we observe a lower variance in $\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)^{adj}$ between the years than in Skogsvik and Skogsvik (2010), which might be due to our larger sample size or lower variance in the independent variable historical ROE.

In Table 4, the total numbers of long and short for each investment strategy are illustrated. As mentioned, our yearly sample is larger than in Skogsvik & Skogsvik (2010), however, the time frame in our study is shorter, resulting in the total number of positions taken over the whole period being quite similar in both studies. As in Skogsvik and Skogsvik (2010), we systematically take more short positions than long positions during the period, which tells us that the combination of a predicted decrease in mid-term ROE, and a positive or neutral market outlook, is more common than the combination of a predicted increase in ROE and a negative or neutral market outlook. This is somewhat expected given the figures in Table 3, showing a median probability of an increase in ROE of less than 50%, combined with a, on aggregate, positive implied market outlook for ROE.

TABLE 4 – NUMBER OF FIRM-YEAR OBSERVATIONS IN THE INVESTMENT STRATEGIES 2008-2019

Investment strategy	Position	Number of firms
Base case strategy	Long	311
	Short	490
	Total	801
Indicator variable strategy		
Zero interval for IND_0:	Long	78
$[-0.1\cdot\beta_0, 0.1\cdot\beta_0]$	Short	312
	Total	390
Zero interval for IND_0:	Long	98
$[-0.2\cdot\beta_0, 0.2\cdot\beta_0]$	Short	343
	Total	441
Zero interval for IND_0:	Long	131
$[-0.4\cdot\beta_0, 0.4\cdot\beta_0]$	Short	406
	Total	537

Table 4 shows the number of firm-year observations for the long, short and hedge portfolios in the base case strategy, IND01, IND02 and IND04.

3.6.1 Abnormal CAPM return - Jensen's alpha

The investment positions have first been evaluated with abnormal CAPM returns measured through the Jensen's alpha metric. The monthly Jensen's alpha has been measured through an OLS regression as:

$$\bar{R}^{exc}_{(*)} = \alpha_{(*)} + \beta_{(*)} * \left(R_{M,t} - R_{f,t}\right) + \tilde{\varepsilon}_{(*),t} \qquad (13)$$

where $\bar{R}^{exc}_{(H),t} = \bar{R}_{(L),t} - \bar{R}_{(S),t} =$ the average excess portfolio return of the hedge portfolio in month *t*,

$\bar{R}^{exc}_{(L),t} = \bar{R}_{(L),t} - R_{f,t} =$ the average excess portfolio return of the long position in month *t*,

$\bar{R}^{exc}_{(S),t} = \bar{R}_{(S),t} - R_{f,t} =$ the average excess portfolio return of the short position in month *t*,

$R_{m,t} =$ the excess return of the market portfolio in month *t*,

$R_{f,t}$ = the risk-free rate in month *t*.

The estimated alphas and market betas are reported in Table 5. Since the regression is performed on portfolio returns, and all proceeds from delisted securities have been invested in the market index, this is a fully implementable trading strategy and hence a test of the realistic trading strategy.

TABLE 5 – ABNORMAL (MONTHLY) CAPM RETUNS OVER 36-MONTH HOLDING PERIODS

Investment strategy	Position	α	β
Base case strategy	Long	-0.006	0.968
		(0.007)	(0.000)
	Short	0.002	1.006
		(0.128)	(0.000)
	Hedge	-0.007	-0.038
		(0.000)	(0.371)
Indicator variable strategy			
Zero interval for IND_0:	Long	-0.010	1.075
[$-0.1 \cdot \beta_0$, $0.1 \cdot \beta_0$]		(0.012)	(0.000)
	Short	0.002	0.976
		(0.125)	(0.000)
	Hedge	-0.012	0.099
		(0.002)	(0.241)
Zero interval for IND0:	Long	-0.012	1.092
[$-0.2 \cdot \beta_0$, $0.2 \cdot \beta_0$]		(0.000)	(0.000)
	Short	0.002	0.999
		(0.067)	(0.000)
	Hedge	-0.014	0.093
		(0.000)	(0.151)
Zero interval for IND0:	Long	-0.010	1.085
[$-0.4 \cdot \beta_0$, $0.4 \cdot \beta_0$]		(0.000)	(0.000)
	Short	0.002	0.981
		(0.054)	(0.000)
	Hedge	-0.012	0.104
		(0.000)	(0.036)

Table 5 presents the results from the regression in equation 13, where α represents the abnormal return and β represents the coefficient for the excess return of the market portfolio. α and β values have been tested with two-tailed t-tests against the null hypothesis of the parameter being equal to zero (p-values in parenthesis).

At first glance, we notice striking differences compared to Skogsvik and Skogsvik (2010), in which positive monthly alphas for the hedge portfolios, in chronological order from base case to *IND04*, are 0.004, 0.008, 0.006 and 0.004. The corresponding monthly Jensen's alpha values for our hedge portfolios are -0.007, -0.012, -0.014 and -0.012. Significant negative abnormal returns are observed for all long portfolios, combined with positive abnormal returns for all short portfolios (mostly not significant), yield strongly significant negative abnormal returns for the hedge portfolios. In Skogsvik and Skogsvik (2010), we also observe positive alphas for the short positions in all investment strategies of 0.001 to 0.002, indicating that it is the long position contributing to the positive alphas for the hedge positions. The beta values do not provide any plausible explanation to our results, where we observe significant market betas of around 1 for both the long and short portfolios, and hence insignificant market betas around zero for the hedge portfolios. Furthermore, we can conclude that the *indicator variable strategy* shows tendencies to yield even worse abnormal returns than the *base case strategy*.

3.6.2 Market-adjusted buy-and-hold abnormal return (realistic return metric)

Continuing to evaluate the realistic[37] return measure, portraying an implementable trading strategy requiring no *ex post* knowledge, the market-adjusted buy-and-hold abnormal return ($MJBH$) for the different portfolios have been calculated as follow:

$$MJBH_{(H),36} = MJBH_{(L),36} - MJBH_{(S),36} \tag{14a}$$

$$MJBH_{(L),36} = \frac{1}{9}\sum_{t=2008}^{2016}\frac{1}{N_{(L),t}}\sum_{j=1}^{N_{(L),t}}\left[\prod_{t=1}^{36}\left(1+R_{j,t}\right)-\prod_{t=1}^{36}\left(1+R_{m,t}\right)\right] \tag{14b}$$

$$MJBH_{(S),36} = \frac{1}{9}\sum_{t=2008}^{2016}\frac{1}{N_{(S),t}}\sum_{j=1}^{N_{(S),t}}\left[\prod_{t=1}^{36}\left(1+R_{j,t}\right)-\prod_{t=1}^{36}\left(1+R_{m,t}\right)\right] \tag{14c}$$

where $MJBH_{(*),36}$ = the realistic market-adjusted buy-and-hold return after 36 months,

$N_{(*),t}$ = the number of stocks in the position in year *t*,

H = Hedge position, L = Long position, S = Short position.

[37] Any proceeds from delisted firms during the period have been reinvested in the market index, requiring no *ex post* of which firms that will become delisted.

TABLE 6 – MARKET-ADJUSTED BUY-AND-HOLD RETURNS (REALISTIC RETURN METRIC) FOR 36-MONTH HOLDING PERIODS

Investment strategy	Position	*2008-2010*	*2011-2013*	*2014-2016*	*2008-2016*
Base case strategy	Long	-0.545	-0.130	0.106	-0.190
					(0.094)
	Short	-0.036	0.167	0.296	0.142
					(0.086)
	Hedge	-0.509	-0.298	-0.190	-0.332
					(0.006)
Indicator variable strategy					
Zero interval for IND_0:	Long	-0.955	-0.225	0.346	-0.278
$[-0.1 \cdot \beta_0, 0.1 \cdot \beta_0]$					(0.148)
	Short	0.001	0.127	0.269	0.132
					(0.067)
	Hedge	-0.956	-0.352	0.078	-0.410
					(0.027)
Zero interval for IND_0:	Long	-0.921	-0.209	0.314	-0.272
$[-0.2 \cdot \beta_0, 0.2 \cdot \beta_0]$					(0.144)
	Short	0.011	0.138	0.275	0.141
					(0.073)
	Hedge	-0.932	-0.347	0.039	-0.413
					(0.035)
Zero interval for IND_0:	Long	-0.726	-0.116	0.186	-0.219
$[-0.4 \cdot \beta_0, 0.4 \cdot \beta_0]$					(0.148)
	Short	-0.069	0.162	0.272	0.122
					(0.107)
	Hedge	-0.657	-0.278	-0.086	-0.340
					(0.014)

Table 6 presents the realistic market-adjusted buy-and-hold returns for 36-month holding periods of the short, long and hedge position for the base case strategy and IND01, IND02 and IND04. The returns are presented for each of the three investment periods, as well as for the entire investment period (2008-2016) The returns of the long, short and hedge positions have been calculated in accordance with equations (14a), (14b) and (14c). Returns for the entire investment period have been tested with two-tailed t-tests against the null hypothesis of the return being equal to zero (p-values in parenthesis).

As illustrated in Table 6, the realistic market-adjusted abnormal returns for the have been divided into subsets. The subsets correspond to each period in which a new predictive model for the change in future mid-term ROE is estimated. For example, the model estimated in 2008 is used for taking positions from 2008 to 2010. On aggregate, we observe negative values for 36-month abnormal return for the long portfolios, positive 36-month abnormal returns for the short portfolios, and subsequently large negative 36-month abnormal returns for the hedge portfolios. There is no indication of the abnormal returns for the hedge portfolios either decreasing or increasing for the *indicator variable strategy* compared to the *base case strategy*. As for the significance levels, we conclude that the significance is weak in general for the long positions and the short positions separately. However, the large negative abnormal returns for the hedge portfolios are all significant. Compared to Skogsvik and Skogsvik (2010), we note that they, for the realistic return metric, had a strong performance for the hedge portfolios, with a market-adjusted 36-month return of 0.2651 for the *base case strategy*, and up to 0.4469 for the *indicator variable strategy*[38].

3.6.3 Market-adjusted buy-and-hold abnormal return (statistical return metric)

As previously mentioned, for the realistic return metric, all forms that have been delisted during the period has been excluded, and all positions taken over the whole period are equally weighted. The realistic measure for average market-adjusted buy-and-hold abnormal return ($\overline{MJBH}$) has been calculated as follows:

$$\overline{MJBH}_{(H),36} = \overline{MJBH}_{(L),36} - \overline{MJBH}_{(S),36} \tag{15a}$$

$$\overline{MJBH}_{(L),36} = \frac{1}{N_{(L)}}\left[\sum_{j=1}^{N_{(L)}}\left(\prod_{t=1}^{36}(1 + R_{J,t}) - \prod_{t=1}^{36}(1 + R_{M,t})\right)\right] \tag{15b}$$

$$\overline{MJBH}_{(S),36} = \frac{1}{N_{(S)}}\left[\sum_{j=1}^{N_{(S)}}\left(\prod_{t=1}^{36}(1 + R_{J,t}) - \prod_{t=1}^{36}(1 + R_{M,t})\right)\right] \tag{15c}$$

where $\overline{MJBH}_{(*),36}$ = the market-adjusted buy-and-hold return after 36 months, $z = 36$,

$R_{j,t}$ = the return of stock *j* in month *t*,

$R_{m,t}$ = the return of the market index *j* in month *t*,

$N_{(*)} = \sum_{t=2008}^{2016} N_{(*),t}$ = the number of stocks in the position in the period 2008-2016,

H = Hedge position, L = Long position, S = Short position.

[38] *Indicator variable strategy* for *IND02*.

TABLE 7 – MARKET-ADJUSTED BUY-AND-HOLD RETURNS (STATISTICAL RETURN METRIC) FOR 36-MONTH HOLDING PERIODS

Investment strategy	Position	α
Base case strategy	Long	-0.123
	Short	0.125
	Hedge	-0.248
Indicator variable strategy		0.000
Zero interval for IND_0:	Long	-0.100
$[-0.1 \cdot \beta_0, 0.1 \cdot \beta_0]$	Short	0.137
	Hedge	-0.237
Zero interval for IND_0:	Long	-0.114
$[-0.2 \cdot \beta_0, 0.2 \cdot \beta_0]$	Short	0.135
	Hedge	-0.248
Zero interval for IND_0:	Long	-0.100
$[-0.4 \cdot \beta_0, 0.4 \cdot \beta_0]$	Short	0.112
	Hedge	-0.212

Table 7 presents the statistical market-adjusted buy-and-hold returns for 36-month holding periods for the short, long and hedge positions for the base case strategy and IND01, IND02 and IND04. The returns of the long, short and hedge positions have been calculated in accordance with equations (15a), (15b) and (15c). Returns for the entire investment period (2008-2016) have been tested with two-tailed t-tests against the null hypothesis of the return being equal to zero (p-values in parenthesis).

The results shown in Table 7 coincide well with the previous results shown in Table 6. We again see a poor performance for both the long and short portfolios, with the long portfolio yielding negative values and the short portfolios yielding positive values, resulting in an impressive negative abnormal return for all hedge portfolios. We see no tendencies for the abnormal to the hedge portfolio to either worsen or improve when we compare the *indicator variable strategy* to the *base case strategy*.

3.6.4 Adjusting for systematic risk factors

Of course, it is not enough to only consider Jensen's alpha and market-adjusted return when evaluating abnormal returns, as argued by man scholars such as Greig (1992). We have used the method for adjusting for common risk factors as used in Skogsvik and Skogsvik (2010). This is performed through OLS regression analysis on panel data with the 36-month statistical market-adjusted abnormal return for each individual investment as the dependent variable. All observations are equally weighted by definition of the OLS regression; hence the results refer to the statistical return metric. Furthermore, delisted companies have been excluded from the sample. Firstly, the independent variable is solely a dummy variable indicating whether the investment is a long or short position. The regression is defined as:

$$MJBH_{j,36} = \theta_0 + \theta_1 * D_{j,0}^{S(*)} + \tilde{\varepsilon}_j \quad (16)$$

where $MJBH_{j,36} = \prod_{t=1}^{36}(1 + R_{J,t}) - \prod_{t=1}^{36}(1 + R_{M,t})$ = market-adjusted 36-month return,

$D_{j,0}^{S}$ = dummy variable equal to 1 if the investment, $S(*)$, for stock *j* is classified as a short position and vice versa, and

$\tilde{\varepsilon}_j$ = error term.

Secondly, four risk proxies have been added as independent variables to the first regression in 16, which are the natural logarithm of book-to-market of owners' equity (the value factor), earnings-to-price, dividend yield, and the natural logarithm of the market cap (the size factor). All risk proxies have been calculated as the three-year arithmetic average of the value at the investment date, one year forward from the investment date, and two years forward from the investment date. The second regression is defined as:

$$MJBH_{j,36} = \theta_0 + \theta_1 * D_{j,0}^{S(*)} + \theta_2 * \overline{ln(B/M_{J,0})} + \theta_3 * \overline{ln(E/P_{J,0})} + \theta_4 * \overline{ln(D/P_{J,0})} + \theta_5 * \overline{ln(MV_{J,0})} + \tilde{\varepsilon}_j \quad (17)$$

where $\overline{ln(B/M_{J,t})}$ = the three years average of the natural logarithm of book value divided by the market value of owners' equity for company *j* at time *t*,

$\overline{ln(E/P_{J,t})}$ = the three years average of the earnings per share for period *t* divided by the stock price for the company at the end of the period,

$\overline{ln(D/P_{J,t})}$ = the three years average of the dividend per share for period *t* divided by the stock price for company *j* at the end of the period, and

$\overline{ln(MV_{J,t})}$ = the three years average of the natural logarithm of the market value of owners' equity at the investment point in time for company *j*.

The coefficients for regression (16) and (17) are reported in table 8.

TABLE 8 – ESTIMATED COEFFICIENTS FOR REGRESSIONS (16) and (17)

Investment strategy	θ_0	θ_1	θ_2	θ_3	θ_4	θ_5	Adj. R^2	No. Obs.
Base case strategy	-0.123	0.248					0.9%	749
	(0.062)	(0.003)						
	0.056	0.128	-0.153	0.339	5.055	-0.040	4.9%	744
	(0.732)	(0.196)	(0.001)	(0.000)	(0.111)	(0.070)		
Zero interval for IND_0:	-0.100	0.237					0.4%	369
$[-0.1 \cdot \beta_0, 0.1 \cdot \beta_0]$	(0.391)	(0.068)						
	0.532	-0.137	-0.292	0.378	2.655	-0.080	7.9%	365
	(0.024)	(0.400)	(0.000)	(0.005)	(0.503)	(0.004)		
Zero interval for IND_0:	-0.114	0.248					0.6%	417
$[-0.2 \cdot \beta_0, 0.2 \cdot \beta_0]$	(0.270)	(0.033)						
	0.485	-0.082	-0.285	0.376	2.637	-0.079	8.2%	414
	(0.028)	(0.563)	(0.000)	(0.003)	(0.481)	(0.003)		
Zero interval for IND_0:	-0.100	0.212					0.5%	508
$[-0.4 \cdot \beta_0, 0.4 \cdot \beta_0]$	(0.252)	(0.035)						
	0.275	-0.150	-0.299	0.315	5.062	-0.056	8.8%	505
	(0.143)	(0.205)	(0.000)	(0.002)	(0.110)	(0.017)		

Table 8 shows the results from the regressions in equations (16) and (17) for the base case strategy and IND01, IND02 and IND04, as well as the adjusted R2 and the number of observations for each regression. The regression (16) is $MJBH_{j,36} = \theta_0 + \theta_1 * D_{j,0}^{S(*)} + \tilde{\varepsilon}_j$ *and the regression (17) is* $MJBH_{j,36} = \theta_0 + \theta_1 * D_{j,0}^{S(*)} + \theta_2 * \overline{ln(\frac{B}{M_{J,0}})} + \theta_3 * \overline{ln(\frac{E}{P_{J,0}})} + \theta_4 * \overline{ln(\frac{D}{P_{J,0}})} + \theta_5 * \overline{ln(MV_{J,0})} + \tilde{\varepsilon}_j$*. The dependent variable, the statistical market-adjusted abnormal return, is defined as* $MJBH_{j,36} = \prod_{t=1}^{36}(1 + R_{J,t}) - \prod_{t=1}^{36}(1 + R_{M,t})$. $D_{j,0}^{S}$ *is a dummy variable equal to 1 if the investment,* $S(*)$*, for stock j is classified as a short position and vice versa,* $\overline{ln(B/M_{J,t})}$ *is the three years average of the natural logarithm of book value divided by the market value of owners' equity for company j at time t,* $\overline{ln(E/P_{J,t})}$ *is the three years average of the earnings per share for period t divided by the stock price for the company at the end of the period,* $\overline{ln(D/P_{J,t})}$ *is the three years average of the dividend per share for period t divided by the stock price for company j at the end of the period, and* $\overline{ln(MV_{J,t})}$ *is the three years average of the natural logarithm of the market value of owners' equity at the investment point in time for company j. All coefficients have been tested with a two-tailed t-test against the null hypothesis of the coefficients being equal to zero (corresponding p-values in parenthesis).*

Firstly, it is important to clarify the interpretation of the coefficients. Starting with the first regression (16), it simply illustrates the effect of a sell signal or a buy signal. As the dummy variable $D_{j,0}^{S(*)}$ takes on the value 1 if the signal is short and the value 0 if the signal is long, the intercept θ_0 of the regression represents the average return of a long position. Subsequently, θ_1 represents the change to the intercept for an average short position. Hence, as the return for the hedge position is the difference between the long and the short position,

θ_1, multiplied with -1, also represents the market-adjusted return for the hedge position. This becomes clear when comparing the coefficients to the market-adjusted return figures for the statistical return metric in Table 7. As such, equation (16) is solely a reformulation of the results in Table 7, and hence does not need to be analyzed further. The adj. R-squared values range from 0.4%-0.9%, which is of course low but expected with only the investment signal included as explanatory variable. The low adj. R-squared values are in line with the results from Skogsvik and Skogsvik (2010).

In equation (17), as in Skogsvik and Skogsvik (2010), additional[39] variables are introduced that has been shown to represent systematic risk factors in previous literature, specifically the factors value (represented by book-to-market ratio), earnings-to-price ratio, dividend yield and size. As for the interpretation of the coefficients, θ_0 and θ_1 have the same interpretation as in equation (16), while coefficient θ_2, θ_3, θ_4, and θ_5 represent the effects from the loadings on the respective risk factor on abnormal returns. In contrast to the paper from Skogsvik and Skogsvik (2010), where no of the risk factors was found to be significant in explaining abnormal returns, we find that three of the four factors are significant on the five percent level (value, earnings-to-price, and size), with the coefficients for earnings-to-price and size showing the right signs, but the coefficient for value showing the wrong sign, which is rather surprising given that the coefficient is significant in our sample. Interestingly, the sign for the value coefficient was negative for Skogsvik and Skogsvik (2010) as well. The adj. R-squared for the regressions are quite strong with values of around 8% for all *indicator variable* strategies. This can be compared to the adj. R-squared in Skogsvik and Skogsvik (2010) of between 2% and 5% for the same strategies. Lastly, and most interestingly, we notice that the previously significant negative abnormal returns to the hedge portfolios from equation (16) vanishes when the additional risk factors are introduced. Furthermore, θ_0 shows large, significant (*IND01* and *IND02*), abnormal returns to the long portfolios using the *indicator variable strategies*, implying a systematic difference in the loading on the risk factors between the long and the short portfolios. These observations are further supported by the descriptive statistics for the risk factors in the respective portfolios reported in Table 9. For detailed descriptive statistics for each risk proxy variable, see *Appendix D.*

[39] For background to the risk variables, see Fama (1992).

TABLE 9 – SUMMARY STATISTICS FOR RISK PROXIES

Investment strategy	Position		B / M	E / P	D / P	MCAP
Base case strategy	Long	Mean	0.690	-0.203	0.008	9,743
		Median	0.502	-0.027	0.000	697
	Short	Mean	0.451	0.033	0.022	44,243
		Median	0.349	0.051	0.022	6,380
Indicator variable strategy						
Zero interval for IND_0:	Long	Mean	1.251	-0.284	0.014	12,238
$[-0.1\cdot\beta_0, 0.1\cdot\beta_0]$		Median	1.191	-0.001	0.007	500
	Short	Mean	0.324	0.049	0.022	44,807
		Median	0.298	0.049	0.022	7,201
Zero interval for IND_0:	Long	Mean	1.164	-0.271	0.013	12,015
$[-0.2\cdot\beta_0, 0.2\cdot\beta_0]$		Median	1.090	0.001	0.007	598
	Short	Mean	0.349	0.050	0.023	42,111
		Median	0.305	0.050	0.022	6,979
Zero interval for IND_0:	Long	Mean	1.144	-0.260	0.013	9,572
$[-0.4\cdot\beta_0, 0.4\cdot\beta_0]$		Median	1.033	0.007	0.007	603
	Short	Mean	0.403	0.048	0.023	39,268
		Median	0.336	0.051	0.022	6,525

Table 9 shows the arithmetic average and median of the risk proxy variables, included in the regression in equation 17, of every year in the entire investment period (2008-2016). B/M is the book-to-market ratio of owners' equity, E/P is the earnings per share divided by the stock price, D/P is the dividend yield, and MCAP is the market capitalisation.

Looking at Table 9, we find support for the factor loadings to be different between the long and short portfolios. The differences in size between the long and short positions are quite striking, and in line with the results from Skogsvik and Skogsvik (2010). Furthermore, we see a large difference between the book-to-market ratios, where the ratio tends to be higher for companies in the long portfolio, indicating a higher loading on the value factor. We also notice that the companies in the long portfolios tend to have higher earnings-to-price ratios. As for dividend yield, we see some tendencies of higher values for the short portfolios. Considering the magnitude of the differences in factor loadings between the long and short portfolios, and subsequently, the net exposure to the factors for the hedge portfolio, combined with the magnitude of the estimated coefficients, a significant part of the negative market-adjusted returns seems to be explained.

3.6.5 Elimination of statistical overfitting in the data

Skogsvik and Skogsvik (2010) acknowledges, in harmony with previous papers, that the overlapping investment periods[40] for each observation can cause significance levels to be overstated. To control for this, the total sample has been divided into three subsamples with non-overlapping data. Subsample I includes the positions taken 2008, 2011 and 2014, subsample II includes the positions taken 2009, 2012 and 2015 and subsample III includes the positions taken 2010, 2013, and 2016[41]. In Table 10, monthly abnormal CAPM for non-overlapping subsamples are presented.

TABLE 10 – ABNORMAL CAPM RETURNS FOR 36-MONTH HOLDING

Investment strategy	Position	Subsample I		Subsample II		Subsample III	
		α	*β*	*α*	*β*	*α*	*β*
Base case strategy	Long	-0.0047	0.9332	-0.0066	0.9891	-0.0065	1.0042
		(0.230)	(0.000)	(0.077)	(0.000)	(0.087)	(0.000)
	Short	0.0013	0.9836	0.0024	1.0276	0.0010	1.0172
		(0.531)	(0.000)	(0.195)	(0.000)	(0.525)	(0.000)
	Hedge	-0.0061	-0.0503	-0.0090	-0.0385	-0.0075	-0.0130
		(0.064)	(0.426)	(0.009)	(0.613)	(0.036)	(0.886)
Indicator variable strategy							
Zero interval for IND_0:	Long	-0.0081	0.8379	-0.0129	1.1863	-0.0103	1.3565
$[-0.1\cdot\beta_0, 0.1\cdot\beta_0]$		(0.124)	(0.000)	(0.004)	(0.000)	(0.277)	(0.000)
	Short	0.0017	0.9669	0.0022	0.9222	0.0018	1.0591
		(0.432)	(0.000)	(0.380)	(0.000)	(0.277)	(0.000)
	Hedge	-0.0098	-0.1290	-0.0151	0.2640	-0.0121	0.2974
		(0.060)	(0.201)	(0.001)	(0.008)	(0.194)	(0.212)
Zero interval for IND_0:	Long	-0.0090	0.9589	-0.0115	1.2000	-0.0153	1.1834
$[-0.2\cdot\beta_0, 0.2\cdot\beta_0]$		(0.071)	(0.000)	(0.007)	(0.000)	(0.018)	(0.000)
	Short	0.0016	0.9937	0.0028	0.9645	0.0021	1.0502
		(0.458)	(0.000)	(0.211)	(0.000)	(0.219)	(0.000)
	Hedge	-0.0106	-0.0349	-0.0143	0.2355	-0.0173	0.1332
		(0.023)	(0.700)	(0.001)	(0.013)	(0.006)	(0.399)
Zero interval for IND_0:	Long	-0.0106	1.0124	-0.0103	1.1213	-0.0095	1.1667
$[-0.4\cdot\beta_0, 0.4\cdot\beta_0]$		(0.017)	(0.000)	(0.006)	(0.000)	(0.022)	(0.000)
	Short	0.0022	0.9935	0.0027	0.9248	0.0017	1.0313
		(0.303)	(0.000)	(0.173)	(0.000)	(0.301)	(0.000)
	Hedge	-0.0128	0.0189	-0.0100	-0.0476	-0.0095	-0.0506
		(0.002)	(0.813)	(0.006)	(0.496)	(0.017)	(0.509)

[40] Since positions are taken each year and held for 36 months, there are many cases where three positions of each type have been held simultaneously.

[41] By dividing the sample in this way, no investment periods are overlapping. For example, positions taken in 2008 is held until 2011, (36 months), and then liquidated right before the new positions are formed in 2011.

Table 10 presents the results from the regression in equation 13 divided into the three different subsamples of investment periods. Positions in subsample I were formed in 2008, 2011 and 2014. Positions in subsample II were formed in 2009, 2012, and 2015. Positions in subsample III were formed in 2010, 2013 and 2016. α represents the abnormal return and β represents the coefficient for the excess return of the market portfolio. α and β values have been tested with two-tailed t-tests against the null hypothesis of the parameter being equal to zero (p-values in parenthesis).

Just as for the abnormal CAPM returns presented in Table 5, these abnormal return metrics refers to the realistic return metric, i.e., corresponding to a trading strategy that could be implemented by investors using only information available at the investment date. From Table 10 we can conclude that results are quite consistent over time when compared to Table 5. The abnormal return to the hedge portfolio for the *base case strategy* is significant in all subsamples, with monthly Jensen's alpha values ranging from -0.0061 to -0.009. For the *indicator variable* strategies, the significance level is a bit more mixed, but all monthly Jensen's alpha values show negative sign. Furthermore, the market betas are significant and close to 1 for both the long portfolio and short portfolio, resulting in insignificant market betas close to zero for the hedge portfolios. The regression in equation (17) has also been performed for the non-overlapping subsamples. The results are shown in Table 11.

TABLE 11 – ESTIMATED COEFFICIENTS ON NON-OVERLAPPING SUBSAMPLES FOR REGRESSION (17)

Investment strategy	Sub-sample	θ_0	θ_1	θ_2	θ_3	θ_4	θ_5	Adj. R^2	No. Obs.
Base case strategy	I	0.126	0.105	-0.136	0.288	4.713	-0.046	1.4%	241
		(0.666)	(0.569)	(0.128)	(0.130)	(0.412)	(0.253)		
	II	-0.014	0.220	-0.152	0.280	5.665	-0.037	3.0%	251
		(0.964)	(0.226)	(0.088)	(0.077)	(0.334)	(0.380)		
	III	0.069	0.051	-0.166	0.499	4.706	-0.037	7.1%	257
		(0.780)	(0.739)	(0.011)	(0.002)	(0.347)	(0.258)		
Indicator variable strategy									
Zero interval for IND_0:	I	1.299	-0.587	-0.397	1.273	-0.325	-0.125	8.0%	117
$[-0.1\cdot\beta_0, 0.1\cdot\beta_0]$		(0.012)	(0.093)	(0.013)	(0.008)	(0.967)	(0.032)		
	II	0.094	-0.054	-0.347	0.168	6.810	-0.057	7.3%	110
		(0.820)	(0.854)	(0.019)	(0.275)	(0.358)	(0.278)		
	III	0.843	-0.139	-0.202	1.085	-4.626	-0.090	6.9%	142
		(0.022)	(0.565)	(0.021)	(0.014)	(0.436)	(0.023)		
Zero interval for IND_0:	I	1.009	-0.363	-0.342	1.156	1.547	-0.116	6.6%	135
$[-0.2\cdot\beta_0, 0.2\cdot\beta_0]$		(0.029)	(0.225)	(0.017)	(0.012)	(0.831)	(0.030)		
	II	0.260	-0.180	-0.366	0.190	4.365	-0.059	6.1%	125
		(0.507)	(0.475)	(0.008)	(0.216)	(0.534)	(0.245)		
	III	0.551	0.091	-0.205	0.621	-1.556	-0.085	8.7%	157
		(0.106)	(0.683)	(0.016)	(0.017)	(0.785)	(0.026)		
Zero interval for IND_0:	I	0.608	-0.342	-0.359	0.456	5.509	-0.080	6.4%	163
$[-0.4\cdot\beta_0, 0.4\cdot\beta_0]$		(0.109)	(0.163)	(0.004)	(0.034)	(0.372)	(0.088)		
	II	-0.027	-0.146	-0.343	0.160	6.210	-0.030	7.2%	155
		(0.935)	(0.472)	(0.002)	(0.257)	(0.259)	(0.479)		
	III	0.308	-0.047	-0.226	0.553	2.023	-0.057	6.7%	188
		(0.285)	(0.800)	(0.003)	(0.023)	(0.691)	(0.107)		

Table 11 shows the results from the regressions in equations (16) and (17) for the base case strategy and IND01, IND02 and IND04 divided into three subsamples, as well as the adjusted R2 and the number of observations for each regression. Positions in subsample I were formed in 2008, 2011 and 2014. Positions in subsample II were formed in 2009, 2012, and 2015. Positions in subsample III were formed in 2010, 2013 and 2016. The regression (16) is $MJBH_{j,36} = \theta_0 + \theta_1 * D_{j,0}^{S(*)} + \tilde{\varepsilon}_j$ *and the regression (17) is* $MJBH_{j,36} = \theta_0 + \theta_1 * D_{j,0}^{S(*)} + \theta_2 * \overline{ln(\frac{B}{M_{J,0}})} + \theta_3 * \overline{ln(\frac{E}{P_{J,0}})} + \theta_4 * \overline{ln(\frac{D}{P_{J,0}})} + \theta_5 * \overline{ln(MV_{J,0})} + \tilde{\varepsilon}_j$*. The dependent variable, the statistical market-adjusted abnormal return, is defined as* $MJBH_{j,36} = \prod_{t=1}^{36}(1 + R_{J,t}) - \prod_{t=1}^{36}(1 + R_{M,t})$. $D_{j,0}^{S}$ *is a dummy variable equal to 1 if the investment,* $S(*)$, *for stock j is classified as a short position and vice versa,* $\overline{ln(B/M_{J,t})}$ *is the three years average of the natural logarithm of book value divided by the market value of owners' equity for company j at time t,* $\overline{ln(E/P_{J,t})}$ *is the three years average of the earnings per share for period t divided by the stock price for the company at the end of the period,* $\overline{ln(D/P_{J,t})}$ *is the three years average of the dividend per share for period t divided by the stock price for company j at the end of the period, and* $\overline{ln(MV_{J,t})}$ *is the three years average of the natural logarithm of the market value of owners' equity at the investment point in time for company j. All coefficients have been tested with a two-tailed t-test against the null hypothesis of the coefficients being equal to zero (corresponding p-values in parenthesis).*

From Table 11 we can conclude that θ_0 and θ_1 are in general insignificant, implying that the significance levels for θ_0 from equation (17) in Table 8 might be overstated due to overlapping subsamples. Furthermore, the significance levels for the risk factors have decreased compared to Table 8. The significance for the value factor is lost for the base case strategy but remains for the indicator variable strategies in all subsamples. The dividend-yield factor remains insignificant in all samples. As for the size factor and earnings-to-price, these are quite systematically significant for the indicator variable strategies in the first and third subsample but becomes insignificant when the second subsample is evaluated. We note that the lower significance levels both can stem from overstated significance levels when using overlapping data as well as to fewer observations included in the regressions.

The realistic 36-month market-adjusted buy-and-hold return for non-overlapping subsamples for the realistic performance measure has also been calculated, shown in Table 12 below.

TABLE 12 – MARKET-ADJUSTED BUY-AND-HOLD RETURNS (REALISTIC RETURN METRIC) FOR 36-MONTH HOLDING PERIODS WITH NON-OVERLAPPING SUBSAMPLES

Investment strategy	Position	Subsample I	Subsample II	Subsample III
Base case strategy	Long	-0.147	-0.255	-0.167
		(0.218)	(0.190)	(0.246)
	Short	0.116	0.195	0.117
		(0.284)	(0.071)	(0.237)
	Hedge	-0.263	-0.450	-0.284
		(0.042)	(0.077)	(0.092)
Indicator variable strategy				
Zero interval for IND_0:	Long	-0.228	-0.343	-0.263
$[-0.1 \cdot \beta_0, 0.1 \cdot \beta_0]$		(0.298)	(0.200)	(0.256)
	Short	0.094	0.144	0.159
		(0.260)	(0.176)	(0.153)
	Hedge	-0.322	-0.487	-0.422
		(0.194)	(0.103)	(0.144)
Zero interval for IND_0:	Long	-0.208	-0.259	-0.349
$[-0.2 \cdot \beta_0, 0.2 \cdot \beta_0]$		(0.304)	(0.256)	(0.174)
	Short	0.093	0.160	0.170
		(0.275)	(0.166)	(0.161)
	Hedge	-0.302	-0.420	-0.519
		(0.193)	(0.186)	(0.096)
Zero interval for IND_0:	Long	-0.212	-0.287	-0.158
$[-0.4 \cdot \beta_0, 0.4 \cdot \beta_0]$		(0.290)	(0.227)	(0.175)
	Short	0.106	0.117	0.143
		(0.257)	(0.226)	(0.206)
	Hedge	-0.318	-0.403	-0.300
		(0.143)	(0.133)	(0.018)

Table 12 presents the realistic market-adjusted buy-and-hold returns for 36-month holding periods for the short, long and hedge position for the base case strategy and IND01, IND02 and IND04 divided into the three subsamples of investment periods. Positions in subsample I were formed in 2008, 2011 and 2014. Positions in subsample II were formed in 2009, 2012, and 2015. Positions in subsample III were formed in 2010, 2013 and 2016. The returns of the long, short and hedge positions have been calculated in accordance with equations (14a), (14b) and (14c). Returns for the investment periods have been tested with two-tailed t-tests against the null hypothesis of the return being equal to zero (p-values in parenthesis).

From Table 12, the overall conclusions stand the same as previously, with negative market-adjusted returns for the long portfolios, positive market-adjusted returns for the short portfolios, and subsequently, negative market-adjusted returns to the hedge portfolio. In Skogsvik and Skogsvik (2010), they conclude that the returns to the hedge portfolios using the *indicator variable* strategies varies a lot between the subsamples, indicating a lack of robustness of the results. This phenomenon is not observed as clearly in our sample, with quite large negative abnormal returns for the hedge portfolios in all samples. It can be noted that the significance level is fluctuating, with several abnormal hedge returns being insignificant.

Finally, Skogsvik and Skogsvik (2010), acknowledges that the investor community continuously change, and they lift some key arguments that would imply that the observed abnormal return would be achievable in the beginning if their sample period, and harder to achieve towards the end. As their investment period stretches from 1983 to 2003, they start by concluding that in the 1980:s, the data availability, as well as the applicable tools for processing the data and operationalizing the trading strategies, would be cumbersome and costly. Secondly, they point out that the first papers operationalising these trading strategies were first published in the late 1980:s and onwards. These two arguments lay the basis for a hypothesis that efficiency in the Swedish stock market could be expected to have increased over time. This hypothesis is in their paper supported by the fact that most of the abnormal returns achieved during the investment period were achieved in the first third of the period, between 1983 and 1991. Subsequently, in the period 1995-2003, negative abnormal return is reported for both the *base case strategy* and the *indicator variable strategy*. Given that the accessibility of accounting information, as well as the possibilities for analyzing large data sets, has improved further since 2003, we conduct the same analysis to evaluate the performance of the investment strategies over time. Figure 2 below shows the 36-month market-adjusted return to the *base case strategy* and the *indicator variable strategy* (*IND01)*, for positions taken each year during the investment period. The results are both similar and different to those in Skogsvik and Skogsvik (2010). The difference is that the value of the abnormal return increases over time rather than decreases. However, the similarity is that the abnormal returns, as in Skogsvik and Skogsvik (2010), seems to progress towards zero over the time period, which would support the hypothesis that the Swedish stock market is getting more efficient over time.

FIGURE 2 – MARKET-ADJUSTED BUY-AND-HOLD RETURNS TO THE HEDGE POSITION (REALISTIC RETURN METRIC)

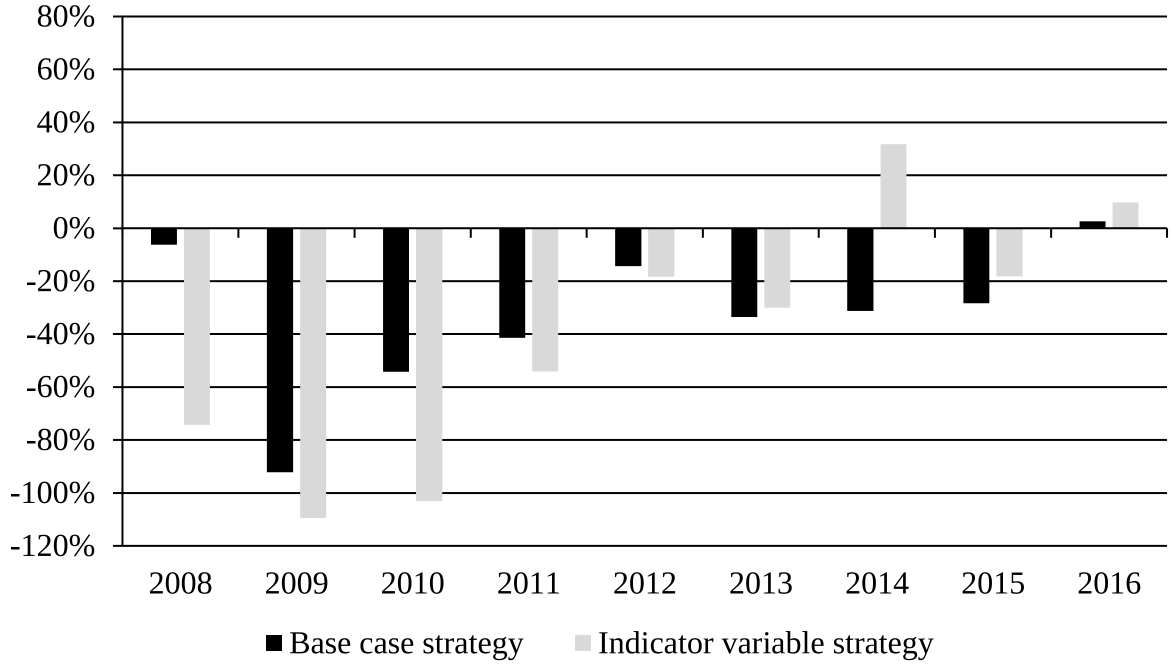

Figure 2 illustrates the realistic market-adjusted buy-and-hold returns to the hedge position for the base case strategy and the IND01 strategy for each year in the investment period. The returns have been calculated according to equation (14a).

3.7 Discussion

At a first glance, the conclusion from Skogsvik and Skogsvik (2010) is supported, with no abnormal return being achieved during the period 2008-2019, implying no mispricing during the period. In fact, our results rather suggest that market-adjusted returns would have been negative during the period. However, the significance disappears when conventional risk measures are controlled for on firm-level. Taking a closer look at the time-series for the realistically achievable market-adjusted returns for the *base case strategy* and the *indicator variable strategy* (*IND01*), the trend supports a development of the abnormal returns towards zero, supporting the hypothesis of investor learning put forth by Skogsvik and Skogsvik (2010). Considering the accuracy of the ROE prediction model in Table 2, we notice worse predictive performance than in Skogsvik and Skogsvik (2010). It is not unreasonable that this is a contributing factor to the *base case strategy* performing worse in our study. Furthermore, most of the abnormal returns to the hedge portfolios in Skogsvik and Skogsvik (2010) is attributable to the performance of the long portfolios, which are amplified due to a strong positive sentiment bias reported in their study. This is measured by comparing the average return for a stock which an unexpected increase in mid-term ROE compared to the return for a stock with an unexpected decrease in mid-term ROE. If the *indicator variable* implied a negative outlook for ROE, but the actual change was positive (i.e. an unexpected increase), the average market-adjusted 36-month return was +144.7%. If the *indicator variable* implied a positive outlook for ROE, but the actual change was negative (i.e. an unexpected decrease), the average market-adjusted 36-month return was merely –23.1%. The corresponding return measures in this study was 65.6% for an unexpected increase and -39.7% for an unexpected decrease, entailing that an average correctly predicted long position taken for the *indicator variable strategy* during 2008-2019, yielding approximately 60 percentage units less abnormal return than would have been achieved between 1983-2003.

Comparing the performance of the *base case strategy* and *the indicator variable strategy,* we see no systematic difference, and hence can only from these tests conclude that the ROE-prediction model is unable to yield a trading strategy generating abnormal returns, but no conclusion is provided whether the *indicator variable* is successful in capturing the expectations from the market. In section *7. Perfect foresight strategy*, the performance of the indicator variable is analysed further.

Quite interestingly, it seems like the explanatory power of conventional risk proxies for abnormal returns have increased over time. As opposed to in Skogsvik and Skogsvik (2010), where it is concluded that no conventional risk factors can fully explain the results, Table 8 shows that these risk proxies manage to completely erode the significance of the market-adjusted returns to the hedge portfolio. Although some caution should be applied to the significance levels due to the overlapping dataset, the hedge portfolios formed from both the base case strategy and the indicator variable strategy seems to have a net loading on the size factors, as suggested in previous studies (Greig, 1992; Ball, 1992). Furthermore, our results indicate net loading also on the value factor and earnings-to-price ratio. This notion is further elaborated in section *4.1 Fama-French-Carhart-model risk-adjusted returns* where alternative risk-adjustment measures are evaluated.

4. Fama-French-Carhart model risk-adjusted returns

To elaborate on the indications for conventional risk proxies to explain the returns from the trading strategies, as well as address the concerns put forth regarding the measurement of abnormal returns in previous papers, the Fama-French-Carhart four-factor model is implemented to test the performance of the trading strategies. As opposed to previous literature restricting the control for systematic risk factors to the statistical return measure, the Fama-French-Carhart regression on portfolio level enables controlling for the systematic risk factors when evaluating the realistic return metric.

The investment strategies are still equal to those from Skogsvik and Skogsvik (2010). The evaluation of the returns has been made using monthly returns on portfolio level, which is the same method used for calculating Jensen's alpha. The abnormal return corresponds to the intercept from the regression specific in equation (18) below, where excess returns for the portfolios are regressed to excess portfolio returns for each factor market, size, value and momentum. The parameters are estimated through an OLS regression as:

$$\bar{R}_{(*)}^{exc} = \alpha_{(*)} + \beta_{Market(*)} * \left(R_{M,t} - R_{f,t}\right) + \beta_{SMB(*)} * SMB_t + \beta_{HML(*)} * HML_t + \beta_{UMD(*)} * MOM_t + \tilde{\varepsilon}_{(*),t} \qquad (18)$$

where $\bar{R}_{(H),t}^{exc} = \bar{R}_{(L),t} - \bar{R}_{(S),t} =$ the average excess portfolio return of the hedge portfolio in month *t*,

$\bar{R}_{(L),t}^{exc} = \bar{R}_{(L),t} - R_{f,t} =$ the average excess portfolio return of the long position in month *t*,

$\bar{R}_{(S),t}^{exc} = \bar{R}_{(S),t} - R_{f,t} =$ the average excess portfolio return of the long position in month *t*,

$\left(R_{M,t} - R_{f,t}\right) =$ excess return on the market portfolio in month *t*,

$SMB_t =$ size factor (small minus big) in month *t*,

$HML_t =$ value factor (high minus low) in month *t*,

$UMD_t =$ momentum factor (up minus down) in month *t*,

$R_{m,t} =$ the return of the market portfolio in month *t*,

$R_{m,t} =$ the risk-free rate in month *t*.

Monthly data for the SMB, HML, and UMD portfolios have been collected from the Swedish House of Finance (SHoF). In Table 13, the regression output for the respective investment strategies is shown.

TABLE 13 – ABNORMAL (MONTLHY) FAMA-FRENCH-CARHART FOUR-FACTOR RETURNS

Investment strategy	Position	α	*β-market*	*β-SMB*	*β-HML*	*β-UMD*
Base case strategy	Long	-0.006	1.154	0.572	-0.182	0.042
		(0.001)	(0.000)	(0.000)	(0.027)	(0.217)
	Short	0.002	1.057	0.125	-0.083	0.011
		(0.101)	(0.000)	(0.000)	(0.085)	(0.566)
	Hedge	-0.008	0.096	0.447	-0.100	0.031
		(0.000)	(0.024)	(0.000)	(0.203)	(0.343)
Indicator variable strategy						
Zero interval for IND_0:	Long	-0.010	1.282	0.623	-0.135	0.089
$[-0.1 \cdot \beta_0, 0.1 \cdot \beta_0]$		(0.007)	(0.000)	(0.000)	(0.430)	(0.207)
	Short	0.002	1.031	0.081	-0.152	0.010
		(0.064)	(0.000)	(0.028)	(0.007)	(0.663)
	Hedge	-0.012	0.251	0.542	0.017	0.079
		(0.001)	(0.007)	(0.000)	(0.923)	(0.265)
Zero interval for IND_0:	Long	-0.012	1.261	0.552	-0.084	0.064
$[-0.2 \cdot \beta_0, 0.2 \cdot \beta_0]$		(0.000)	(0.000)	(0.000)	(0.520)	(0.231)
	Short	0.002	1.059	0.093	-0.145	0.018
		(0.029)	(0.000)	(0.007)	(0.006)	(0.402)
	Hedge	-0.015	0.202	0.459	0.061	0.046
		(0.000)	(0.004)	(0.000)	(0.635)	(0.382)
Zero interval for IND_0:	Long	-0.010	1.234	0.491	-0.017	0.081
$[-0.4 \cdot \beta_0, 0.4 \cdot \beta_0]$		(0.000)	(0.000)	(0.000)	(0.859)	(0.047)
	Short	0.002	1.045	0.107	-0.139	0.023
		(0.021)	(0.000)	(0.001)	(0.005)	(0.261)
	Hedge	-0.013	0.188	0.385	0.122	0.058
		(0.000)	(0.000)	(0.000)	(0.213)	(0.148)

Table 13 presents the results from the regression in equation (18) of the monthly excess return for the entire investment period. α represents the abnormal return, β-market represents the coefficient for the excess return of the market portfolio. β-SMB represents the coefficient for the size factor (small minus big), β-HML represents the coefficient for the value factor (high minus low) and β-UMD represents the coefficient for the momentum factor (up minus down). α and β values have been tested with two-tailed t-tests against the null hypothesis of the parameter being equal to zero (p-values in parenthesis).

From Table 13 we can conclude that the intercepts are negative for the hedge portfolio for all strategies. All intercept to the long and hedge positions are significant, while the significance levels vary for the short positions. As for the risk factors, the market beta and the size factor are significant throughout the sample, while the value factor and momentum factor are insignificant. The net exposures to the market beta for the hedge portfolios are significant and ranges from 0.1 to 0.25, with a tendency to be higher for the *indicator variable strategy*-portfolios than for the base case portfolio. The net exposure to the size factor for the hedge portfolios varies between 0.38 and 0.54 and show no tendencies to increase nor decrease for the *indicator variable strategy* compared to the *base case strategy*.

When comparing to the Jensen's alpha values in Table 5, we conclude that the values for abnormal returns are similar, but we see tendencies of higher significance levels for the Fama-French-Carhart regressions. We can also compare the market beta values, for which the results are quite different. As opposed to when estimating market beta through the CAPM, we in Table 13 observe significant positive market betas for the hedge portfolio for all investment strategies. This entails that there are systematic cross-sectional differences in market beta between the long and short portfolios, where we observe significant betas higher than 1 for the long portfolios and significant betas of approximately 1 for the short portfolios. These trends are seen both for the base case portfolio and the portfolios formed using the *indicator variable* strategies. Hence, there is reason to believe that the estimated probability of an increase in future ROE, which lays the basis for both investment strategies, covaries with market beta. Given these results, a simple market-adjusted abnormal return metric is not sufficient to capture the systematic cross-sectional differences in market beta.

When turning to the other risk factors, value and momentum, we note that betas are mainly insignificant in the regression. When we compare the figures with the risk-factor regression in Table 8, it is important to note that these two approaches are very different. Firstly, the Fama-French-Carhart regression is estimated using monthly portfolio data, as opposed to the regression in equation (17), which is estimated on 36-month data for individual firm-year observations. Secondly, the coefficients for the risk factors in the Fama-French-Carhart regression represents the covariance between excess returns to the investment portfolio and excess returns to the factor portfolio (with excess returns to the factor portfolios retrieved from the SHoF[42] database), while they in Table 8 represents the covariance between the 36-month abnormal returns for each position and the firm-specific value for each risk proxy. However, since both the value factor and the size factor are included in both regressions, some comparisons can be made. We can conclude that the size factor is significant in both regressions, adding support to the conclusion that the size factor should be considered when evaluating abnormal returns. We also note that the value factor, which is significant in

[42] Swedish House of Finance.

explaining abnormal returns in Table 8, loses its significance in Table 13, except for in the short portfolios for which the value-beta is significant. Potential reasons for this include; (i) The Fama-French-Carhart regressions are performed on portfolio level rather than on company level, and hence more dependent on the time-series relationships, with less emphasis put on cross-sectional variance within firms, (ii) Due to the overlapping nature of the sample, significance levels in Table 8 suffer the risk of being overstated, (iii) The returns in Table 8 represents the statistical return measure since all investments over the whole period are equally weighted, as opposed to the analysis in Table 13, which represents the realistic return measure, which of course is a great advantage for the Fama-French-Carhart model since it is the realistic return measure that is of highest interest for investors. Furthermore, the Fama-French-Carhart regressions have been estimated on non-overlapping subsamples, which is presented in Table A1 in *appendix A*. As expected, p-values are higher when the issue of overlapping data is mitigated. We note the market beta loses its significance in several regressions, implying that the significance in Table 8 might be overstated due to overlapping data. The size factor remains significant in general.

In the next section, we introduce the risk of bankruptcy risk into the RIV-model, which is a central component of the *indicator variable strategy*.

5. Introducing bankruptcy risk

All companies face some risk of going bankrupt, and thus investors are exposed to the risk of losing their investment. When determining the value of owners' equity, as described in section *3.2 Roe as value driver of owners' equity*, equation (3), the RIV valuation model assumes unconditioned expected values for the numerators. However, reported accounting numbers and analyst forecasts are conditioned on firm survival. Thus, the values one gets from simply forecasting the future development will be systematically too high because one ignores the risk of bankruptcy. This means that these projections are non-valid measures of the unconditioned expected values. Hence, to achieve a non-biased value of owner's equity using the RIV-model in equation (3), one should account for the risk of bankruptcy. This affects the historically motivated value of owner's equity in equation (11) and hence affects the indicator variable, which is used to take positions in the *indicator variable strategy.*

This section continues by (i) briefly describing the operationalisation of adding bankruptcy risk to the RIV-model, (ii) reporting descriptive statistics showing the estimated bankruptcy risks in the sample, and (iii) analysing the effects on the investment positions and returns from the adding bankruptcy risk to the RIV-model. A detailed method for calculating the risk of bankruptcy is described in *Appendix B.*

To account for the risk of bankruptcy, a firm-specific probability of bankruptcy, p_{fail}, has been incorporated in the RIV model-based valuation of owners' equity. Instead of adjusting the numerators in equation (11) from conditional to unconditional values, one can calibrate the cost of equity instead, allowing the expected values conditioned on firm survival to still be used (Skogsvik, 2017). The p_{fail} has been estimated in accordance with the bankruptcy prediction model developed by Skogsvik (1990). The model is based on a sample of 379 (328 surviving firms and 51 firms going bankrupt) Swedish manufacturing firms, and thus, the model can with advantage be applied to the sample of Swedish manufacturing firms in this study. The bankruptcy prediction model can be used for estimating firm-specific year-by-year bankruptcy probabilities for up to six years ahead. To simplify the modelling, this study, in line with Anesten et al. (2020), has used the average of the estimated p_{fail} for the years $t = 1, 3, and\ 5$, assuming that this average $p_{fail}$is constant from $t = 1$ to $T = 3$. The estimated p_{fail} has further been calibrated in accordance with Anesten et al. (2020) to account for the sample bias due to the sample proportion of companies going bankrupt in the estimation sample for the model in Skogsvik (1990) being different from the *a priori* proportion of firms going bankrupt. See *appendix B* for a detailed overview of the operationalisation of adding bankruptcy risk to the RIV-model. Table 14 below shows the summary statistics for the calculated probability of failure for the sample.

TABLE 14 – SUMMARY STATISTICS FOR RISK OF BANKRUPCY IN SAMPLE

Year	No. of firms	P-fail 1-year		P-fail 3-year		P-fail 5-year		Average p-fail		Calibrated p-fail	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
2008	90	0.024	0.001	0.029	0.017	0.055	0.054	0.036	0.026	0.004	0.003
2009	88	0.040	0.002	0.044	0.022	0.072	0.061	0.052	0.029	0.008	0.003
2010	86	0.038	0.003	0.023	0.010	0.044	0.030	0.035	0.018	0.004	0.002
2011	83	0.031	0.001	0.020	0.009	0.040	0.032	0.030	0.018	0.003	0.002
2012	85	0.022	0.001	0.022	0.010	0.042	0.032	0.029	0.017	0.003	0.002
2013	87	0.031	0.001	0.026	0.009	0.044	0.027	0.034	0.015	0.004	0.001
2014	87	0.033	0.001	0.027	0.009	0.044	0.031	0.035	0.014	0.004	0.001
2015	95	0.048	0.001	0.041	0.010	0.051	0.030	0.047	0.014	0.008	0.001
2016	100	0.026	0.000	0.021	0.005	0.038	0.021	0.028	0.011	0.003	0.001
All years	801	0.033	0.001	0.028	0.010	0.048	0.033	0.036	0.018	0.005	0.002

Table 14 shows the average and median probability of bankruptcy with a 1-year forecast horizon, a 3-year forecast horizon and a 5-year forecast horizon, as well as the average probability of bankruptcy of the different forecast horizons and the calibrated probability of bankruptcy for each year in the total investment period. The values of all p-fails are calculated at the investment point in time with data from the year-end of the previous financial year.

As shown in Table 14, the average and median for the calibrated p_{fail} for all years is 0.5% and 0.2% respectively, indicating a rather skewed distribution. There is no distinct trend in the development of the average p_{fail} over time, but as one would expect, the highest average calibrated p_{fail} was observed in the year of the financial crisis in 2008[43]. Furthermore, the average p_{fail} seems to increase with the time-horizon of the prediction, in which the average 1-year and 5-year p_{fail} are 3.3% and 4.8% respectively. In Table 15 below, the number of long and short positions for each investment strategy when considering the risk of default is considered when calculating the *indicator variable*.

TABLE 15 – NUMBER OF FIRM-YEAR OBSERVATIONS IN THE INVESTMENT STRATEGIES 2008-2019 WITH BANKRUPTCY RISK

Investment strategy	Position	*Number of firms excluding bankruptcy risk*	*Number of firms including bankruptcy risk*
Base case strategy	Long	311	311
	Short	490	490
	Total	801	801
Indicator variable strategy			
Zero interval for IND_0:	Long	78	78
$[-0.1 \cdot \beta_0, 0.1 \cdot \beta_0]$	Short	312	315
	Total	390	393
Zero interval for IND_0:	Long	98	96
$[-0.2 \cdot \beta_0, 0.2 \cdot \beta_0]$	Short	343	343
	Total	441	439
Zero interval for IND_0:	Long	131	130
$[-0.4 \cdot \beta_0, 0.4 \cdot \beta_0]$	Short	406	412
	Total	537	542

Table 15 illustrates the number of firm-year observations with and without incorporating bankruptcy risk for the long, short and hedge portfolios in the base case strategy, IND01, IND02 and IND04.

[43] The value of p-fail is calculated at the investment point in time with data from the year-end of the previous financial year. Thus, for example, the p-fail for the year 2009 in the table corresponds to 2008 year-end figures.

Since the incorporation of bankruptcy risk only is implementable in the *indicator variable strategy*, it has no effect on the *base case strategy*. With respect to the *indicator variable strategy*, there is a difference in the number of investments made. The largest difference is for *IND04*, in which six more short positions are taken and one less long position during the investment period. We note that the overall magnitude of the differences for the indicator variable strategy when bankruptcy risk is included is quite low, implying that the effect from p_{fail} on the cost of equity is limited. In Table 16, the realistic market-adjusted buy-and-hold returns when including the risk of bankruptcy are reported.

TABLE 16 – MARKET-ADJUSTED BUY-AND-HOLD RETURNS WITH BANKRUPTCY RISK (REALISTIC RETURN METRIC)

Investment strategy	Position	*2008-2010*	*2011-2013*	*2014-2016*	*2008-2016*
Base case strategy	Long	-0.545	-0.130	0.106	-0.190
					(0.094)
	Short	-0.036	0.167	0.296	0.142
					(0.086)
	Hedge	-0.509	-0.298	-0.190	-0.332
					(0.006)
Indicator variable strategy					
Zero interval for IND_0:	Long	-0.955	-0.225	0.346	-0.278
$[-0.1 \cdot \beta_0, 0.1 \cdot \beta_0]$					(0.148)
	Short	0.001	0.116	0.269	0.129
					(0.066)
	Hedge	-0.957	-0.342	0.078	-0.407
					(0.028)
Zero interval for IND_0:	Long	-0.921	-0.209	0.301	-0.276
$[-0.2 \cdot \beta_0, 0.2 \cdot \beta_0]$					(0.139)
	Short	0.011	0.138	0.275	0.141
					(0.073)
	Hedge	-0.932	-0.347	0.026	-0.418
					(0.033)
Zero interval for IND_0:	Long	-0.726	-0.116	0.191	-0.217
$[-0.4 \cdot \beta_0, 0.4 \cdot \beta_0]$					(0.150)
	Short	-0.086	0.159	0.320	0.131
					(0.121)
	Hedge	-0.639	-0.276	-0.129	-0.348
					(0.008)

Table 16 presents the realistic market-adjusted buy-and-hold returns with bankruptcy risk incorporated for 36-month holding periods of the short, long and hedge position for the base case strategy and IND01, IND02 and IND04. The returns are presented for each of the three investment periods, as well as for the entire investment period (200-2016) The returns of the long, short and hedge positions have been calculated in accordance with equations (14a), (14b) and (14c). Returns for *the entire investment period have been tested with two-tailed t-tests against the null hypothesis of the return being equal to zero (p-values in parenthesis).*

Overall, the results in Table 16 show no major differences compared to the market-adjusted returns without adjusting for bankruptcy risk in Table 6. For the whole investment period, we observe negative abnormal returns for the hedge portfolio of -40.7%, -41.8% and -33.2% for the *IND01*, *IND02* and *IND04* respectively. In line with the realistic market-adjusted return without bankruptcy risk, the best performance is shown in the third investment period (2014-2016), where both the *IND01* and *IND02* achieved positive abnormal returns to the hedge portfolios of 7.8% and 2.6% respectively.

When incorporating the risk of bankruptcy in the RIV-model for the historically motivated value of owners' equity, the riskiness of the company increases, and equivalently the required return on owners' equity, implying a lower historically motivated value of owners' equity. This leads to higher values of the *indicator variable*, and thus the implied market outlooks for mid-term ROE becomes more positive. However, the difference in both the number of long and short positions, as well as in the performance of the investment portfolios is negligible. Thus, the incorporation of bankruptcy risk adds robustness to the initial *indicator variable strategy* without bankruptcy risk. The main conclusion is that, although it is more theoretically correct, in our sample, the estimated p_{fail} is too low to have any material effect on the investment positions taken during the period, and hence appears redundant in this setting.

6. Estimating the ROE prediction model with fixed effects logistic regression

In this section, an alternative method for estimating the ROE prediction model is tested. Skogsvik and Skogsvik (2010), estimated the ROE prediction model through ordinary logistic regression. One alternative to this approach would be to utilise the fixed effects logistic regression method for estimating the prediction model. Since the estimation sample consists of panel data, with multiple firm values measured across different points in time, there is presumably some firm-specific attributes not varying across time. Since we want to isolate the effect of only the level of historical mid-term ROE on future mid-term ROE, independently from fixed firm-specific attributes, as well as remove any omitted variable bias, a fixed effects logistic model has been estimated, where the cross-sectional time-invariant variation is controlled for.

The firm fixed effect logistic regression is performed in the statistics software R and is based on an unconditional maximum likelihood approach through a pseudo-demeaning algorithm. A comparison between the performance of the ordinary logistic regression prediction model and the fixed effects logistic regression prediction model is reported in Table 17 below.

TABLE 17 – PERFORMANCE OF ADJUSTED ROE PREDICTION MODELS

	Holdout period I: 2007-2009	Holdout period II: 2010-2012	Holdout period III: 2013-2015
Ordinary logistic regression			
No. of firm-year observations	270	241	255
% overall correct predictions	63.7%	58.9%	51.8%
X^2-value	10.94	7.69	6.72
(p-value)	(0.001)	(0.006)	(0.010)
% increases correctly predicted	41.7%	42.7%	33.5%
% decreases correctly predicted	77.2%	74.2%	81.4%
Fixed effects logistic regression			
No. of firm-year observations	270	241	255
% overall correct predictions	65%	58%	50%
X^2-value	12.87	6.62	6.69
(p-value)	(0.000)	(0.010)	(0.010)
% increases correctly predicted	40%	36%	27%
% decreases correctly predicted	80%	79%	87%

Table 17 shows the validation results from the initial ROE prediction model and the ROE prediction model estimated using fixed effects logistic regression over holdout period I, holdout period II and holdout period III. A probability cut-off value of 0.5 has been used. For both the initial model and the fixed effects models, the probability of changes in the medium-term

ROE have been predicted with the three different logistic regression models and calibrated with the calibration formula in equation (8) with the a priori probability, π, set to 0.5 The χ^2 values are from $2 * 2$ contingency table tests.

Table 17 shows that the performance of the models is similar. The overall accuracy in each period is almost identical. There seem to be some differences regarding the accuracy of predicting increases in mid-term ROE versus decreases, with the fixed effects regression prediction model showing even worse predictive power when mid-term ROE is increasing, but higher predictive power when mid-term ROE is decreasing. When comparing the abnormal returns to the investment strategies based on the respective prediction models, we also conclude that the returns are in large the same. See *appendix C* for reported market-adjusted buy-and-hold 36-month returns for the investment strategies using the ROE prediction model estimated through fixed effects logistic regression.

7. The perfect foresight strategy

The results from the *indicator variable strategy* have overall shown poor performance with mostly negative abnormal returns. Whether this is a result of the performance of the ROE prediction model or the RIV model-based estimation of the market expectations of future ROE is further investigated in this section. As done in many previous studies, compare the performance of the implemented investment strategies with a hypothetical strategy based on *ex post* knowledge of the change in the key value driver (the perfect foresight strategy). As a first step, in order to investigate the performance of the ROE prediction model, we restrict the analysis to the *base case strategy*. As a second step, we investigate the ability of the RIV-model to measure the market expectations of future mid-term ROE by combining the perfect foresight strategy with the *indicator variable*. Of course, this is a highly hypothetical strategy, but it provides additional tools for dissecting the performance of the *indicator variable strategy*. For the *base case strategy,* 36-month market-adjusted returns to the long, short and hedge portfolio from positions taken each year are presented in figure 3, and the corresponding metrics for the perfect foresight strategy are presented in figure 4.

FIGURE 3 – MARKET-ADJUSTED BUY-AND-HOLD RETURNS TO THE LONG, SHORT AND HEDGE POSITION (BASE CASE - REALISTIC RETURN METRIC)

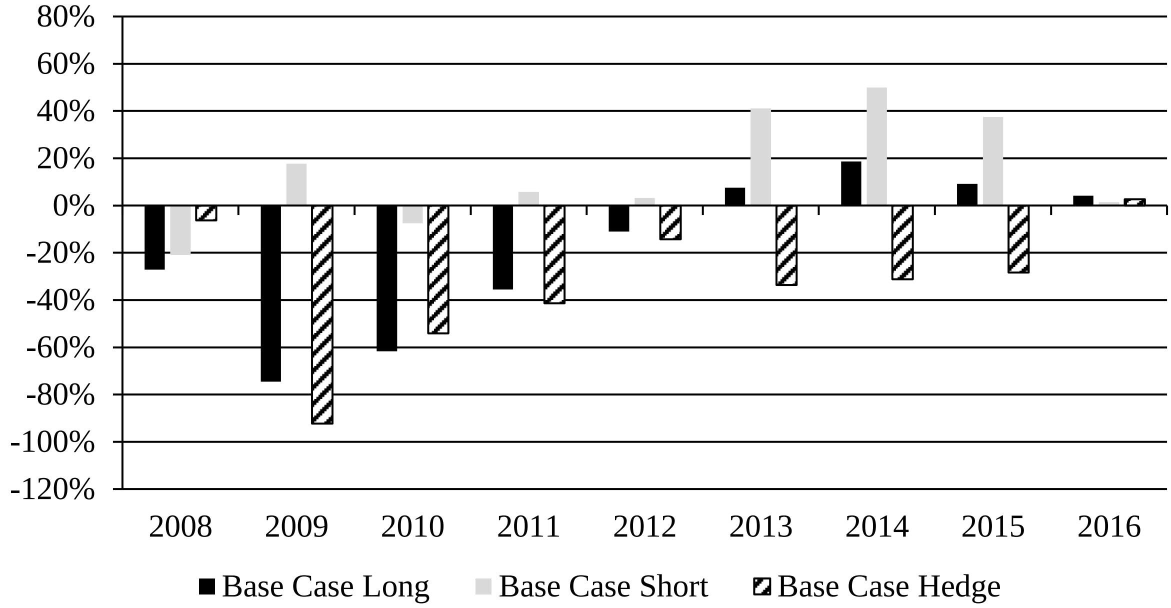

Figure 3 illustrates the 36-month realistic market-adjusted buy-and-hold returns to the long, short and hedge position for the base case strategy for each year in the investment period. The returns have been calculated according to equation (14a).

FIGURE 4 – MARKET-ADJUSTED BUY-AND-HOLD RETURNS TO THE LONG, SHORT AND HEDGE POSITION (PERFECT FORESIGHT – REALISTIC RETURN METRIC)

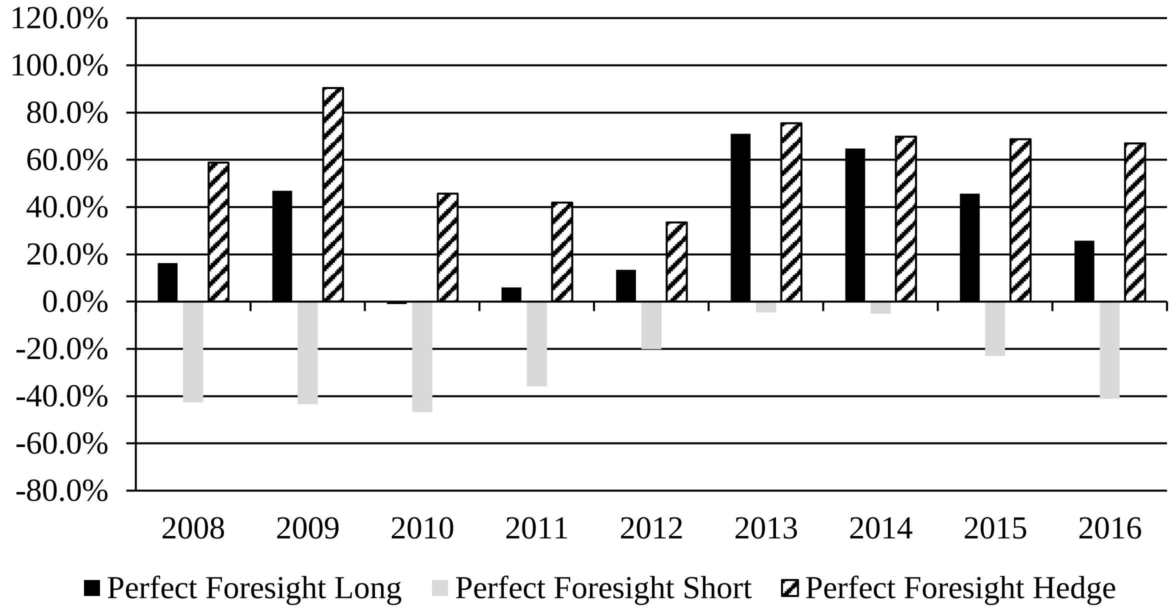

Figure 4 illustrates the 36-month realistic market-adjusted buy-and-hold returns to the long, short and hedge position for the hypothetical perfect foresight strategy for each year in the investment period. The returns have been calculated according to equation (14a).

Overall, when comparing the realistic market-adjusted returns for the *base case strategy* with the perfect foresight strategy, the difference is striking. The *base case strategy*, as shown in figure 3, shows negative market-adjusted returns to the hedge position for every year (except for 2016 which is slightly above 0%), while the perfect foresight strategy yields large market-adjusted returns all years. When looking at the development over time, the magnitude of the abnormal returns (positive or negative) seems to be decreasing over the years for the *base case strategy*, while the perfects foresight strategy shows some variation in the first half of the total investment period and more stable abnormal returns in the second half of the total investment period in the range of approximately 65% to 75%. Furthermore, the returns to the hedge position in the perfect foresight strategy are mostly explained by the short positions in the first half of the investment period, and by the long positions in the second half of the investment period. Compared to the perfect foresight strategy, the return to the hedge position for the *base case strategy* shows the opposite in the split of long and short portfolio returns over time.

The results from the perfect foresight strategy clearly highlight the poor performance of the *base case strategy*. An obvious reason for the poorer performance of the base case strategy compared to the perfect foresight strategy is of course the lack of perfect foresight, with the accuracy of the base case strategy for predicting the change in mid-term ROE amounts to between 61% to 66% during the period.

We have concluded that the *base case strategy*, in general, does not show any signs of ability to achieve positive abnormal returns, however, the isolated effect from adding the indicator variable analysis is still ambiguous. Hence, to further investigate *the Indicator variable's* ability to capture the market expectations, we construct a trading strategy in which the indicator variable strategy is combined with perfect foresight strategy, called the *perfect foresight indicator variable strategy*, for which the market-adjusted buy-and-hold returns are presented in Table 18 below.

TABLE 18 – MARKET-ADJUSTED BUY-AND-HOLD RETURNS (PERFECT FORESIGHT – REALISTIC RETURN METRIC)

Investment strategy	Position	*2008-2010*	*2011-2013*	*2014-2016*	*2008-2016*
Prefect foresight strategy	Long	0.207	0.301	0.454	0.321
					(0.004)
	Short	-0.443	-0.202	-0.231	-0.292
					(0.000)
	Hedge	0.650	0.503	0.685	0.613
					(0.000)
Perfect foresight indicator variable strategy					
Zero interval for IND_0:	Long	0.353	0.582	0.725	0.553
$[-0.1\cdot\beta_0, 0.1\cdot\beta_0]$					(0.008)
	Short	-0.700	-0.203	-0.326	-0.410
					(0.003)
	Hedge	1.052	0.785	1.051	0.963
					(0.001)
Zero interval for IND_0:	Long	0.303	0.619	0.695	0.539
$[-0.2\cdot\beta_0, 0.2\cdot\beta_0]$					(0.009)
	Short	-0.642	-0.249	-0.330	-0.407
					(0.001)
	Hedge	0.944	0.869	1.024	0.946
					(0.000)
Zero interval for IND_0:	Long	0.237	0.568	0.591	0.465
$[-0.4\cdot\beta_0, 0.4\cdot\beta_0]$					(0.010)
	Short	-0.546	-0.222	-0.292	-0.353
					(0.000)
	Hedge	0.783	0.789	0.883	0.819
					(0.000)

Table 18 presents the realistic market-adjusted buy-and-hold returns for 36-month holding periods for the long, short and hedge position for the perfect foresight strategy and IND01, IND02 and IND04 (indicator variable strategy combined with the perfect foresight strategy) divided into the three subsamples of investment periods. The returns of the long, short and hedge positions have been calculated in accordance with equations (14a), (14b) and (14c). Returns for the entire investment period (2008-2016) has been tested with two-tailed t-tests against the null hypothesis of the return being equal to zero (p-values in parenthesis).

Overall, the *base case strategy* based on perfect foresight shows major positive market-adjusted abnormal returns for all the investment periods, as also seen in figure 4, and a significant market-adjusted abnormal return to the hedge position of 61% for the entire investment period. The *perfect foresight indicator variable strategy* shows even higher returns with significant market-adjusted abnormal return to the hedge position over the entire investment period of 96%, 95% and 82% for *IND01*, *IND02* and *IND04* respectively. This actually provides support for the *indicator variable's* ability to measure the markets expectations for mid-term ROE. Assuming that the share price reaction is larger for unexpected changes in mid-term ROE, *the perfect foresight indicator variable strategy* manages to filter out some of the, by the market, expected changes in mid-term ROE, increasing abnormal returns compared to the perfect foresight strategy with of 35%, 34% and 21% for *IND01*, *IND02* and *IND04* respectively. Given the notion that the indicator variable successfully captures the market expectations of change in mid-term ROE, the poor results to the investment strategies considered in previous sections can presumably be attributed to an inability of the ROE prediction model to make predictions not already priced in by the market.

8. Concluding remarks

In this paper, a comprehensive re-examination of the usefulness of historical financial information in achieving abnormal returns has been conducted. After several previous papers (see for example Ou and Penman, 1989; and Setiono and Strong, 1998) showed that abnormal returns are achievable using this type of fundamental analysis, Skogsvik and Skogsvik (2010) surprisingly reaches the conclusion that this is not the case from 1995 and onwards. We have tested this hypothesis by applying the investment strategy on a similar sample of Swedish manufacturing firms between 2008 to 2019, and indeed find that no abnormal returns are achieved in this period, supporting the notion that investor learning and decreasing costs for procuring and analysing large sets of data have contributed to increased efficiency in the Swedish stock market. Furthermore, as mentioned in Skogsvik and Skogsvik (2010), most of the abnormal returns generated to the hedge portfolios were attributable to the long portfolios, for which the returns were probably overstated due to large positive market sentiment bias[44]. This notion is supported in this study, where the time period is coupled with drastically lower positive sentiment bias, resulting in lower returns to the long portfolios and subsequently the hedge portfolios.

The test design is sophisticated by introducing the Fama-French-Carhart framework for calculating abnormal returns and introducing bankruptcy risk to the RIV-model. The Fama-French-Carhart regression results support the conclusion that no abnormal returns are

[44] Concluded from analysing the difference in 36-month market-adjusted returns for stocks with unexpected increases in mid-term ROE versus stocks with unexpected decreases in mid-term ROE. The figures amounted to 144.7% and -23.1% respectively in Skogsvik and Skogsvik (2010) compared to 65.5% and -39.7% in our study.

achieved during the period. The introduction of bankruptcy risk to the RIV-model results in quite minor differences to the positions taken in the respective investment strategies, with the average risk of bankruptcy in the sample being low, and hence not having any major effect on the cost of capital used in the RIV-model. Given the stability of the results after these additions to the test design, we consider the conclusion of no market inefficiency with respect to historical financial statement information during this period quite robust.

Additional analysis has been conducted to isolate the performance of the indicator variable's ability to unveil the market expectations of future ROE. This is done by combining the investment signals from the ROE prediction model used for the indicator variable strategies, to the investment signals one would get if one had perfect foresight of the development of future ROE. This measure is called the *perfect foresight indicator variable strategy*, and hence any difference in returns between the ordinary perfect foresight strategy, where positions are formed solely based on the sign of the change in ROE, and the *perfect foresight indicator variable strategy*, can be attributed to the *indicator variable's* ability to capture the market expectations. As it turns out, the indicator variable performs well, adding a significant portion of market-adjusted return. The notion that one can use straightforward fundamental modelling to get a measure for the market expectations for the development in some key value driver is of course valuable in itself and should arguably be a component of any attempt to achieve abnormal returns using fundamental analysis.

We notice that the ability to use the historical average value of ROE to predict the change in future mid-term ROE has decreased compared to Skogsvik (2008) and Skogsvik and Skogsvik (2010). Our ROE-prediction model is estimated both using logistic regression and fixed effects logistic regression, controlling for firm-specific variation, but the accuracy remains the same for the two methods. One reason for the worse predictive performance could be that the time period 2008-2019 is coupled with quite high turbulence, starting with the financial crisis in 2008.

A consistent theme in previous research is the critique put forth by Greig (1992) and Ball (1992), that investment strategies based on the predicted change in some key value driver are systematically loading on specific systematic risk factors, where it has been argued that the probability of an increase in EPS covaries significantly with the size factor, implying that the strategy yields long positions in small companies and short positions in larger companies. We address these claims using two methods. Firstly, as in Skogsvik and Skogsvik (2010) we estimate a cross-sectional regression model using firm-year observations, where the statistical measure for market-adjusted returns is regressed on the investment signals for the strategies, along with the potential systematic risk factors value, earnings-to-price ratio, dividend yield and size. Secondly, the realistic return measure on portfolio level is regressed on the return of the factor portfolios market, size, value and momentum. The results show support for the investment strategies to constitute proxies for some factor-loading strategy, where both the size, value and earnings-to-price tend to explain market-adjusted returns in OLS regression on firm-year observations, however, when eliminating statistical overfitting in the sample by evaluating non-overlapping subsamples, only the value factor remains strictly significant. Furthermore, from the Fama-French-Carhart regression, we find that there is a significant positive beta to the market factor and the size factor for the indicator variable strategies, however, after controlling for statistical overfitting only the size factor remains significant. This suggests that cross-sectional differences in size between the long and short portfolios, covarying with the estimated probability of an increase in mid-term ROE, which supports the critique put forth by Greig (1992) and Ball (1992).

Overall, the findings in this paper support the conclusions that the Swedish stock market has become more efficient over time, as proposed by Skogsvik and Skogsvik (2010), and that self-financing investment strategies based on predicting the change in some key value driver using historical financial statements provide net exposure to systematic risk factors, predominantly size for the realistic return metric, indicating that sophisticated methods for adjusting for expected returns need to be used in order to accurately evaluate the performance of such a strategy.

Limitations and suggestions for further research

Firstly, when analysing the usefulness of historical financial information in achieving abnormal returns, this paper is limited to covering manufacturing companies in Sweden. The reasons for choosing manufacturing companies are (i) better comparability with previous studies on Swedish data, and (ii) the possibility to use the bankruptcy model from Skogsvik (1990), in which manufacturing companies are analysed. However, previous studies have covered a wider range of industries, with the benefits of (i) increasing the number of observations in the sample, and (ii) limiting the risk of incorrectly extrapolating some conclusion that only is true for some specific industry, by assuming that it holds for a larger population. Hence, it would be worthwhile to test a similar investment strategy in either another industry or multiple industries. Secondly, some parts of the method for operationalising the *indicator variable* are relatively old, specifically the model for estimating the risk of bankruptcy (Skogsvik, 1990), as well as the exogenously determined values for the permanent measurement bias of owners' equity, estimated by Runsten in 1998. Hence, the method for calculating the historically motivated value of owners' equity can be further sophisticated by deploying a more recent model for estimating the bankruptcy risk as well as estimating new values for the permanent measurement bias of owners' equity, which would require an extensive mapping of the listed companies in Sweden, and hence is unfortunately out of scope for the purpose of this paper. Lastly, it may be worthwhile to revisit the ROE prediction model. In this study, the conclusion from Skogsvik (2008), that a univariate model with mid-term historical average values of ROE has better accuracy than other multivariate estimation models, has been the argument for only considering the univariate prediction model. However, given the relatively poor performance of the ROE estimation models estimated in this study, one conclusion might be that the explanatory power of the mid-term historical average ROE has decreased over time, suggesting that a multivariate model using a set of accounting ratios could possibly increase the accuracy of the prediction model.

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10. Appendix

Appendix A: Fama-French-Carhart regression on non-overlapping subsamples.

TABLE A1 – ABNORMAL (MONTLHY) FAMA-FRENCH-CARHART FOUR FACTOR RETURNS WITH NON-OVERLAPPING SUBSAMPLES

Investment strategy	Position	Subsample I					Subsample II					Subsample III				
		α	*β-market*	*β-SMB*	*β-HML*	*β-UMD*	*α*	*β-market*	*β-SMB*	*β-HML*	*β-UMD*	*α*	*β-market*	*β-SMB*	*β-HML*	*β-UMD*
Base case strategy	Long	-0.0052	1.1197	0.5870	-0.1202	0.0313	-0.0074	1.1748	0.5248	-0.1968	0.0104	-0.0058	1.1595	0.6288	-0.2578	0.0996
		(0.0985)	(0.0000)	(0.0000)	(0.3868)	(0.5849)	(0.0213)	(0.0000)	(0.0000)	(0.1642)	(0.8592)	(0.0682)	(0.0000)	(0.0000)	(0.1008)	(0.1182)
	Short	0.0013	1.0471	0.1633	-0.1020	-0.0038	0.0023	1.0640	0.0942	-0.0339	0.0090	0.0015	1.0546	0.1061	-0.1137	0.0296
		(0.5271)	(0.0000)	(0.0048)	(0.2657)	(0.9202)	(0.2182)	(0.0000)	(0.0996)	(0.6823)	(0.7922)	(0.3451)	(0.0000)	(0.0364)	(0.1388)	(0.3404)
	Hedge	-0.0064	0.0726	0.4237	-0.0181	0.0351	-0.0096	0.1108	0.4306	-0.1630	0.0013	-0.0073	0.1049	0.5227	-0.1441	0.0699
		(0.0236)	(0.2627)	(0.0000)	(0.8853)	(0.5000)	(0.0017)	(0.1580)	(0.0000)	(0.2252)	(0.9809)	(0.0225)	(0.2124)	(0.0000)	(0.3549)	(0.2691)
Indicator variable strategy																
Zero interval for IND0:	Long	-0.0089	1.0258	0.6662	-0.1060	0.0044	-0.0137	1.3058	0.4006	-0.1143	-0.0204	-0.0093	1.5809	0.8015	-0.1581	0.3019
[-0.1*β0, 0.1*β0]		(0.0480)	(0.0000)	(0.0000)	(0.5958)	(0.9577)	(0.0012)	(0.0000)	(0.0020)	(0.5351)	(0.7897)	(0.3242)	(0.0000)	(0.0094)	(0.7324)	(0.1101)
	Short	0.0021	1.0512	0.1305	-0.1554	0.0251	0.0025	0.9635	0.0461	-0.1499	-0.0135	0.0023	1.0804	0.0334	-0.1237	0.0078
		(0.3187)	(0.0000)	(0.0267)	(0.0989)	(0.5170)	(0.3401)	(0.0000)	(0.5589)	(0.1931)	(0.7776)	(0.1721)	(0.0000)	(0.5440)	(0.1413)	(0.8187)
	Hedge	-0.0110	-0.0253	0.5357	0.0494	-0.0207	-0.0161	0.3423	0.3545	0.0356	-0.0069	-0.0116	0.5005	0.7681	-0.0344	0.2941
		(0.0206)	(0.8144)	(0.0001)	(0.8138)	(0.8113)	(0.0002)	(0.0025)	(0.0075)	(0.8508)	(0.9297)	(0.2123)	(0.0441)	(0.0117)	(0.9399)	(0.1149)
Zero interval for IND0:	Long	-0.0097	1.1445	0.6729	0.0007	0.0518	-0.0122	1.3392	0.4204	-0.1393	-0.0024	-0.0149	1.3215	0.5464	-0.0899	0.1561
[-0.2*β0, 0.2*β0]		(0.0236)	(0.0000)	(0.0000)	(0.9972)	(0.5104)	(0.0025)	(0.0000)	(0.0008)	(0.4311)	(0.9740)	(0.0197)	(0.0000)	(0.0085)	(0.7726)	(0.2180)
	Short	0.0018	1.0706	0.1493	-0.1441	0.0075	0.0031	1.0265	0.0660	-0.1424	0.0229	0.0027	1.0752	0.0340	-0.1347	0.0170
		(0.3902)	(0.0000)	(0.0111)	(0.1234)	(0.8461)	(0.1656)	(0.0000)	(0.3286)	(0.1485)	(0.5734)	(0.1166)	(0.0000)	(0.5332)	(0.1064)	(0.6141)
	Hedge	-0.0115	0.0739	0.5236	0.1448	0.0444	-0.0153	0.3127	0.3544	0.0031	-0.0253	-0.0176	0.2462	0.5124	0.0449	0.1391
		(0.0076)	(0.4500)	(0.0000)	(0.4466)	(0.5724)	(0.0002)	(0.0032)	(0.0045)	(0.9861)	(0.7315)	(0.0051)	(0.1341)	(0.0113)	(0.8823)	(0.2598)
Zero interval for IND0:	Long	-0.0108	1.1978	0.5559	-0.0831	0.0630	-0.0110	1.2544	0.4077	-0.1103	0.0061	-0.0101	1.2663	0.4777	0.1976	0.1744
[-0.4*β0, 0.4*β0]		(0.0059)	(0.0000)	(0.0000)	(0.6310)	(0.3788)	(0.0016)	(0.0000)	(0.0002)	(0.4683)	(0.9224)	(0.0119)	(0.0000)	(0.0003)	(0.3113)	(0.0292)
	Short	0.0023	1.0622	0.1493	-0.1076	0.0101	0.0031	0.9984	0.0807	-0.1653	0.0277	0.0023	1.0660	0.0720	-0.1413	0.0283
		(0.2627)	(0.0000)	(0.0089)	(0.2346)	(0.7868)	(0.1196)	(0.0000)	(0.1819)	(0.0614)	(0.4465)	(0.1523)	(0.0000)	(0.1639)	(0.0739)	(0.3748)
	Hedge	-0.0131	0.1357	0.4066	0.0244	0.0529	-0.0141	0.2560	0.3269	0.0550	-0.0216	-0.0124	0.2002	0.4057	0.3389	0.1460
		(0.0010)	(0.1296)	(0.0003)	(0.8877)	(0.4601)	(0.0001)	(0.0047)	(0.0023)	(0.7179)	(0.7328)	(0.0017)	(0.0521)	(0.0015)	(0.0758)	(0.0598)

Table A1 presents the results from the regression in equation (18) of the monthly excess return divided into the three subsamples of investment periods. Positions in subsample I were formed in 2008, 2011 and 2014. Positions in subsample II were formed in 2009, 2012, and 2015. Positions in subsample III were formed in 2010, 2013 and 2016.. α represents the abnormal return, β-market represents the coefficient for the excess return of the market portfolio. β-SMB represents the coefficient for the size factor (small minus big), β-HML represents the coefficient for the value factor (high minus low) and β-UMD represents the coefficient for the momentum factor (up minus down). α and β values have been tested with two-tailed t-tests against the null hypothesis of the parameter being equal to zero (p-values in parenthesis).

Appendix B: Operationalisation of the bankruptcy risk in the RIV-model

The probability of bankruptcy for 1-year, 3-year, and 5-year forecast horizons is calculated as:

1-year forecast horizon: $V_1 = -1.5 - 4.3 * R_A + 22.6 * R_L + 1.6 * TIV - 4.5 * ER + 0.2 * E' - 0.1 * Diff(R_L)$

2-year forecast horizon: $V_3 = -1.1 + 13.2 * R_L + 0.2 * t(1) + 1.3 * TIV - 0.5 * LI - 3.3 * ER$

5-year forecast horizon: $V_5 = -1.1 + 13.5 * R_L + 0.9 * TIV - 1 * LI - 1.8 * ER$

Where:

$R_A = \frac{EBIT_t}{(Total\ assets_t + Total\ assets_{t-1})/2}$,

$R_L = \frac{Interest\ cost_t}{(Liabilities_t + Liabilities_{t-1})/2}$,

$TIV = \frac{(Inventory_t + Inventory_{t-1})/2}{Sales_t}$

$ER = \frac{Owners'\ equity_t}{Total\ assets_t}$,

$E' = \frac{(Owners'\ equity_t - Owners'\ equity_{t-1})}{Owners'\ equity_t}$,

$t(1) = \frac{Tax\ cost_t}{EBT_t}$,

$LI = \frac{Cash\ assets_t}{Current\ liabilities_t}$,

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

$V_{(*)}$= normally distributed index value of failure.

The estimated value of $V_{(*)}$ is normally distributed, from which the probability of bankruptcy is obtained. Since there is a risk of a sample bias when applying the model due to the sample proportion of companies going bankrupt being different from the population proportion of companies going bankrupt, the average p_{fail} from the 1-year, 3-year, and 5-year regression models have been adjusted with the calibration method used in Skogsvik and Skogsvik (2013). The calibration formula is defined as:

$$p(fail)_{POP,i} = p(fail)_{EST,i} * \left[\frac{\varphi*(1-prop)}{prop*(1-\varphi)+p(fail)_{EST,i}*(\varphi-prop)}\right]$$

where: $prop$: number of *failure companies* in relation to the total number of companies in the *estimation sample,*

φ: proportion of *failure companies* in the *population* of companies,

$p(fail)_{EST,i}$: the probability of failure in the estimation sample for company i,

$p(fail)_{POP}, i$: the probability of failure in the population of companies.

The number of failure companies in relation to the total number of companies in the estimation sample, $prop$, attracts the value $\frac{51}{379} = 0.1346$ from the estimation sample in Skogsvik (1990). The proportion of failure companies in the population of companies, φ, has in line with Anesten et al. (2020) been set to 0.015, due to the similarity in samples in which this study also considers Swedish manufacturing firms. The purpose with the approach of calibrating the estimated probabilities of failure is to determine a more unbiased and valid cost of equity in the RIV-model valuation.

In Skogsvik (2006), two alternatives are suggested to adjust for the bankruptcy risk in equity valuation. The first is performed in the numerator by multiplying the expected cash flow conditioned on firm survival with the probability of survival up to some point in time. The second is performed in the denominator by adjusting the cost of equity with the probability of bankruptcy. In this study, the second approach is performed in line with Anesten et al. (2020). To implement this, the adjusted average of the 1-year, 3-year, and 5-year probability of bankruptcy has been used to calibrate the cost of equity. The calibration of the cost of equity is performed as:

$$\rho_{E,i}^{*} = \frac{(\rho_{E,i} + p_{fail,i})}{(1 - p_{fail,i})}$$

$\rho_{E,i}^{*}$: bankruptcy calibrated cost of equity for company *i*,

$\rho_{E,i}$: cost of equity for company *i*,

$p_{fail,i}$: probability of bankruptcy for company *i*.

In order to incorporate the bankruptcy risk, the cost of capital in the initial RIV model is substituted with the bankruptcy calibrated cost of equity. Thus, the historically motivated value of owners' equity is defined as:

$$V_0^{(h)} = B_0 + \sum_{t=1}^{3} \frac{B_0 * (1 + \overline{ROE}_h - \overline{DS}_h)^{t-1} * (\overline{ROE}_h - \rho_t)}{\prod_{t=1}^{t}(1 + \rho_t^{*})} + \frac{B_0 * E_{(0)}(1 + \overline{ROE}_h - \overline{DS}_h)^{3} * \bar{q}_h(B_3)}{\prod_{t=1}^{3}(1 + \rho_t^{*})}$$

ρ_t^{*}: the bankruptcy calibrated cost of equity.

Appendix C: Realistic return metrics using fixed effects logistic regression

TABLE C1 – MARKET-ADJUSTED BUY-AND-HOLD RETURNS (REALISTIC RETURN METRIC) FOR 36-MONTH HOLDING PERIODS WITH ALTERNATIVE PREDICTION MODELS

Investment strategy	Position	Fixed effects
Base case strategy	Long	-0.230
		(0.052)
	Short	0.121
		(0.108)
	Hedge	-0.350
		(0.005)
Indicator variable strategy		
Zero interval for IND_0:	Long	-0.414
$[-0.1 \cdot \beta_0, 0.1 \cdot \beta_0]$		(0.074)
	Short	0.120
		(0.074)
	Hedge	-0.534
		(0.018)
Zero interval for IND_0:	Long	-0.375
$[-0.2 \cdot \beta_0, 0.2 \cdot \beta_0]$		(0.096)
	Short	0.131
		(0.082)
	Hedge	-0.506
		(0.033)
Zero interval for IND_0:	Long	-0.270
$[-0.4 \cdot \beta_0, 0.4 \cdot \beta_0]$		(0.148)
	Short	0.101
		(0.137)
	Hedge	-0.371
		(0.039)

Table C1 presents the realistic market-adjusted buy-and-hold returns for 36-month holding periods of the short, long and hedge position for the base case strategy and IND01, IND02 and IND04 for the fixed effects estimated ROE prediction model. The returns are presented for the entire investment period (2008-2016) The returns of the long, short and hedge positions have been calculated in accordance with equations (14a), (14b) and (14c). Returns for the entire investment period have been tested with two-tailed t-tests against the null hypothesis of the return being equal to zero (p-values in parenthesis).

Appendix D: Additional descriptive risk proxy statistics

TABLE D1 – MEAN-ADJUSTED MARKET CAPITALISATIONS

Year	Long position		Short position		Difference in means	Difference in medians
	Mean	Median	Mean	Median	(short-long)	(short-long)
Base case strategy						
2008	-1.590	-1.394	0.868	0.757	2.458	2.151
2009	-1.261	-1.653	0.777	0.596	2.038	2.250
2010	-1.125	-1.233	0.662	0.637	1.787	1.871
2011	-0.761	-1.141	0.828	0.741	1.589	1.882
2012	-0.967	-1.081	0.839	0.860	1.807	1.941
2013	-1.068	-1.323	0.768	0.770	1.836	2.093
2014	-0.937	-1.592	0.798	0.368	1.735	1.960
2015	-1.006	-1.710	0.978	0.657	1.984	2.367
2016	-1.570	-1.966	0.744	0.463	2.314	2.429
Ind 01						
2008	-1.542	-1.542	0.846	0.756	2.388	2.298
2009	-1.065	-1.808	-0.688	-0.881	0.378	0.927
2010	-2.282	-2.282	0.819	0.776	3.101	3.058
2011	-0.681	-1.516	0.987	0.742	1.668	2.258
2012	-0.735	-2.062	1.031	0.909	1.766	2.972
2013	-1.574	-2.339	0.984	1.308	2.558	3.647
2014	-1.503	-2.431	1.085	0.847	2.588	3.278
2015	-1.587	-2.256	1.168	0.781	2.754	3.037
2016	-0.725	-1.779	0.850	0.495	1.574	2.274

Table D1 shows the average and median of the mean-adjusted values of the natural logarithm of the market capitalisation at the investment point in time for each separate year in the entire investment period.

TABLE D2 – MEAN-ADJUSTED BOOK-TO-MARKET RATIOS

Year	Long position Mean	Long position Median	Short position Mean	Short position Median	Difference in means (short-long)	Difference in medians (short-long)
Base case strategy						
2008	-0.002	0.146	-0.091	0.139	-0.089	-0.007
2009	-0.192	-0.553	0.018	0.280	0.210	0.833
2010	-0.277	-0.206	0.065	0.210	0.342	0.415
2011	0.309	0.610	-0.281	-0.158	-0.590	-0.768
2012	0.383	0.563	-0.294	-0.248	-0.677	-0.811
2013	0.358	0.464	-0.223	-0.171	-0.581	-0.634
2014	0.279	0.530	-0.129	-0.035	-0.408	-0.565
2015	0.194	0.015	-0.187	0.000	-0.382	-0.015
2016	0.378	0.581	-0.195	0.027	-0.573	-0.554
Ind 01						
2008	1.538	1.538	-0.154	-0.087	-1.693	-1.625
2009	0.961	1.359	-0.558	-0.631	-1.519	-1.990
2010	1.172	1.172	-0.132	0.011	-1.304	-1.161
2011	1.247	1.390	-0.454	-0.264	-1.701	-1.654
2012	0.785	1.218	-0.644	-0.445	-1.428	-1.663
2013	1.063	1.275	-0.464	-0.313	-1.527	-1.588
2014	1.234	1.386	-0.253	-0.065	-1.487	-1.451
2015	1.710	1.444	-0.268	-0.028	-1.977	-1.472
2016	1.194	1.336	-0.211	0.017	-1.404	-1.319

Table D2 shows the average and median of the mean-adjusted values of the natural logarithm of the book-to-market ratios at the investment point in time for each separate year in the entire investment period.

TABLE D3 – MEAN-ADJUSTED EARNINGS-TO-PRICE RATIOS

Year	Long position		Short position		Difference in means	Difference in medians
	Mean	Median	Mean	Median	(short-long)	(short-long)
Base case strategy						
2008	-0.153	-0.025	0.110	0.114	0.262	0.139
2009	-0.173	-0.043	0.175	0.177	0.347	0.220
2010	-0.009	-0.014	0.095	0.106	0.105	0.120
2011	-0.220	0.137	0.208	0.205	0.428	0.067
2012	-0.176	0.083	0.165	0.161	0.341	0.078
2013	-0.061	-0.006	0.090	0.088	0.151	0.094
2014	-0.097	0.049	0.112	0.117	0.209	0.068
2015	-0.153	0.112	0.150	0.147	0.303	0.034
2016	-0.243	0.033	0.110	0.112	0.353	0.079
Ind 01						
2008	-0.389	-0.389	0.112	0.114	0.501	0.503
2009	-0.239	0.001	0.115	0.110	0.354	0.110
2010	-0.060	-0.060	0.090	0.102	0.150	0.162
2011	0.087	0.173	0.203	0.203	0.116	0.031
2012	-0.030	0.099	0.147	0.148	0.177	0.049
2013	-0.045	0.010	0.087	0.086	0.132	0.076
2014	-0.168	0.009	0.112	0.118	0.281	0.109
2015	-0.872	0.130	0.140	0.146	1.012	0.016
2016	0.022	0.086	0.111	0.111	0.088	0.025

Table D3 shows the average and median of the mean-adjusted values of the earnings-to-price ratio at the investment point in time for each separate year in the entire investment period.

TABLE D4 – MEAN-ADJUSTED DIVIDEND YIELDS

Year	Long position		Short position		Difference in means	Difference in medians
	Mean	Median	Mean	Median	(short-long)	(short-long)
Base case strategy						
2008	-0.020	-0.022	0.009	0.012	0.030	0.034
2009	-0.019	-0.024	0.009	0.011	0.027	0.035
2010	-0.011	-0.012	0.005	0.002	0.016	0.014
2011	-0.007	-0.017	0.006	0.006	0.013	0.023
2012	-0.009	-0.020	0.007	0.007	0.015	0.026
2013	-0.009	-0.019	0.006	0.006	0.015	0.024
2014	-0.007	-0.015	0.007	0.007	0.014	0.021
2015	-0.004	-0.015	0.005	0.006	0.009	0.021
2016	-0.010	-0.016	0.005	0.006	0.015	0.022
Ind 01						
2008	-0.022	-0.022	0.011	0.014	0.033	0.036
2009	-0.005	-0.020	0.006	-0.002	0.011	0.018
2010	-0.012	-0.012	0.004	0.000	0.015	0.012
2011	-0.002	-0.002	0.006	0.005	0.008	0.007
2012	-0.007	-0.017	0.005	0.006	0.012	0.023
2013	0.001	-0.003	0.004	0.005	0.003	0.008
2014	-0.004	-0.015	0.008	0.008	0.012	0.022
2015	0.000	-0.015	0.005	0.006	0.005	0.021
2016	0.001	-0.014	0.006	0.006	0.005	0.019

Table D4 shows the average and median of the mean-adjusted values of the dividend yield at the investment point in time for each separate year in the entire investment period.