ACCOUNTING FOR THE MEASUREMENT BIAS

A STUDY OF MARKET EFFICIENCY IN THE UNITED STATES AND THE RELEVANCE OF EXTENSIVE FUNDAMENTAL ANALYSIS IN EQUITY VALUATION

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Abstract

This thesis investigates abnormal returns over the period 1983–2021 from an investment strategy that is based on public accounting information. Investment positions are taken in US manufacturing firms and are held for 36 months using a self-financing (hedged) portfolio. The strategy is comprised of (1) an accounting-based prediction model estimating the probability of an increase in future return on owners' equity (ROE), and (2) a consideration of the market's expectation of the development in ROE using the residual income valuation (RIV) model. Investment positions are taken when (1) and (2) differ, enabling an assessment of whether market prices incorporate the statistical prediction. Horizon values in the RIV model are estimated using both a 'sophisticated method' based on fundamental analysis of the accounting valuation bias and a 'parsimonious method' based on reverse-engineering horizon values through stock prices. By deploying these two methods, the utility of a theoretically sound approach of estimating horizon values can be assessed through a comparative evaluation with an approach that holds practical relevance due to its simplicity. The investment strategy utilizing fundamental analysis of horizon values generated a 25.8% return above the S&P 500 index and an equivalent abnormal CAPM return of 11.4%. The results point to a discontinuance of market mispricing over time, and the mispricing in earlier periods is found to be sensitive to the choice of abnormal return metric. Regardless, estimating horizon values through fundamental analysis resulted in more significant and prolonged returns compared to when using reverse-engineering through stock prices. This indicates that utilizing fundamental analysis when estimating horizon values should not be neglected in future research of market efficiency, nor amongst practitioners.

Keywords:

Accounting valuation bias; Fundamental analysis; Horizon Value; Market mispricing; Residual income valuation

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1. INTRODUCTION

An essential aspect of fundamental analysis (measuring firm value with public accounting information) is generating information that is relevant for investment decisions. If fundamental analysis can properly be used to generate fundamental values that deviate from observed prices, then abnormal investment returns could theoretically be generated since observed prices will drift toward fundamental prices and positions could be taken in the interim (Ou & Penman, 1989). Whether an investor can indeed utilize financial statement information to generate durable and predictable abnormal returns in practice is, however, a vastly debated topic. Any definitive conclusion on this matter would theoretically imply substantial significance for the semi-strong version of the efficient markets hypothesis (EMH), which states that market prices incorporate all publicly available information (Fama, 1970). Since utilizing fundamental analysis to extract firm values is pursued in countless institutions daily and has a significant impact on how accounting information is consumed, this matter indeed has economic significance.

This thesis investigates the abnormal returns from an investment strategy that is solely based on public accounting information. By doing so, it inherently constitutes a test of the EMH over time. Studying the utility of fundamental analysis through investment strategies has historically been a prominent endeavor, not least since the publication of Ou and Penman (1989) which found that public accounting information of US firms is not fully incorporated in observed stock prices and could subsequently be utilized to achieve abnormal returns. A plethora of research in the field has since been conducted, (e.g., Holthausen & Larcker 1992; Greig 1992; Stober 1992; Setiono & Strong 1998; Abarbanell & Bushee 1998; Dorey et al., 2016), which tends to differ extensively in overall methodology. Skogsvik (2008) conducted a study on Swedish data, investigating the results of Ou and Penman (1989) across countries and over time. The strategy was based on predicting the development of future return on owners' equity (ROE) using public accounting information, and the returns based on such predictions were subsequently evaluated. Skogsvik (2008) concluded that the deployed model had a significant predictive ability. However, an evaluation of the EMH was deemed elusive, due to the results being sensitive to the choice of abnormal return metric.

These aforementioned studies have, however, not considered the market's expectation of future firm performance. Instead, solely statistical techniques based on accounting information have been utilized. This arguably constitutes a limitation, since a 'good stock' (identified as an expected increase in a certain accounting variable, e.g., ROE or EPS) is not necessarily a logical investment because this may already be incorporated into the stock price. Through fundamental valuation however, the market's expectation of the development in a certain accounting variable can be incorporated. Skogsvik and Skogsvik (2010) uniquely considered this proposition by analyzing the difference between the observable stock price and the 'historically motivated' stock price using the residual income valuation (RIV) model and public accounting information of Swedish firms. When combining this technique with the accounting-based prediction model as utilized in Skogsvik (2008), investment positions were taken when the market's expectation differed with the prediction model. Indeed, Skogsvik and Skogsvik (2010) observed intriguing returns using this strategy and concluded that fundamental valuation was a valuable extension. In addition to this particular contribution, Skogsvik and Skogsvik (2010) elaborated on precedent research (e.g., Ou & Penman, 1989; Stober, 1992) which either (1) employed unrealistic investment strategies due to required foreknowledge, (2) incorporated the market's expectation although without a direct link to fundamental analysis, or (3) utilized independent variables which have been alleged to be redundant.

Naturally, incorporating fundamental valuation as in Skogsvik and Skogsvik (2010) demands a valuation model, which involves forecasting value drivers. Beyond a certain point in time, however, conducting accurate forecasts may be difficult, and a common method is therefore to use truncation based on 'horizon values', also known as 'terminal values' (Penman, 1998). Utilizing such a technique, however, may have pertinent effects on the magnitude of the estimation of fundamental values, which emphasizes the importance of considerably assessing its components (Francis et al., 2000). One method of estimating horizon values is the Gordon-growth formula, which demands a perpetual growth rate (Gordon & Shapiro, 1956; Gordon, 1959). In precedent research utilizing fundamental valuation, however, this is often associated with arbitrary assumptions (e.g., Kaplan & Ruback, 1995; Penman & Sougiannis, 1998; Francis et al., 2000).

An alternative to deploying the Gordon-growth formula was proposed by Skogsvik (1998) based on the "goodwill-to-book ratio", referred to as the "valuation measurement bias of owners' equity". This bias is comprised of both "business goodwill" resulting from positive NPV investments, and a "cost matching bias" stemming from conventional accounting. In a competitive economic environment, the business goodwill component can be assumed to equal zero, if the horizon point is set to a sufficiently large value. The second component however, assuming conservative accounting, can be considered permanent and non-negative (Skogsvik, 1998). Using this decomposition of the horizon value may, compared to other alternatives, enable more robust estimations of fundamental values by decreasing ad hoc assumptions (Skogsvik & Skogsvik, 2010).

A subsequent intriguing question is how one might properly estimate the persisting cost matching bias to estimate fundamental values. To do so, Runsten (1998) developed a methodology based on financial statement analysis and conducted industry-specific estimates of the cost matching bias, referred to as the permanent measurement bias (PMB), on Swedish firms. The study of Skogsvik and Skogsvik (2010) indeed utilized the goodwill-to-book ratio decomposition to estimate horizon values in the RIV model. To estimate the cost matching bias, an exogenous estimation from Runsten (1998) was collected directly. However, since no alternative method of estimating horizon values was presented, the degree of which the observed mispricing was dependent on fundamental analysis of horizon values remains unanswered.

This thesis attempts to replicate the study of Skogsvik and Skogsvik (2010) to investigate the EMH over time in the United States. Furthermore, the methodology developed by Runsten (1998) is used to conduct a 'sophisticated method' of estimating horizon values. By doing so, a more precise comparability with Skogsvik and Skogsvik (2010) is enabled, and since market mispricing may be subject to change over time (Holthausen & Larcker, 1992; Dorey et al., 2016), and cross-nationally (Setiono & Strong, 1998; Skogsvik, 2008), this comparison may improve the current understanding of market efficiency. To further elaborate on Skogsvik and Skogsvik (2010), a 'parsimonious method' of estimating horizon values based on reverse-engineering through stock prices is also considered, to allow for a comparative evaluation. Given the practical relevance of the parsimonious method due to its simplicity, a comparison with a more theoretically sound approach may arguably constitute a valuable contribution.

The results can be summarized as follows. The investment strategy utilizing the sophisticated method in which horizon values were estimated based on fundamental analysis generated an average 36-month return of 25.8% above the S&P 500 between 1983–2021. An equivalent abnormal CAPM return of 11.4% was also generated over the same period. When utilizing the parsimonious method based on reverse-engineering through stock prices, however, no statistically significant returns were generated. Furthermore, regardless of method used to estimate horizon values, the investment returns decreased over time, which points to an increase in market learning during the period of 1983–2021. Consistent with Skogsvik and Skogsvik (2010), incorporating the market's expectation implied in stock prices was a valuable component to the investment strategy.

Despite an observed decrease in mispricing over time, the market-adjusted returns using the sophisticated method during the later period 2001–2021 were still statistically significant, although the same cannot be observed for the abnormal CAPM returns. These market-adjusted returns were, however, highly dependent on the long positions, which could not be explained by discrepancy in prediction accuracy. Instead, a positive sentiment bias seems to have been prevalent, which is deemed to hamper the reliability of these returns and subsequently corroborates a decrease in market mispricing over time. When controlling for risk proxies and overlapping data distributions, only the market-adjusted returns persisted, which indicates that the observed mispricing during the period of 1983–2003 is affected by the choice of abnormal return metric. Lastly, the returns during this period are also presumed to be somewhat inflated, mainly due to limitations associated with the short positions. Conclusively, estimating horizon values through fundamental analysis generated more significant and prolonged returns compared to when using reverse-engineering based on stock prices. Although, since the evidence indicates a discontinuance of the abnormal returns in later periods, this casts doubt on the ability of the investment strategy to detect significant market mispricing in future years.

2. THEORETICAL BACKGROUND

In this section, information from precedent studies as well as foundational theory is outlined. Precedent studies have investigated whether public accounting information can be utilized to generate abnormal returns. Foundational theory discusses the efficient markets hypothesis (EMH), equity valuation models, the estimation of horizon values, and the challenges associated with studying the EMH.

2.1. Efficient Markets Hypothesis and Information Perspective of Accounting

An investor who utilizes financial statement information implicitly assumes there is utility in analyzing public information for predicting future price movements. In semi-strong efficient markets, however, observable stock prices already reflect all publicly available information (for example annual reports and ‘calendar-trends’). Thus, the proposition of accounting information being relevant for predicting price-movements inherently opposes the semi-strong efficient markets hypothesis as well as the theory of random walks (future prices are independent from historical prices and alter in unison with a probability distribution). Simultaneously, market prices need not correspond to “true values”, since the world is fraught with uncertainty, and opinions differ between individuals. Observed stock prices are therefore mere individual representations of fundamental values, which according to the EMH are exhaustively based on a multitude of both “political and firm-specific” information (Fama, 1965; Fama, 1970).

There are several available techniques for studying market efficiency, (see for example Bernard & Thomas, 1989; Bartov et al., 1998; Foster, 1979; Haugen, 1999), of which constructing an investment strategy based on public information constitutes one alternative. If an investment strategy based solely on public information (such as financial statements) can yield abnormal returns that are both predictable and persist over time, this would theoretically constitute opposing evidence of the EMH. Empirical observations of the development of the EMH over time can theoretically be explained by the respective development of three conditions that affect market efficiency. These are (1) transaction costs, (2) the cost of distributing information, and (3) the consensus of what implication current information has on prices (Fama, 1970). Related to the EMH, there is a perspective of accounting referred to as the ‘information perspective’, which suggests that observable stock prices suffice as an indicator of a stock’s fundamental value and that accounting information is merely evaluated for its ‘information content’ with respect to observed prices (Penman, 1992). The alleged logic behind this perspective is that accounting information is merely a function of non-homogenous factors and can be subject to manipulation (Ball & Brown, 1968). Contrastingly with this perspective of accounting, fundamental analysis (the value measurement of a security based on public information with an explicit focus on accounting) is synonymous with discovering fundamental values without reference to observed prices (Penman, 1992).

In order to ascertain whether fundamental analysis can be utilized to generate abnormal returns, however, causality first needs to be established. That is, the value relevance of accounting information needs to be confirmed, of which the renowned study by Ball and Brown (1968) often serves as a theoretical foundation of support. In an attempt to empirically investigate the information perspective, Ball and Brown (1968) analyze the relationship between the announcements of financial information and stock price reactions with a perfect foresight strategy (a strategy where positions are taken with ex-ante information about the outcome in consideration.). The financial information is specifically defined as earnings, as the authors state this to be of particular interest to investors. Income numbers from 1946-1966 using the Standard and Poor's Compustat tapes are collected, and the sample of firms is divided into two portfolios that are going to announce 'good news' and 'bad news' respectively in twelve months' time. Returns are then calculated from t = -12 to t = 0. The authors conclude that:

> "The results demonstrate that the information contained in the annual income number is useful in that it is related to prices". (Ball and Brown, 1968, p. 174).

Ball and Brown (1968) further state that with superior knowledge of future earnings, abnormal returns can be generated. The theoretical utility of these findings is substantial, as it indicates that accounting information has value relevance. The practical relevance, however, is inherently limited since utilizing a perfect foresight strategy is not realistic. Although, the findings of Ball and Brown (1968) have been scrutinized by Lev (1989) from a statistical point of view. Lev (1989) finds that the relation between earnings and stock returns is low, and subsequently opposes the findings of Ball and Brown (1968). Runsten (1998) postulates however that there are many explanations for the results of Lev (1989). For example, analyzing periods with varying levels of inflation and a heterogenous data sample could generate a biased effect. Nevertheless, incorporating a perfect foresight strategy may still be useful to include as a benchmark (Skogsvik, 2008).

2.2. Fundamental Analysis

In contrast to Ball and Brown (1968), precedent studies that are practically relevant have not utilized a perfect foresight strategy when predicting increases in earnings. One example is the study of Ou and Penman (1989) that used accounting ratios to predict the development of earnings per share (EPS), which was then used to either take a long or short position in a self-financing portfolio. The study commences with a discussion regarding how fundamental analysis can specifically be used to extract firm values. Ou and Penman (1989) outline a "simple valuation model" used to describe firm values based on expected future dividends, and since dividends are a result of paid out earnings, (Penman, 2013, p. 266), the following model can be derived:

$$V_0 = \frac{DIV_1}{\rho} = \frac{Earnings_1 \cdot \overline{pr}}{\rho} \tag{1}$$

where:

V_0 = value of owners' equity at time 0,

DIV_1 = expected dividends in the next period after the valuation date,

ρ = rate at which future dividends are discounted,

$Earnings_1$ = expected earnings in the next period after the valuation date, and

$\overline{pr}$ = share of earnings expected to be paid out as dividends (payout ratio).

Ou and Penman (1989) argue for the discount rate to reflect security risk, and that fundamental valuation entails analysis of both the future expected dividends (numerator) and the discount rate (denominator). The probability of a one-year future increase in EPS (denoted as $\widehat{Pr}$) is estimated through logistic regression based on 68 accounting ratios as the independent variables. Investment positions are taken during 1973-1983 at the end of the third month after the fiscal year-end. It is thus assumed that the information is available to the public at this point in time. Stocks are assigned to a long position if $\widehat{Pr}$ is greater than 0.6 and a short position if $\widehat{Pr}$ is less than or equal to 0.4. Firms with a predicted probability of an increase in EPS within this range are subsequently considered to have no clear indication of future development, and no position is therefore taken in these circumstances. The result of this strategy was a two-year market-adjusted return of 12.5% to the hedged portfolio (19.6% for a three-year period), which decreases, although persists, when controlling for "size-effects". According to Ou and Penman (1989), this constitutes evidence of accounting information not being fully incorporated in market prices and subsequently disapproving evidence of market efficiency.

Following Ou and Penman's (1989) study, presumably due to its intriguing findings, several studies have utilized alterations in methodology to scrutinize their conclusions. One of several papers that have done so is Holthausen and Larcker (1992) which recreates the study of Ou and Penman (1989) but utilizes a model which, instead of earnings, predicts excess returns. Holthausen and Larcker (1992) utilize three abnormal return metrics, (1) market-adjusted returns, (2) excess returns based on the capital asset pricing (CAPM) model, and (3) size-adjusted returns. As for the market-adjusted returns, these are calculated in two separate ways. The first one being when firm-year observations are equally weighted over time, and the second one is when firm-year observations are equally weighted within a year and then equally weighted over time. They state that unlike the second method, the first method is "non-implementable", since when taking investment positions it requires foreknowledge of the total number of firm-specific positions over the entire period. During the investment period 1978-1988, they generate a 12-month market-adjusted return to the implementable method of 7.3% on average. When controlling for size, the return increases to 7.9%, and lastly an abnormal CAPM return of 9.5% is generated. Further, Holthausen and Larcker (1992) found that predicting excess returns directly generated superior results compared to predicting earnings (as in Ou & Penman, 1989) during 1978-1988. Since Holthausen and Larcker (1992) found the strategy of Ou and Penman (1989) to perform poorly in the period 1983-1988, (a period not included in their study), they argue that this implies a reduced robustness of Ou and Penman's (1989) findings over time. Ultimately, the authors' findings do however support Ou and Penman (1989) in terms of accounting information not being fully incorporated in stock prices. Simultaneously, Holthausen and Larcker (1992) state that it is possible that the mispricing will decrease in future periods. Another study that re-examines Ou and Penman (1989) is Greig (1992). Greig (1992) states the following regarding the accounting ratios utilized by Ou and Penman (1989) as the independent variables in their logistic regression:

> "While these ratios vary systematically across firms as a function of future earnings changes, they also vary systematically cross-sectionally as a function of risk, size and other determinants of expected return." (Greig, 1992, p. 415).

Consequently, Greig (1992) implements a more detailed analysis of these "determinants of expected return". More specifically, Greig (1992) seems to be especially concerned with the "size-effect", as he postulates accounting ratios of small firms to be significantly different from that of larger firms. Indeed, Greig (1992) finds similar results to Ou and Penman (1989) when replicating their methodology, but states that when including the size-effect, the abnormal returns vanish since the portfolio based on firm-size doubles the portfolio based on $\widehat{Pr}$. Thus, Greig (1992) not only questions the robustness of the findings in Ou and Penman (1989) due to a size-effect, but also the findings in Holthausen and Larcker (1992) of persistence in abnormal returns after controlling for firm size.

A study that creatively developed Ou and Penman's (1989) methodology is the one of Stober (1992), which distinguishes between the information in the measure $\widehat{Pr}$ and the information contained within analyst earnings forecasts. Stober (1992) tested the success of such a strategy by utilizing two samples, the first contained observations of which $\widehat{Pr}$ agreed with consensus estimates, and the other where these differed. That is, the logistic regression disagreed with consensus estimates. Interestingly, Stober (1992) finds that taking investment positions based on $\widehat{Pr}$ only generates abnormal returns when $\widehat{Pr}$ differs with analyst forecasts. However, the abnormal return from the $\widehat{Pr}$-strategy consists for up to 72 months after the release of the necessary data to construct $\widehat{Pr}$. Considering the findings of Ou and Penman (1989) that $\widehat{Pr}$ on average predicts the direction of earnings changes 36 months ahead, questions can be raised as to what is truly the underlying driver of the strategy's success. This conundrum according to Stober (1992) strengthens the arguments brought forward by Holthausen and Larcker (1992) as well as Greig (1992) that $\widehat{Pr}$ (probability of an increase in earnings) is a proxy for cross-sectional differences in expected returns, rather than a "predictor of earnings".

Another study that scrutinizes Ou and Penman (1989) is Abarbanell and Bushee (1998), which states that Ou and Penman (1989) do not attempt to identify any conceptual arguments as to why these accounting ratios are in fact related to earnings. Consequently, Abarbanell and Bushee (1998) conducted a study using alternative accounting ratios. The authors collected these accounting ratios from the study of Lev and Thiagarajan (1993), which listed twelve ratios that have been collected by investigating the value-relevance of accounting ratios from a practitioner's perspective through analyzing journals, publications, and newsletters of firms. Using nine of these ratios, Abarbanell and Bushee (1998) conducted a fundamental analysis strategy in the spirit of Ou and Penman (1989) during the period 1974-1988 using a self-financing portfolio on US firms. The result of this strategy was an average 12-month size-adjusted return of 13.2%. Similar to findings in Ou and Penman (1989), the authors claim to have found evidence of accounting information not being fully incorporated in market prices, as the returns are allegedly unexplainable as a premium for risk. Abarbanell and Bushee (1998) emphasize however that the returns may have been affected by the "short investment period" of 15 years, and the fact that the returns were insignificant during the last three years.

To elaborate on Ou and Penman's (1998) methodology and assess its robustness over time and cross-nationally, Skogsvik (2008) conducted a study on Swedish firms using data from the period 1970–1994 and an accounting-based prediction model to predict the change in medium-term (three-year-ahead) return on owners' equity (ROE). Skogsvik (2008) defends the focus of medium-term rather than one-year-ahead prediction as used in Ou and Penman (1989) by stating that three years is presumably more of interest in an investor-context. Two sets of prediction models are used, a univariate and a multivariate. The univariate model comprised of historical ROE as the independent variable, and the multivariate model comprised of a set of accounting ratios as well as the historical ROE as the independent variables. Similar to Ou and Penman (1989), positions are taken three months after the fiscal year-end. Furthermore, Skogsvik (2008) elaborates on market-adjusted return metrics used in precedent research by constructing a "realistic return metric". Similar to Holthausen and Larcker (1992), the metric weights firm-year observations equally within each year and then equally over time. Further, somewhat similarly with precedent research such as Setiono and Strong (1998), liquidity becoming unleashed from firms being de-listed is re-invested into the market. Ultimately, precedent research that has not utilized such a return metric (e.g., Ou & Penman, 1989) but instead excluded sample-firms that were delisted in the future, may have reported inflated abnormal returns due to survivorship bias (Skogsvik, 2008). However, for reasons of comparability with precedent research, Skogsvik (2008) still incorporates the same return metric utilized in Ou and Penman (1989), denominated as the "statistical return metric".

Skogsvik (2008) finds that the univariate model (consisting solely of ROE as an independent variable) had an overall better prediction accuracy than the multivariate model, although not for predicting increases in ROE specifically. According to Skogsvik (2008), this points to the possibility that accounting ratios (other than ROE) may still be useful for an investment strategy. More specifically, the univariate investment strategy generated a statistically significant market-adjusted 36-month hedge return of 28.8% on average, during the entire investment period. Indeed, the statistical return metric generated far better results compared to the realistic return metric of 40.7%. A statistically significant abnormal CAPM return (Jensen's alpha) was however not generated for the same investment period. Similar to Holthausen and Larcker (1992), Skogsvik (2008) finds that the Swedish stock market seems to have been more sophisticated in incorporating public accounting information in later compared to earlier periods. This is simultaneously deemed to not be entirely clear-cut, due to low levels of significance of the prediction model during the later periods. Lastly, an asymmetry between the returns of the long and short portfolio is observed, as the long positions perform significantly better than the short positions. Furthermore, this cannot be explained by any observations pertaining to discrepancies in prediction accuracy. Skogsvik (2008) therefore postulates that there seems to have been a pervasive positive sentiment during this period.

More recently, Dorey et al. (2016) investigated the robustness of Abarbanell and Bushee's (1998) findings over time by replicating the methodology and extending the period by 15 years. The findings of Dorey et al. (2016) corroborate Skogsvik (2008) as well as Holthausen and Larcker (1992) of an incremental improvement in market usage of accounting information over time. More specifically, the results of Dorey et al. (2016) indicate the abnormal returns to have statistical insignificance in the later period. Dorey et al. (2016) further elaborate on this observation by stating two alternative explanations: First, the value relevance of the independent variables has decreased over time. Second, the ability of investors to utilize fundamental analysis has decreased over time. The authors conclusively ascertain, however, that neither of these constitute a reasonable alternative explanation to the observations of a decrease in market mispricing over time.

2.3. Fundamental Valuation

The precedent studies discussed so far have utilized fundamental analysis to investigate market mispricing, but not fundamental valuation specifically. Fundamental valuation relies on valuation models that have an established link between financial statement information and firm value, which enables consideration of market expectations about the development of accounting variables implied in observable stock prices.

2.3.1. Incorporating the Market's Expectation Implied in Stock Prices

The main contribution of Skogsvik and Skogsvik (2010) is the incorporation of the market's implied expectation by analyzing the difference between the observable stock price with the price generated by historical accounting information and the RIV model, a technique denominated as the "indicator variable strategy". Positions are subsequently taken when the market's expectation of the future development of ROE differs from the prediction that is generated by the accounting-based prediction model. The logic behind this technique is that utilizing a prediction model while excluding the market's expectation of the development in the dependent variable does not consider whether the prediction model's assessment is already incorporated into the stock price. In other words, 'a good firm' (increase in ROE predicted) is not necessarily 'a good buy' (observed price does not incorporate the predicted increase in ROE). Skogsvik and Skogsvik (2010) also considers the strategy based solely on the accounting-based prediction of future ROE (in the spirt of Skogsvik, 2008), denominated as the "base case strategy". This subsequently allows for the investigation of two sets of mispricing factors:

> "Forecasting mispricing: that is, that stock prices do not fully reflect the forecasting ability of published accounting information with respect to some value driver(s). Modelling mispricing: that is, stock prices do not reflect the valuation implications of forecasted value driver(s) appropriately". (Skogsvik & Skogsvik, 2010, p. 388).

Indeed, the indicator variable strategy uniquely deployed in Skogsvik and Skogsvik (2010) is rather powerful, as it elaborates on methodology from precedent research in section 2.2 which solely incorporated forecasting mispricing. Stober (1992) did however incorporate the market's expectation, although through using consensus estimates which presumably entail more extensive information than in forecasted value driver(s). Thus, this approach is not deemed to be suitable for investigating modelling mispricing (Skogsvik & Skogsvik, 2010). The investment period stretches from 1983-2003, and once again the sample is limited to Swedish manufacturing firms, with a medium-term focus which the authors state may mitigate the effects of transitory items on earnings, in contrast to one-year predictions. The indicator variable strategy using a realistic return metric generated a significant 36-month market-adjusted return of 42.0% on average during the entire investment period, as well as a significant monthly Jensen's alpha of 0.8%. The authors conclude that the indicator variable strategy was important for the returns since it approximately doubled the returns of a strategy solely incorporating forecasting mispricing as used in precedent research. Furthermore, the returns were evidently unsensitive to risk-proxies, although when controlling for overlapping data distributions in the statistical tests, the significance of the market-adjusted returns weakened.

As in Skogsvik (2008), there is once again a discussion of a positive sentiment bias being prevalent in the Swedish market, which was subsequently ascertained to exist through testing. Skogsvik and Skogsvik (2010) state that such a sentiment bias decreases any validity regarding out-of-sample inferences of mispricing. The authors conclusively remark that the results indicate that Swedish market participants have become better in utilizing financial information over time and that both factors of mispricing have vanished by the mid-1990s. Ultimately, since the market's expectation of future ROE was found to be relevant in identifying market mispricing, this points to the necessity of incorporating fundamental valuation in future research of market efficiency. When estimating horizon values, Skogsvik and Skogsvik (2010) utilized an exogenous estimate based on fundamental analysis from precedent research by Runsten (1998) on Swedish data. However, since no comparative method of estimating horizon values is presented, whether the observed mispricing in Skogsvik and Skogsvik (2010) was dependent on estimations of horizon values through fundamental analysis remains unanswered.

2.3.2. Applying the RIV Model in Fundamental Valuation

There are multiple equity valuation models, the dividend discount model (DDM) presumably being the most renowned. The RIV model (operationalized by Skogsvik & Skogsvik, 2010) is an alternative model that was first proposed by Preinreich (1938), Edwards and Bell (1961), Ohlson (1995), as well as Feltham and Ohlson (1995). The established version estimates the value of owners' equity as the current book value plus the net present value of residual income (also referred to as abnormal earnings). Assuming the clean surplus relation holds (the change in book value of owners' equity is solely a result of the periods' earnings plus dividends net of capital contributions), the RIV model depicted below can be derived from the DDM:

$$V_0 = B_0 + \sum_{t=1}^{\infty} \frac{B_t \cdot (ROE_t - \rho)}{\prod_{t=1}^{t}(1+\rho)} \qquad (2)$$

where:

V_0 = value of owners' equity at time 0,

B_t = book value of owners' equity in period t,

ROE_t = return on owners' equity in period t,

ρ = discount rate, and

$(ROE_t - \rho)$ = residual income (or abnormal earnings) in period t.

The sophistication of the RIV model is corroborated by Penman and Sougiannis (1998) who argue that a model which incorporates accrual earnings and book values generates less valuation errors compared to dividends and cash flows. Dechow et al. (1999) in turn finds only minor empirical evidence of the RIV model's superiority compared to the dividend-discount model, although states that the characteristics of the RIV model in terms of both incorporating book values and earnings makes it a useful framework for future research. Penman (1991) argues for ROE being a sound complement to solely using earnings, due to book values being informative about the transitory nature of earnings. Furthermore, Penman (2013) supports valuation models that consist of residual income in combination with book values (such as the RIV model), due to the consistency with the "value conservation principle". More specifically, Penman (2013) states that:

> "An accounting method that changes current book value changes future residual income, but it does not change the value calculated because the change in residual income is exactly offset, in present value terms, by the change in current book value." (Penman, 2013, p. 558).

Similarly, Francis et al., (2000) state the benefit of valuation models such as RIV to be rooted in containing both a stock component (book value) and a flow component (earnings), as opposed to other "pure flow-based models" (e.g., the dividend-discount model and the free cash flow model). In summary, the RIV model may serve as a sophisticated valuation model due its connection between firm value and accounting information (Ohlson, 1995; Penman, 2013, page. 161), and its empirically ascertained robustness (Penman & Sougiannis, 1998; Jorgensen et al., 2011; Anesten et al., 2020).

2.3.3. Horizon Values in Fundamental Valuation

When engaging in fundamental valuation, it might pose a problem to utilize extensive explicit forecast horizons, since financial information such as earnings may be difficult to accurately forecast beyond a certain point in time. Alternatively, one might truncate the valuation model through a horizon value beyond the explicit forecast period, based on the assumption that the firm will grow at a constant rate in perpetuity (Penman, 1998). One way of constructing such a truncated valuation model is to utilize the Gordon-growth formula which was developed by Shapiro (1956) and Gordon (1959) and involves estimating the value of a company based on expected future dividends:

$$V_T = \frac{DIV_1}{\rho - g} \qquad (3)$$

where:

V_0	= value of owners' equity at time 0,
DIV_1	= expected net dividend distributed to shareholders next period,
ρ	= rate at which future dividends are discounted, and
g	= expected perpetual growth rate of future dividends.

Notably, this model is only applicable when the discount rate exceeds the growth rate. Furthermore, since the horizon value may account for a significant part of the estimated value of a firm (Francis et al., 2000; Jorgensen et al., 2011), this infers that thoughtful consideration of the variables in this section is essential. In precedent research that utilize fundamental valuation (e.g., Kaplan & Ruback, 1995; Penman & Sougiannis, 1998; Francis et al., 2000) estimations of horizon values are, however, often made with arbitrary assumptions of perpetual growth rates. Undoubtedly, this constitutes a parsimonious approach to fundamental valuation, which Penman (2013, p. 92) defines as a method with a limited amount of information-gathering, although with sound practical relevance due to its simplicity. Simultaneously, parsimonious methods are criticized for not being rooted in fundamental analysis, but rather on ad hoc long-term forecasts of certain value drivers (Penman, 1998; Skogsvik & Skogsvik, 2010). An alternative approach to the Gordon-growth formula that allows for a more thoughtful consideration of horizon values was proposed by Skogsvik (1998). Consider the following expression of the RIV model (Brief & Lawson, 1992, as cited in Skogsvik, 1998) when utilizing an explicit forecast horizon and a horizon value (denoted as $V_T - B_T$ in the RIV model):

$$V_0 = B_0 + \sum_{t=1}^{T} \frac{B_t \cdot (ROE_t - \rho_E)}{\prod_{t=1}^{t}(1 + \rho_E)} + \frac{V_T - B_T}{\prod_{t=1}^{T}(1 + \rho_E)} \tag{4a}$$

To estimate this horizon value in the RIV model, Skogsvik (1998) defines a so called "goodwill-to-book ratio" ($q(B)_T$), referred to as a "valuation measurement bias of owners' equity" (which is a ratio of the book value of owners' equity (B_T)):

$$q(B)_T = \frac{V_T - B_T}{B_T} \rightarrow V_T - B_T = B_T \cdot q(B)_T \tag{4b}$$

Which can be incorporated into the RIV model as follows:

$$V_0 = B_0 + \sum_{t=1}^{T} \frac{B_t \cdot (ROE_t - \rho_E)}{\prod_{t=1}^{t}(1 + \rho_E)} + \frac{B_T \cdot q(B)_T}{\prod_{t=1}^{T}(1 + \rho_E)} \tag{4c}$$

This expression of the horizon value component ($q(B)_T$) can further be decomposed into two parts, the business goodwill ($q(BG)_t$) and the cost matching bias ($q(CMB)_t$):

$$q(B)_T = q(BG)_T + q(CMB)_T \tag{5}$$

The business goodwill component is a result of the expected future financial performance of the firm, i.e., projects that have expected positive net present values. The cost matching bias in turn stems from the present accounting regime, macro-economic conditions (e.g., historical inflation), and firm characteristics (Skogsvik, 1998). More specifically, the cost matching bias stems from the concept of conventional accounting, which inherently is characterized by a number of principles that exist in order for the accounting regime to describe an entity in a relevant, yet reliable way. Relevant accounting conventions has led to measurement principles characterized by objectivity and reliability. This entails prudence through undervaluing assets and overvaluing liabilities, which is associated with conservative accounting. Further, conventional accounting is associated with historical cost accounting (HCA), that partly entails booking assets to historical acquisition-values with linear depreciation (Runsten, 1998). While the difference between the market value and book value of owners' equity as a result of business goodwill partially diminishes over time, the difference that stems from the cost matching bias is considered permanent. This can facilitate the estimation of the goodwill-to-book ratio at the horizon point in time as it is solely comprised of the cost matching bias, assuming a competitive economic environment and a "large" value of T (Skogsvik, 1998).

A study which early on conducted an estimation of the cost matching bias was the one by Fruhan (1979). More specifically, Fruhan adjusted book values of owners' equity for estimated replacement cost of long-lived assets and the capitalization of expensed investments in research and development (R&D) and marketing. This was done for 72 "high performing" US firms that consistently earned a ROE above the cost of equity capital. Runsten (1998) later developed a more extensive method to calculate the cost matching bias, partially based on Fruhan's (1979) methodology and refers to the goodwill-to-book ratio that only consists of the cost matching bias as the permanent measurement bias (PMB). The magnitude and implications of the PMB in a valuation context further differs depending on industry due to variations in innate business activities. Therefore, Runsten (1998) conducted industry-specific PMB estimations for 16 industries on Swedish data using historical financial statement information. The PMB is also hypothesized to differ considerably between firms in different countries due to differences in inflation, taxes, business cycles, and exchange rates (Runsten, 1998).

2.4. Contribution

In this thesis, market mispricing in the US is investigated through an investment strategy in the spirit of Skogsvik and Skogsvik (2010). To do so, horizon values in the RIV model are subsequently estimated through fundamental analysis of the goodwill-to-book ratio as outlined in Skogsvik (1998). This allows for a more precise comparison with Skogsvik and Skogsvik (2010) where horizon values were estimated based on fundamental analysis from research by Runsten (1998). Given that Skogsvik and Skogsvik (2010) elaborates on precedent research (e.g., Ou & Penman, 1989; Holthausen & Larcker 1992; Greig 1992; Stober 1992; Setiono & Strong 1998; Abarbanell & Bushee 1998) through a consideration of modelling mispricing, a cross-national and timewise comparison is arguably a valuable contribution. Precedent research attempting to replicate Skogsvik and Skogsvik (2010) on US data has instead utilized a method of estimating horizon values based on reverse-engineering through stock prices (Motzet & Schwarzenberg, 2016). While this is a simpler method, it is arguably contradictory when investigating market mispricing as stock prices are assumed to be sound estimates of fundamental values which constitutes an information perspective. However, given the utility of this parsimonious method due to its simplicity, it may still have relevance in the practical field. In an attempt to investigate the discrepancy between practical relevance and theoretical soundness, this study also contributes by conducting a comparison between a method of estimating horizon values based on fundamental analysis and a method of reverse-engineering horizon values through stock prices. Such a comparison has, to our knowledge, not previously been conducted in a market mispricing setting. Ultimately, this comparison may bring economic significance due to the pervasiveness of parsimony when estimating horizon values in both precedent research and amongst practitioners (Penman, 1998; Penman & Sougiannis, 1998; Skogsvik & Skogsvik, 2010).

2.5. Challenges in Investigating Market Mispricing

Precedent research has investigated mispricing cross-nationally and over time. However, there are certain challenges related to conclusions of market mispricing and subsequent suggestions of how to adjust the method accordingly which are discussed in this section.

2.5.1. Risk-Adjustments of Investment Returns

Notable in section 2.2, there is a pervasive discussion of how to properly risk-adjust the investment returns. Several studies investigating market efficiency utilize the capital asset pricing model (CAPM) as developed by Sharpe (1964) and Lintner (1965). There are however those who oppose this model, such as Fama and French (2004) due to its alleged poor empirical observations. Fama and French (2004) state that the model may display poor empirical performance due to (1) over-simplified assumptions that inhibit theoretical logic, and (2) difficulties in implementing the model in a proper manner. As an extension to elaborate on the alleged oversimplicity of the CAPM, Fama and French (1992) developed the three-factor model, of which CAPM is used as the foundation but also considers two additional factors which they consider to be sound proxies for risk. These are the size factor (market value of owners' equity) and the growth-versus-value factor (the book value divided by the market value of owners' equity).

2.5.2. Transaction Costs and Technical Limitations of Investment Positions

Investment strategies are associated with transaction costs, which most precedent studies do not consider. Ou and Penman (1989) have alluded the exclusion of transaction costs to the low degree of portfolio re-balancing. Ball (1994), however, states that such activities only constitute one of two relevant factors. Depending on the complexity of the model, the activity of designing and subsequently managing the strategy may not constitute an insignificant cost either. Accounting for this factor in practice, is however more difficult. Further, these effects have presumably decreased over time. According to French (2008), trading costs have decreased by approximately 60% between the year 1980 and 2006. Another challenge relates to the short positions, as the activity of short-selling firms may be associated with significant costs and/or, depending on the country and time period, regulatory restrictions. Further, the availability of executing short positions may depend on firm size and the demand (Grünewald et al., 2010).

2.5.3. Causality and Limitations of Independent Variables

Several precedent studies have utilized independent variables which have no direct link to earnings (e.g., Ou & Penman, 1989; Abarbanell & Bushee, 1998), or arguably a mere dubious link to fundamental analysis such as analyst forecasts (e.g., Stober, 1992). In terms of accounting ratios which do not have a direct relation to earnings, some of these have been found to be redundant to implement in an investment strategy compared to solely using a variable with a direct link to earnings, although not for certain specific predictions (Skogsvik, 2008). Further, there are contrasting arguments in previous studies of which accounting ratios truly have value relevance (Abarbanell & Bushee, 1998). Thus, due to the discrepancies of alleged causality in precedent research, out-of-sample inferences regarding mispricing may be hampered when utilizing independent variables that can be argued to not have a direct link to earnings of the firm.

3. METHODOLOGY

To investigate market mispricing over time, investment strategies are deployed on the US market between 1983–2021. Each position is held for 36 months, and the last position is taken in 2018 (evaluated until 2021). Twelve periods are considered in total, each comprised of a model estimation period and an investment period. Further, two investment strategies are considered. First, a "base case strategy", utilized by Skogsvik (2008) in the spirit of Ou and Penman (1989), based on logistical regression to predict future increases in ROE. Second, an "indicator variable strategy", incorporating the market's expectation of future ROE, in the spirit of Skogsvik and Skogsvik (2010).

Since the study by Skogsvik and Skogsvik (2010) serve as a foundation to this thesis, our research design closely follows their methodology. In addition, to investigate the effect of different methods of estimating horizon values, two methods are considered. First, an estimation of the permanent measurement bias (PMB) through fundamental analysis, henceforth denominated as the 'sophisticated method'. Second, based on reverse-engineering through stock prices, henceforth denominated as the 'parsimonious method'. Table 1 reports an overview of the time period included in this study, and the respective estimation and investment periods. The time period overlaps with that of Skogsvik and Skogsvik (2010), although extended to cover the period 1983–2021.

Table 1: Data Sample

Period	Estimation periods	No. obs (No. firms)	Investment periods	No. obs
I	1972–1979	2,218 (759)	1983–1985	1,992
II	1975–1982	2,654 (697)	1986–1988	1,768
III	1978–1985	3,551 (640)	1989–1991	1,658
IV	1981–1988	3,483 (642)	1992–1994	1,687
V	1984–1991	3,198 (596)	1995–1997	1,580
VI	1987–1994	2,939 (491)	1998–2000	1,283
VII	1990–1997	2,899 (368)	2001–2003	1,007
VIII	1993–2000	2,846 (307)	2004–2006	832
XI	1996–2003	2,620 (258)	2007–2009	699
X	1999–2006	2,332 (231)	2010–2012	644
XI	2002–2009	2,001 (214)	2013–2015	590
XII	2005–2012	1,735 (209)	2016–2018	574

The table shows the time periods used to estimate the accounting-based prediction model and the evaluation periods of the investment strategies. Each position is taken at the end of the third month after the fiscal year-end each year within the investment period based on the same estimation period and held for 36 months. Number of observations in the column after estimation periods refers to the number of firm-year observations used to estimate the regression models. Number of firms in parentheses refers to the number of unique firms. Number of observations in the column after the investment periods refers to the number of firm-year observations used in the investment strategies for each period.

3.1. Accounting-Based Prediction Model

To develop the accounting-based prediction model, a univariate model using the return on owners' equity (ROE) as the independent variable is deployed. The prediction model is estimated using logistic regression where the probability of an increase in the medium-term ROE was estimated using the past average historical ROE. Logistic regression uses binary variables as the dependent variable to estimate the probability of the event occurring. In this instance, a binary variable is used which takes the value 1 when the change in medium-term ROE for firm i is positive, and zero otherwise. The change in average ROE for each firm-year observation in the sample is calculated as:

$$\Delta(\overline{ROE}_{i,mt}) = \overline{ROE}_{i,f} - \overline{ROE}_{i,h} \tag{6}$$

where:

$$ROE_{i;t} = \frac{Earnings_{i;t}}{B_{i;t-1}}$$

$$\overline{ROE}_{i;\,f} = \frac{ROE_{i;\,t+1} + ROE_{i;\,t+2} + ROE_{i;\,t+3}}{3}$$

$$\overline{ROE}_{i;h} = \frac{ROE_{i;\,t-2} + ROE_{i;\,t-1} + ROE_{i;\,t}}{3}$$

The logistic regression estimates the probability of an increase in the medium-term ROE ($\Delta(ROE_{mt})$) for each individual firm using the coefficients from the linear combination between historical ROE and the medium-term ROE as:

$$\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot \overline{ROE}_h)}} \tag{7}$$

The logistical regression is estimated over a period of 8 years, starting in 1972–1979. Data is pooled over firms and over time, which increases the information included in the estimated parameters (Ou & Penman, 1989). Investment positions are then taken for three years based on each estimation period. The first position is taken four years after the last year of the estimation period to ensure no information included when estimating the prediction model is used as inputs when estimating out-of-sample probabilities. For example, the estimation period 1972–1979 are used to form investment positions in 1983, 1984, and 1985 and the input variable ($\overline{ROE}_h$) is calculated based on ROE in 1980–1982, 1981–1983 and 1982–1984.

Each estimation period contains a non-exhaustive amount of US manufacturing firms. Thus, the proportion of increases/decreases of ROE in the sample might be different from the actual proportion (following Skogsvik and Skogsvik, 2010, we assume 'a priori' probability of 0.5). If not adjusted for, this can bias the result of the prediction model (Palepu, 1986). To adjust for this, the methodology used in Skogsvik and Skogsvik (2010) is followed using the calibration formula developed by Skogsvik (2005):

$$\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)^{adj} = \hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0) \cdot \left[\frac{\pi \cdot (1 - prop)}{prop \cdot (1-\pi) + \hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0) \cdot (\pi - prop)}\right] \quad (8)$$

where:

π = 'a priori' probability of an increase in medium-term ROE (= 0.5),

$prop$ = proportion of increase in medium-term ROE in each sample, and

$\hat{p}(\Delta(\overline{ROE}_{mt}) \geq 0)$ = model-based (unadjusted) probability of an increase in medium-term ROE.

3.2. Indicator Variable Strategy

To incorporate the market's expectation into the investment strategy and thereby allow for an investigation of both forecasting and modelling mispricing (as explained in section 2.3.1), Skogsvik and Skogsvik (2010) deployed the "indicator variable strategy". This is defined as the difference between the market value of owners' equity (P_0) and the 'historically motivated' value of owners' equity (V_0^h) calculated using the residual income valuation (RIV) model ($IND_0 = P_0 - V_0^h$). The horizon value in the RIV model is estimated through the derivation presented in Skogsvik (1998), based on the "goodwill-to-book ratio" ($q(B)_T$) in accordance with Equation 4b. The goodwill-to-book ratio is further comprised of business goodwill and the cost matching bias (see Equation 5). The 'historically motivated' value of owners' equity is estimated using the following formula:

$$V_0^{(h)} = B_0 + \sum_{t=1}^{T} \frac{B_t \cdot (ROE_t - \rho_{E;t})}{\prod_{t=1}^{t}(1+\rho_{E;t})} + \frac{B_T \cdot q(B)_T}{\prod_{t=1}^{T}(1+\rho_{E;t})} \quad (9)$$

where:

$V_0^{(h)}$ = 'historically motivated' value of owners' equity at the investment point in time,

B_0 = book value of owners' equity at the investment point in time,

B_t = book value of owners' equity at time t,

ROE_t = future return on owners' equity at time t,

$\rho_{E;t}$ = required return of owners' equity at time t, and

$q(B)_T$ = goodwill-to-book ratio.

By assuming that the clean surplus relationship holds, the expected book value of equity can be rewritten as $B_t = B_{t-1}(1 + ROE_t - DS_t)$ where DS_t = net dividends at time t divided by the book value of owners' equity at $t-1$. One benefit of using this definition of a 'dividend share' instead of the payout ratio (dividends divided by earnings) is that it avoids the modelling complications when earnings are negative. Assuming that the expected future ROE and the dividend share are constant and equal to the medium-term, the RIV model can be rewritten as:

$$V_0^{(h)} = B_0 + \sum_{t=1}^{3} \frac{B_0(1+\overline{ROE}_h - \overline{DS}_h)^{t-1} \cdot (\overline{ROE}_h - \rho_{E;t})}{\prod_{t=1}^{t}(1+\rho_{E;t})} + \frac{B_0(1+\overline{ROE}_h - \overline{DS}_h)^{3} \cdot q(B_3)}{\prod_{t=1}^{T}(1+\rho_{E;t})} \quad (10)$$

This derivation of the RIV model is useful for modelling purposes since it allows future book values of owners' equity to be estimated based on historical data. It is further assumed that the differences between model-based values of owners' equity and observed stock prices are solely due to differences in expected future ROE. The input values for the RIV model are based on a 3-year historical average for ROE ($\overline{ROE}_h$) and the dividend share ($\overline{DS}_h$). The goodwill-to-book ratio in the horizon point in time ($q(B)_3$) is estimated using both a sophisticated method based on fundamental analysis and a parsimonious method using reverse-engineering based on previous market values of owners' equity (see section 3.3 below for further details). The required return of equity is calculated using the CAPM where β-values have been estimated based on 48 months of trailing data using standard regressions. The required return of equity for each firm i is thus calculated as:

$$\rho_{E;t} = r_{f;t} + \beta_i \cdot \left(E(R_m) - r_{f;t}\right) \quad (11)$$

For firms where 48 months of historical stock returns were not available, the average beta of the sample for that year was used. The risk-free rate ($r_{f;t}$) used for t = 1 is the one-year US bond rate observed at the investment point in time. For t = 2 and t = 3, the observed two-year and three-year US bond rate was used. Lastly, the market risk premium ($E(R_m) - r_f$) was set to 5.5% (Fernandez, et al., 2021).

3.3. Horizon Value in the RIV Model

The horizon value in the RIV model is estimated based on the goodwill-to-book ratio outlined in section 2.3.3. This is a representation of the difference between the market value and book value of owners' equity, in relation to the book value of equity as outlined in Equation 4b. To allow for an evaluation of the usefulness of fundamental analysis as outlined in the beginning of section 3, the goodwill-to-book ratio in the horizon point in time ($q(B)_3$) is estimated using two endogenous approaches, a 'sophisticated method' and a 'parsimonious method'. The sophisticated method involves estimating the cost matching bias for US manufacturing firms using historical financial statement information based on the methodology presented by Runsten (1998). This cost matching bias is referred to as the permanent measurement bias (PMB) by Runsten (1998) and it is defined as the goodwill-to-book ratio that only consists of the cost matching bias as defined in Equation 5. The parsimonious method, in contrast, estimates the current goodwill-to-book ratio using reverse-engineering based on the market value of owners' equity in the period before the investment date (P_{t-1}).

3.3.1. Sophisticated Method of Estimating Horizon Values

The methodology in Runsten (1998) used to estimate the permanent measurement bias (PMB) is based on the 'unbiased' book value of owners' equity. This unbiased value is, in turn, estimated based on the reported book value, adjusted for inflation, and the capitalization of inflation-adjusted expensed investments (e.g. research and development (R&D)). The main source of the PMB for manufacturing firms is likely to result from the historical cost valuation of long-lived assets (i.e., property, plant, and equipment, referred to as 'tangible assets') during periods of high inflation, R&D and marketing expenses not being capitalized, and inventory (Runsten, 1998). Therefore, the estimation of the PMB will focus on these items and associated deferred tax liabilities that arise due to the unrealized holding gains. The amount of accounting bias associated with each asset type is combined for each firm to estimate the unbiased book value of owners' equity and the PMB is subsequently calculated based on the following formula:

$$PMB_T = \frac{\left(B_T^{(r)} + Bias_T\right) - B_T^{(r)}}{B_T^{(r)}} = \frac{B_T^{(UB)}}{B_T^{(r)}} - 1 \qquad (12)$$

where:

PMB_T = permanent measurement bias at time T,

$B_T^{(r)}$ = reported book value of owners' equity at time T,

$Bias_T$ = estimated accounting bias net of additional deferred tax liabilities at time T, and

$B_T^{(UB)}$ = 'unbiased' book value of owners' equity at time T.

Investment positions are taken between 1983–2018. Since the market characteristics are presumably prone to change over time (Runsten, 1998) and to avoid an ex-post bias, the PMB is estimated in 1983, 1992, 2001, and 2010 and subsequently used for the following three investment periods. The sample used in each estimation year include 50 firms with the highest market value of owners' equity three months after the fiscal year-end.

Tangible Assets

The PMB for tangible assets is calculated based on current cost accounting where assets are revalued based on estimated replacement costs. The following assumptions are made: (1) each asset decreases linearly in value each year, (2) firms hold a balanced portfolio of each asset type (meaning the average remaining economic life is approximately equal to half of the economic life), (3) each asset is bought at the beginning of the year and one asset is simultaneously scrapped, (4) all assets have the same economic life, and (5) the salvage value of each asset is zero (Runsten, 1998). The book value is then adjusted for both the depreciation pattern and inflation to estimate the remaining 'current value'. When estimating replacements costs for tangible assets, the Producer Price Index (OECD, 2023) is applied as the inflation rate. The accounting bias related to tangible assets is subsequently the difference between the 'current value' and the book value. More specifically, the portion of the measurement bias adhering to tangible assets for each firm is calculated as:

$$Bias_{TA} = \sum_{t=1}^{T}(CV_t) - BV_{TA}^{(r)} = \sum_{t=1}^{T}\left(\underbrace{\prod_{t=1}^{t}(1 + i_t^{PPI})}_{\substack{inflation \\ component}} \cdot \underbrace{\left(Inv_t \cdot \left(1 - t \cdot \bar{f}\right)\right)}_{\substack{depreciation \\ component}}\right) - BV_{TA}^{(r)} \tag{13}$$

where:

$Bias_{TA}$	= estimated accounting bias of tangible assets at the time of estimation,
$\sum_{t=1}^{T}(CV_t)$	= estimated total 'current value' of tangible assets in the estimation point in time,
$BV_{TA}^{(r)}$	= reported book value of tangible assets in the estimation point in time,
i_t^{PPI}	= annual inflation rate (Producer Price Index) for the period t ($\prod_{t=1}^{t}(1 + i_t^{PPI})$ is the accumulated inflation until period t),
Inv_t	= net investments for period t, and
$\bar{f}$	= estimated annual value decrease of tangible assets (the inverse of which is the assumed economic life of the asset).

The net investments for each period is calculated as the change in tangible assets adjusted for depreciation and impairments $(Inv_t = BV_{TA;t}^{(r)} - BV_{TA;t-1}^{(r)} + Depreciaiton_t + Impairments_t)$. The time period ($T$) goes backwards and is equal to the number of previous years when the accumulated investments equal the reported accumulated acquisition costs of tangible assets. For example, an asset purchased in 1982 would have a t = 1 when estimating the PMB in 1983, an asset purchased in 1981 would have a t = 2, and so on. Furthermore, the annual value decrease ($\bar{f}$) is estimated using the reported book value of tangible assets according to the following equation:

$$\sum_{n=1}^{T}\left(Inv_t \cdot (1 - t \cdot \bar{f})\right) = BV_{TA}^{(r)} \tag{14}$$

Intangible Assets

When a firm invests in R&D and marketing (referred to as 'intangible assets'), a PMB may arise when these are expensed rather than capitalized (Runsten, 1998). For intangible assets, we assume: (1) the economic life of investments in R&D is seven years and three years for marketing, (2) expenditures have been made at the beginning of each year, (3) the new intangible assets are amortized linearly over the same period (Runsten, 1998). This means that the intangible assets are also comprised of a balanced portfolio (average remaining economic life is approximately equal to half of the economic life). The 'current value' of the intangible assets is then calculated by capitalizing historical expenses and adjusting for amortization and inflation. The inflation applied for intangible assets is the Consumer Price Index (OECD, 2023), and since there is no book value for these 'assets', the measurement bias is equal to the 'current value':

$$Bias_{IA} = \sum_{t=1}^{T}\left(\underbrace{\prod_{t=1}^{t}(1 + i_t^{CPI})}_{\substack{inflation \\ component}} \cdot \underbrace{\left(I_t \cdot \frac{T-t}{T}\right)}_{\substack{amortization \\ component}}\right) \tag{15}$$

where:

$Bias_{IA}$	= accounting bias for investments in 'intangible assets' that were previously expensed (IA = R&D or marketing),
i_t^{CPI}	= annual inflation rate (Consumer Price Index) for the period t ($\prod_{t=1}^{t}(1 + i_t^{CPI})$ is the accumulated inflation until period t),
I_t	= investment (expenditure) in 'intangible assets' in period t,
T	= economic life for 'intangible assets', and
$T - t$	= remaining economic life of 'intangible assets'.

Inventory

According to Runsten (1998), the accounting bias for inventory may be significant depending on the accounting principle and the nature of the business. While Runsten (1998) does not outline a detailed methodology for estimating this accounting bias, the study states that it may be substantial for manufacturing firms since large amounts of inventory may be held. Before these goods are sold, an accounting bias is present due to the value added by the firm's manufacturing process (Runsten, 1998). Since US GAAP also allows firms to utilize the LIFO method when accounting for inventory (Robinon et al., 2020), there might be utility in considering the PMB related to this line-item since the LIFO method can lead to lower book values when prices increase over time.

For manufacturing firms, inventory is often comprised of raw materials, work-in-progress, and finished goods. These items are measured at the lower of cost, market value, or net realizable value depending on what valuation method is applied (Robinon et al., 2020). Inventory is assumed to remain on the books for one year and since raw materials have not yet been affected by any value added from the manufacturing process, it has no accounting bias. Work-in-progress and finished goods on the other hand can be expected to have an accounting bias as the firm transforms raw materials into finished goods which are sold at a 'mark-up'. Work-in-progress is assumed to constitute a balanced portfolio, and 50% of the mark-up the firm charges is therefore applied. For finished goods, 100% of the mark-up is applied. This mark-up is in turn calculated as the operating profit (EBIT) divided by the cost of goods sold. Lastly, to estimate the accounting bias based on a uniform set of accounting principles, if the LIFO method was used to account for inventory, it is calculated to FIFO using the LIFO reverse. The proportion allocated to work-in-progress and finished goods is based on the respective components' share of total inventory. The PMB for inventory is thus calculated as:

$$Bias_{Inv} = \frac{\left(\frac{EBIT}{COGS} \cdot Inv_{WIP}^{(r)}\right)}{2} + \frac{EBIT}{COGS} \cdot Inv_{FG}^{(r)} \qquad (16)$$

where:

$Bias_{Inv}$ = accounting bias for inventory,

$Inv_{WIP}^{(r)}$ = reported book value of the 'work-in-progress' component,

$Inv_{FG}^{(r)}$ = reported book value of the 'finished goods' component, and

$\frac{EBIT}{COGS}$ = mark-up charged by the firm.

Deferred Tax Liabilities

Each accounting bias is associated with a deferred tax liability (DTL) due to the unrealized holding gain. This DTL is a representation of the additional future tax reductions that would have been available to the firm if the accounting bias had been included on the balance sheet. These DTL are calculated as the reversal of the accounting bias times the statutory tax rate and due to this time lag, the DTL is adjusted by the time value of money, discounted at the cost of debt after tax (Runsten, 1998). The reversal is in turn based on the remaining useful life of the corresponding asset (i.e., as the asset is depreciated/amortized). For inventory, the tax benefits would instead arise due to a larger cost of goods sold and the reversal time is assumed to be one year. Because a linear depreciation and amortization was assumed for tangible and intangible assets, a linear pattern for the reversal of deferred tax liabilities is also assumed. The present value of the DTL is calculated using the present value of annuity formula:

$$DTL_k = \left(\underbrace{\frac{Bias_k \cdot \tau}{n}}_{\substack{annual\ reversal \\ of\ DTL}} \right) \cdot \left(\underbrace{\frac{1 - \left(\frac{1}{(1 + r_D)^n} \right)}{r_D}}_{\substack{present\ value \\ of\ an\ annuity}} \right) \tag{17}$$

where:

DTL_k	= present value of additional deferred tax liability due to the accounting bias estimated for asset k,
$Bias_k$	= accounting bias estimated for asset k,
n	= expected reversal time of the additional deferred tax liability,
τ	= tax statutory tax rate at the time of estimation, and
r_D	= cost of debt after tax at the time of estimation.

Permanent Measurement Bias

An 'incremental PMB' is subsequently estimated for each component and for each firm based on the accounting bias and the associated deferred tax liabilities as follows:

$$PMB_k = \frac{BV_k^{(r)} + Bias_k - DTL_k}{B_0^{(r)}} - 1 = \frac{BV_k^{(UB)}}{B_0^{(r)}} - 1 \tag{18}$$

where:

PMB_k	= estimated 'incremental PMB' for asset type k (k = tangible assets, R&D, marketing, or inventory),
$BV_k^{(r)}$	= reported book value for asset type k,
DTL_k	= associated deferred tax liability for asset type k,
$B_0^{(r)}$	= reported book value of owners' equity, and
$BV_k^{(UB)}$	= estimated unbiased book value of asset type k.

To estimate the total PMB directly (as in Equation 12), the unbiased book value of equity for each firm is required. This is estimated by adding the accounting bias for each asset, net of DTL, to the reported book value. By using Equation 18 instead, the 'incremental PMB' for each component can be estimated which allows for firms where data is missing for some of the PMB components to be included. The median value of each component is then added to generate a sample-representative estimate of the PMB as follows:

$$PMB_T^* = median(PMB_{Tangible\ assets}) + median(PMB_{R\&D}) + median(PMB_{marketing}) + median(PMB_{Inventory}) \quad (19)$$

where:

PMB_T^* = estimated total PMB for the sample.

The reason for using the median value is to remove the effects of outliers (Runsten, 1998). As previously mentioned, the goodwill-to-book ratio consists of both business goodwill and the cost matching bias, while business goodwill can be assumed to be zero at the horizon point in time, given a sufficiently large value of T (in Equation 9). However, empirical evidence for US firms indicates that the erosion-process of business goodwill takes between five to six years (Penman, 1991, as cited in Skogsvik & Skogsvik, 2010). Since the medium-term of 3 years will be used, this indicates that part of the goodwill-to-book ratio that stems from business goodwill still persists at the horizon point in time. Therefore, following Skogsvik and Skogsvik (2010), the goodwill-to-book ratio of owners' equity at t = 3 is estimated through a weighting formula consisting of the price-to-book factor $(P_0/B_0 - 1)$ and the PMB-factor $(V_T/B_T - 1 = PMB_T)$, where T in V_T/B_T refers to a horizon point in time where business goodwill is assumed to be zero:

$$q(B_3) = (1 - \omega) \cdot (P_0/B_0 - 1) + \omega \cdot (PMB_T) \quad (20)$$

By assuming that business goodwill diminishes linearly over six years, the weight (ω) is consequently set to 0.5. The goodwill-to-book ratio in the horizon point in time is therefore calculated as $(1 - 0.5) \cdot (P_0/B_0 - 1) + 0.5 \cdot (PMB_T)$, when using the sophisticated method of estimating horizon values.

3.3.2. Parsimonious Method of Estimating Horizon Values

Horizon values are also estimated using an alternative approach of reverse-engineering based on market values to allow for an assessment of the utility of fundamental analysis. This was previously utilized by Motzet and Schwarzenberg (2016) to test market mispricing using the indicator variable strategy. Motzet and Schwarzenberg (2016) estimated the goodwill-to-book ratio based on the previous year's market value of owners' equity. Instead of the 'historically motivated' value of owners' equity (V_0^h), the previous year's market value (P_{t-1}) is used in Equation 10. This is henceforth referred to as the 'parsimonious method' of estimating horizon values. The accounting numbers used in the model are also based on information available one year prior. This formula estimates the goodwill-to-book ratio directly at the investment date, and no weighting-procedure in accordance with Equation 20 is applicable. Interestingly, Penman (2013, p.491–492) proposes a similar approach to estimate the perpetual growth rate based on current market values. However, using current market values when deploying the indicator variable strategy would not be feasible, as it would generate an indicator variable of zero (since 'historically motivated' value of owners' equity would equal observed market value). While the parsimonious method is arguably simpler and less resource-intense, the effectiveness can be questioned due to not anchoring the estimation on accounting numbers but rather market values directly which constitutes an 'information perspective'.

3.4. Investment Positions

Investment positions are taken three months after the fiscal year-end to ensure that all information used in the strategies are available for each firm. While this time-lag has presumably decreased over time, it is utilized nonetheless to simplify comparability with Skogsvik and Skogsvik (2010). Each position is held for 36 months, equal to the time it takes for the result of the prediction of change in ROE to be made apparent. In spirit of Skogsvik and Skogsvik (2010), this thesis aims to analyze both forecasting and modelling mispricing. To achieve this, investment positions are first taken based solely on the accounting-based prediction model as deployed in Skogsvik (2008), referred to as the base case strategy. This involves taking a long position if the estimated probability of an increase in ROE ($\hat{p}(\Delta(\overline{ROE}_{mt}) > 0)$) is above 0.5, and a short position if it is below 0.5. Using this method, forecasting mispricing is investigated. To further investigate modelling mispricing, the indicator variable strategy is used. This strategy combines the accounting-based prediction model and the market's expectation of the development of medium-term ROE when taking investment positions. The indicator variable as calculated in section 3.2 shall be interpreted as follows:

- If the 'historically motivated' value of owners' equity is higher than the current market value, ($IND_0 < 0$), the market is said to have a 'negative outlook' and expects the future ROE to be lower than the historical ROE.
- If the 'historically motivated' value of owners' equity is lower than the current market value, ($IND_0 > 0$), the market is said to have a 'positive outlook' and expects the future ROE to be higher than the historical ROE.
- If the 'historically motivated' value of owners' equity is equal to the current market value, ($IND_0 = 0$), the market is said to have a 'neutral outlook' and expects the future ROE to be equal to the historical ROE.

The following decision rules, summarized in Table 2, are then applied when taking investment positions based on the indicator variable strategy:

- If the indicator variable is negative (the market has a negative outlook), and the accounting-based prediction model indicates an increase in medium-term ROE, a long position is taken.
- If the indicator variable is positive (the market has a positive outlook), and the accounting-based probabilistic prediction model does not indicate an increase in medium-term ROE, a short position is taken.

- If the indicator variable is zero, the accounting-based prediction model is the sole determining factor if a long or short position is taken.

When the indicator variable is close to zero, the implication of either a negative or a positive market outlook is questionable. Further, the scenario that the indicator variable equals exactly zero is exceptionally low. Therefore, following Skogsvik and Skogsvik (2010) a certain interval based on the book value of owners' equity is utilized where the indicator variable is considered zero for the purpose of determining investment positions. These intervals are $[-0.1 \cdot B_0;\ +0.1 \cdot B_0]$ ('narrow zero interval'), $[-0.2 \cdot B_0;\ +0.2 \cdot B_0]$ ('medium zero interval'), and $[-0.4 \cdot B_0;\ +0.4 \cdot B_0]$ ('wide zero interval'). Notably from Table 2, the wider the zero interval, the more firms will be classified as either long or short since if the indicator variable is zero, a position is always taken.

Table 2: Investment criteria for the indicator variable strategy

		Accounting-based probability of an increase in ROE	
		$\hat{p}(\Delta(\overline{ROE}_{mt}) > 0) > 0.5$	$\hat{p}(\Delta(\overline{ROE}_{mt}) > 0) < 0.5$
Indicator variable	$IND_0 < 0$	Long position*	(—)
	$IND_0 = 0$	Long position	Short position
	$IND_0 > 0$	(—)	Short position*

*Positions are also taken if the accounting-based probability is equal to 0.5.

3.5. Evaluating the Returns of the Investment Strategies

In this section, the return metrics used to evaluate the investment strategies are presented. The return metrics considered are (1) the abnormal CAPM return, (2) a market-adjusted 'statistical return metric' useful for comparison with precedent studies, and (3) a market-adjusted 'realistic return metric' which corresponds to a more implementable strategy.

3.5.1. Abnormal CAPM Returns

The first return metric used to evaluate the performance of the investment strategies is the abnormal CAPM returns, also known as Jensen's alpha. Average monthly portfolio abnormal returns (returns in excess of the risk-free rate) for each month and year have been regressed on the market risk premium. The intercept measures the abnormal return (α) of the portfolio while the coefficient for the market risk premium measures the beta value. The long, short, and hedged portfolios are analyzed using the following regression:

$$\bar{R}^{exc}_{(.);z} = \alpha_{(.)} + \beta_{(.)} \cdot \left(R_{M;z} - R_{f;z}\right) + \tilde{\varepsilon}_{(.);z} \qquad (21)$$

where:

$\bar{R}^{exc}_{(H);z} = \bar{R}_{(L);z} - \bar{R}_{(S);z}$= average portfolio excess return to the hedged position in month z,

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

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

$R_{m;z}$ = market return for month z,

$R_{f;z}$ = risk-free rate for month z, and

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

As an extension of the abnormal CAPM, the three-factor model developed by Fama and French (1992), is also utilized to analyze how the abnormal monthly returns are affected by risk proxies. In addition to the market risk premium, a multivariate regression is conducted that also includes the "size factor" (market value of owners' equity) and the "growth-to-value factor" (book value to market value of owners' equity)[1]:

$$\bar{R}^{exc}_{(.);z} = \alpha_{(.)} + \beta_{1;(.)} \cdot \left(R_{M;z} - R_{f;z}\right) + \beta_{2;(.)} \cdot SMB_z + \beta_{3;(.)} \cdot HML_z + \tilde{\varepsilon}_{(.);z} \quad (22)$$

where:

SMB_z = "small minus big", is the average return for small portfolios minus the average return for big portfolios in month z, and

HML_z = "high minus low", is the average return of value portfolios minus the average return on growth portfolios in month z.

The abnormal CAPM returns, and the three-factor model have only been estimated for December year-end firms and each regression contain 1,296 observations (36 investment dates with 36 monthly returns each). Any remaining receipts from securities being delisted were reinvested in the market index for the remaining months.

3.5.2. Statistical Return Metric

To further evaluate the investment strategies, a market-adjusted return metric used by Ou and Penman (1989) as well as Skogsvik and Skogsvik (2010) is used. The market-adjusted return for the 36-month holding period is calculated as the average return for all positions taken. Only firms that have been listed throughout the entire 36-month holding period are included. Furthermore, non-December year-end firms are included in the return metric. Market-adjusted returns are then calculated as follows:

$$\overline{MJBH}'_{(H);36} = \overline{MJBH}'_{(L);36} - \overline{MJBH}'_{(S);36} \quad (23)$$

[1] The SMB factor and HML factor were retrieved from Kenneth R. French's (2016) database: (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html).

$$\overline{MJBH'}_{(L);36} = \frac{1}{N_{(L)}} \sum_{i=1}^{N_{(L)}} \left[\left(\prod_{z=1}^{36} \left(1 + R_{i;\,z}\right) - \prod_{z=1}^{36} \left(1 + R_{m;z}\right) \right) \right] \tag{24}$$

$$\overline{MJBH'}_{(S);36} = \frac{1}{N_{(S)}} \sum_{i=1}^{N_{(S)}} \left[\left(\prod_{z=1}^{36} \left(1 + R_{i;z}\right) - \prod_{z=1}^{36} \left(1 + R_{m;z}\right) \right) \right] \tag{25}$$

where:

$\overline{MJBH'}_{(.);36}$ = market-adjusted buy-and-hold return at the end of month $z = 36$ (H = hedged position, L = long position, and S = short position),

$R_{i;z}$ = return on stock i in month z,

$R_{m;z}$ = return on the market index in month z, and

$N_{(.)} = \sum_{t=1983}^{2018} N_{(.);t}$ = number of stocks in the position over the periods 1983–2018 (L = long position and S = short position).

This formula implies that all positions taken between 1983–2018 are equally weighted, i.e., that the amount invested is the same in each position taken. Therefore, to know the amount to invest each year, foreknowledge of future trading signals is required. This means that the statistical return metric evaluates a non-implementable investment strategy (Holthausen & Larcker, 1992; Skogsvik, 2008). However, this metric is used as it allows for a better comparison with precedent research. To test the statistical significance of the statistical return metric, the following regression is conducted:

$$MJBH'_{i;36} = \beta_0 + \beta_1 \cdot D_{i;0}^{Str(.)} + \tilde{\varepsilon}_i \tag{26}$$

where:

$MJBH'_{i;36} = \prod_{z=1}^{36}\left(1 + R_{i;z}\right) - \prod_{z=1}^{36}(1 + R_{m;z})$, and

$D_{i;0}^{Str(.)}$ = binary variable equal to 1 if the investment strategy classified the stock as a short position and 0 if it was classified as a long position (H = hedged position, L = long position, and S = short position).

In this regression model, the intercept (β_0) corresponds to the market-adjusted return to the long position and the coefficient for the binary variable (β_1) is the market-adjusted return to the hedged position multiplied by (-1). To also test the statistical return metric's sensitivity to risk proxies, a multivariate regression analysis following Skogsvik and Skogsvik (2010) is also conducted. Each variable has been calculated as the arithmetic average (denominated as "$\overline{...}$") of the variable based on the investment point in time, 12 months after, and 24 months after. The following regression is tested:

$$\begin{aligned} MJBH'_{i;36} = \beta_0 + \beta_1 \cdot D_{i;0}^{Str(.)} + \beta_2 \cdot \overline{\ln\left((B/M)_{i;0}\right)} + \beta_3 \cdot \overline{(E/P)}_{i;0} \\ + \beta_4 \cdot \overline{(D/P)}_{i;0} + \beta_5 \cdot \overline{\ln\left(MV_{i;0}\right)} + \tilde{\varepsilon}_i \end{aligned} \tag{27}$$

where:

$\ln((B/M))_{i;t}$ = natural logarithm of book value divided by market value of owners' equity for the firm i at time t,

$(E/P)_{i;t}$ = earnings per share for the period t divided by stock price at the end of the period for the firm i,

$(D/P)_{i;t}$ = dividend per share for period t divided by stock price at the end of the period for the firm i, and

$\ln(MV_{i;t})$ = natural logarithm of market value of owners' equity for firm i at the investment point in time.

Following previous research (e.g., Holthausen & Larcker, 1992; Skogsvik, 2008), these additional variables have been mean-adjusted each individual year.

3.5.3. Realistic Return Metric

An alternative to the statistical return metric is the realistic return metric utilized by Skogsvik and Skogsvik (2010). This is only calculated for December year-end firms and any remaining receipts from securities being delisted are reinvested in the market index. This corresponds with an implementable strategy and the returns are calculated as:

$$MJBH_{(H);36} = MJBH_{(L);36} - MJBH_{(S);36} \tag{28}$$

$$MJBH_{(L);36} = \frac{1}{36}\sum_{t=1983}^{2018}\frac{1}{N_{(L);t}}\sum_{i=1}^{N_{(L);t}}\left[\left(\prod_{z=1}^{36}(1+R_{i;z}) - \prod_{z=1}^{36}(1+R_{m;z})\right)\right] \tag{29}$$

$$MJBH_{(S);36} = \frac{1}{36}\sum_{t=1983}^{2018}\frac{1}{N_{(S);t}}\sum_{i=1}^{N_{(S);t}}\left[\left(\prod_{z=1}^{36}(1+R_{i;z}) - \prod_{z=1}^{36}(1+R_{m;z})\right)\right] \tag{30}$$

where:

$MJBH_{(.);36}$ = realistic market-adjusted buy-and-hold return to the position after 36 months (H = hedged position, L = long position, and S = short position), and

$N_{(.);t}$ = number of stocks included in the position during year t (L = long position and S = short position).

This return metric is used to calculate the market-adjusted return as an equally weighted average for each year and equally over time. Therefore, the amount of trading signals does not impact the amount invested each year, and it does not require foreknowledge of future trading signals to invest. Instead, it is assumed that an equal amount is used in the investment strategies each year.

4. DATA

4.1. Data Collection and Sample Selection

All accounting data was gathered from COMPUSTAT while the stock price data was retrieved from CRSP. Accounting data was gathered between 1960–2021. To estimate the logistical regressions for the accounting-based prediction model, data between 1969–2018 was required, an additional three years were collected to verify the prediction. The estimation of the permanent measurement bias (PMB) in turn required data back to 1960 to accurately estimate the accounting bias related to long-lived assets. For the stock prices, data between 1979–2021 was collected. To calculate the returns to the investment strategies, data between 1983–2021 was required while the 48 months trailing beta calculations required data back to 1979. The stock returns used were the total monthly returns, adjusted for dividends, buybacks, and splits.

The sample of firms was limited to the manufacturing sector, for multiple reasons. First, since the studies Skogsvik (2008) as well as Skogsvik and Skogsvik (2010) constitute a foundation for this thesis and both exclude other sectors, doing the same improves comparability. Second, applying an investment strategy to a sector-heterogenous sample would demand that representative PMB-estimates are performed for different sectors separately, since they have been found to vary significantly depending on innate business activities (Runsten, 1998). Performing sector estimations of the PMB is not considered a reasonable approach for an investment strategy of this kind, since if done extensively would arguably be too time-consuming for it to have practical relevance. Furthermore, to mitigate risks of subconsciously picking favorable firm-specific data, the industry SIC-codes by French (2016) have been utilized. The SIC-codes included were limited to only capture manufacturing firms. More specifically, the sectors included comprise: Machinery, Trucks, Planes, Chemicals, Off-Furniture, Paper, and Commercial Printing[2].

Apart from the beta values estimated from the stock price, the risk-free rate was required to estimate the required return of equity according to the CAPM model (see Equation 11 in section 3.2). Therefore, the one-, two-, and three-year US bond rates (monthly) were retrieved from CapitalIQ between 1983–2018. When calculating market-adjusted returns, the S&P 500 Composite Index was used. This was retrieved from CRSP and since the total stock returns were used for the individual firms, an index adjusted for reinvested dividends was used as well. Furthermore, the market index used was also value-weighted since this arguably constitutes a better proxy for the overall US stock market than an equally weighted market index. When estimating the PMB, inflation data was also required and the producer price index (PPI) and the consumer price index (CPI) between

[2] The SIC codes included are: 2520–2589, 2600–2699, 2750–2769, 2800–2829, 2840–2899, 3000–3099, 3200–3569, 3580–3629, 3700–3709, 3712–3713, 3715–3715, 3717–3749, 3752–3791, 3793–3799, 3830–3839, and 3860–3899.

1960-2010 were retrieved from OECD. For the PMB estimation, the statutory tax rate was also required to estimate the deferred tax liabilities. The US statutory corporate tax rate of 46% in 1983, 34% in 1992, and 35% in 2001 and 2010 was retrieved from Internal Revenue Service (IRS).

4.2. Sample Adjustments

Subsequent to retrieving data from COMPUSTAT, CRSP, and the other databases, some adjustments to the dataset were made. First, firms with negative book value of owners' equity were dropped from the sample. US GAAP permits firms to report negative equity (in contrast with IFRS). Naturally, ROE is not a relevant measure if the denominator is negative. Therefore, these firms were excluded from the sample. Second, firms with an observed ROE of $\pm$ 100% were also dropped from the sample, since not doing so would presumably include firms with a book value of equity close to zero which arguably will report a non-representative ROE for manufacturing firms. Third, firms in the top and bottom one-percentile of market value to book value of owners' equity (price-to-book ratio) were dropped from the sample. The reasoning behind removing the top percentile is that solely firms with 'low-to-reasonable' price-to-book ratios can be included for it to be inferred that business goodwill no longer exist in six years' time. The bottom percentile was also removed to ensure that only mature and stable firms were included in the sample. Fourth, firms with a nonsensical dividend share (exceeding 100% of equity) were excluded from the sample. Fifth, firms where data was unavailable for 14 consecutive years (three years before to three years after each estimation period) were dropped from that estimation period. Each estimation period is 8 years, and the calculation of historical ROE requires data for three years before the estimation period ends (see section 3.1). Data for three years after the estimation is also required as input for the independent variable of the accounting-based prediction model to estimate the probability of an increase in ROE (Equation 7). An overview of the number of observations in the estimation periods and the investment periods is available in Table 11 (Appendix B).

5. RESULTS

This section presents the descriptive statistics for the sample, the estimation results and accuracy of the accounting-based prediction model, the estimation of the goodwill-to-book ratio, and the returns to the investment strategies.

5.1. Descriptive Statistics and Prediction Performance

5.1.1. Base Case Strategy

Table 3 presents the descriptive statistics for the variables used to estimate the prediction model. The estimation result of the accounting-based prediction model is presented in Table 10 (Appendix A). The coefficient for $\overline{ROE}_h$ is consistently negative and statistically significant in all periods, which means that the higher the historical ROE, the lower the probability of a future increase in ROE, and vice versa. This indicates that ROE follows a mean-reversion process over time which is consistent with precedent research (Freeman et al., 1982; Skogsvik, 2008; Skogsvik & Skogsvik, 2010).

Table 3: Descriptive statistics of historical, forward, and medium-term ROE

Period	Years	No. obs	$\overline{ROE}_h$		$\overline{ROE}_f$		$\overline{ROE}_{mt}$	
			Mean	Median	Mean	Median	Mean	Median
I	1972–1979	1,251	0.117	0.123	0.138	0.142	0.020	0.014
II	1975–1982	2,429	0.138	0.140	0.125	0.133	-0.014	-0.009
III	1978–1985	3,178	0.140	0.145	0.113	0.128	-0.027	-0.019
IV	1981–1988	3,004	0.126	0.137	0.100	0.118	-0.026	-0.021
V	1984–1991	2,806	0.110	0.123	0.090	0.108	-0.021	-0.016
VI	1987–1994	2,587	0.102	0.115	0.096	0.110	-0.006	-0.011
VII	1990–1997	2,521	0.107	0.114	0.109	0.118	0.002	-0.006
VIII	1993–2000	2,417	0.116	0.122	0.123	0.129	0.008	-0.002
XI	1996–2003	2,191	0.134	0.137	0.102	0.108	-0.032	-0.030
X	1999–2006	1,973	0.113	0.117	0.097	0.103	-0.017	-0.018
XI	2002–2009	1,737	0.108	0.110	0.106	0.112	-0.003	-0.005
XII	2005–2012	1,528	0.121	0.119	0.119	0.122	-0.002	-0.001
All periods		27,622	0.119	0.123	0.110	0.118	-0.010	-0.010

The table shows the variables used for estimating the accounting-based prediction model for an increase in ROE. Number of observations refer to firm-year observations used in each estimation period.

The sophistication of the prediction model was assessed by calculating the out-of-sample prediction accuracy over time, presented in Table 4. The average accuracy was 65.2% for all investment periods (1983–2018). Moreover, in contrast with Skogsvik and Skogsvik (2010), the prediction model has been significantly more accurate in predicting increases in ROE with 68.0% accuracy for all investment periods, compared to 61.5% for decreases.

Further, the accuracy of the prediction model for predicting both increases and decreases in ROE has worsened over time. However, in some periods the accuracy is statistically insignificant, which is intriguing since it does not seem to be explained by abnormalities in the number of observations nor prediction accuracy within these periods. Furthermore, when not utilizing the calibration formula in Equation 8, the prediction of increases in ROE had an accuracy of 59.8% while decreases 70.4% (the overall accuracy is in this case was 65.8%). Interestingly, this is in contrast with Skogsvik and Skogsvik (2010), in which the calibration formula generated an improvement of the prediction performance.

Table 4: Out-of-sample prediction accuracy for the accounting-based prediction model

Period	Years	Number of observations			Correctly predicted			χ^2	p-value
		Total	Inc.	Dec.	Total	Inc.	Dec.		
I	1983–1985	1,534	626	908	62.2%	72.0%	55.4%	43.68	(0.000)
II	1986–1988	1,309	654	655	63.9%	74.3%	53.6%	60.96	(0.000)
III	1989–1991	1,349	400	949	66.0%	83.0%	58.8%	73.42	(0.000)
IV	1992–1994	1,369	737	632	71.2%	82.4%	58.2%	96.67	(0.000)
V	1995–1997	1,256	642	614	67.2%	62.9%	71.7%	10.86	(0.001)
VI	1998–2000	1,007	281	726	69.8%	51.6%	76.9%	61.33	(0.000)
VII	2001–2003	848	295	553	62.5%	68.5%	59.3%	6.89	(0.009)
VIII	2004–2006	675	448	227	68.4%	76.8%	52.0%	42.91	(0.000)
XI	2007–2009	597	182	415	66.2%	67.0%	65.8%	0.09	(0.766)
X	2010–2012	575	331	244	66.4%	64.7%	68.9%	1.11	(0.292)
XI	2013–2015	515	187	328	59.4%	47.6%	66.2%	17.02	(0.000)
XII	2016–2018	489	260	229	58.9%	65.4%	51.5%	9.66	(0.002)
All periods		11,523	5,043	6,480	65.2%	68.0%	61.5%	101.50	(0.000)

The table shows the prediction accuracy for the accounting-based prediction model, which is measured as the correctly identified increases or decreases in ROE for the investment positions taken during each period. Only firms that remain listed over the 36-month holding period are included in the accuracy calculations. The accuracy reported for all periods is the equally weighted accuracy of period I–XII. χ^2-values are from a 2–2 contingency table test.

5.1.2. Indicator Variable Strategy

Table 13 (Appendix D) presents the mean and median values of $\overline{ROE}_h$, $\overline{ds}_h$, beta value, required return of equity, and the goodwill-to-book ratio for both methods used to estimate horizon values. The goodwill-to-book ratio when using the sophisticated method is considerably lower than when using the parsimonious method. Two possible explanations for this difference are that the market is implicitly assuming (1) a more substantial business goodwill component and/or (2) a higher cost matching bias component in the horizon point in time (see Equation 5).

5.2. Horizon Value in the RIV Model

5.2.1. Sophisticated Method

The result of the sophisticated method to estimate the permanent measurement bias (PMB) using fundamental analysis is presented in Table 5 together with summary statistics of the relevant factors affecting the PMB. The estimated PMB was 0.42 in 1983, 0.31 in 1992, 0.26 in 2001, and 0.18 in 2010, respectively. When estimating the PMB of inventory, the mark-up charged by firms was calculated over a five-year period. The same approach was also used when estimating the cost of debt. This was done to mitigate the effect of outliers. The estimated PMB for the samples were then used in accordance with Equation 20 to estimate the goodwill-to-book ratio in the horizon point in time ($q(B)_3$).

Table 5: PMB estimated for US manufacturing firms in 1983, 1992, 2001, and 2010

Source of the accounting bias	1983	1992	2001	2010
Tangible assets	0.25 (47)	0.08 (47)	0.04 (47)	0.05 (50)
R&D activity	0.13 (43)	0.14 (37)	0.14 (41)	0.08 (46)
Marketing	0.03 (19)	0.06 (14)	0.06 (10)	0.02 (14)
Inventory	0.02 (29)	0.03 (31)	0.02 (37)	0.02 (43)
Permanent measurement bias	0.42	0.31	0.26	0.18
Summary statistics				
Solvency	51.7%	44.8%	36.1%	39.3%
Statutory tax rate	46.0%	34.0%	35.0%	35.0%
PPI, 10 years avg.	9.8%	1.8%	1.4%	3.4%
CPI, 7 years avg. (3 years avg.)	8.7% (10.0%)	3.9% (4.8%)	2.5% (2.4%)	2.6% (2.1%)
Useful life of tangible assets	15.5	15.8	13.2	13.8
Tangible assets, % of total assets	43.5%	41.2%	26.1%	19.2%
R&D, % of total assets	2.8%	2.6%	2.4%	1.7%
Marketing, % of total assets	1.8%	4.4%	4.5%	1.4%
Inventory, % of total assets	18.7%	14.5%	11.6%	10.5%
Mark-up	13.3%	17.1%	18.0%	17.8%
Cost of debt before tax	12.2%	11.0%	8.5%	6.6%

The table presents the estimated PMB based on 50 US manufacturing firms with the largest market value of owners' equity three months after the fiscal year-end in the sample used in the investment strategies, reported net of additional deferred tax liabilities. The number of observations for each component is reported in parentheses. Solvency and the useful life of tangible assets is the median of the sample. Tangible assets-, R&D-, marketing-, and inventory as a percentage of total assets is the median of the sample. For R&D- and marketing expenses as a percentage of total assets, the value is calculated based on a 7- and 3-year historical average, based on the assumed useful life. The mark-up is calculated as the operating profit for the period divided by the cost of goods sold and the value presented is the median of a 5-year average for the sample. The cost of debt before tax is estimated as the 5-year historical average of interest expenses divided by the opening balance of interest-bearing debt. The inflation rate applied to estimate replacement costs is the Producer Price Index (PPI) for tangible assets and the Consumer Price Index (CPI) for intangible assets (R&D and marketing).

Notably, the composition of the PMB as well as its magnitude has changed substantially over time. The reason for this change is multifaceted and depends on the individual components of the PMB: (1) Tangible assets: the drop in the PMB for tangible assets is due to its decreased proportion of the balance sheet and the decreased inflation over the estimation periods. (2) R&D activity: before 2010, the PMB related to R&D was stable due to the consistent R&D expenses in relation to total assets. While inflation was high in the earlier periods and later decreased, it did not have a substantial impact on the PMB for R&D due to its shorter assumed useful life compared to tangible assets. This is also the case for the PMB related to marketing. (3) Marketing: the relatively short assumed useful life of marketing expenditures makes the incremental PMB related to marketing inherently volatile since only considers expenses occurred within the last two years. (4) Inventory: while the inventory share of total assets has decreased, the mark-up used to estimate the PMB has also increased over the same period for the sample, causing the PMB to remain stable. Furthermore, certain firm characteristics have also changed over time, which has affected the estimated PMB. More specifically, solvency has decreased, which has a positive effect on the PMB. The decrease in cost of debt subsequently decreases the effect of the time value of money and therefore increases the deferred tax liability associated with the accounting bias which has a negative effect on the PMB.

5.2.2. Parsimonious Method

To allow for an evaluation of the usefulness of fundamental analysis in estimating the goodwill-to-book ratio, a parsimonious method was also utilized. This method involves solving for the goodwill-to-book ratio from the RIV model as outlined in section 3.3.2 and is similar to the methodology of Motzet and Schwarzenberg (2016). The result from the parsimonious estimation of the goodwill-to-book ratio is presented in Table 12 (Appendix C). The average and median goodwill-to-book ratio was 1.34 and 0.68 over the entire investment period. Notably, especially in the later periods, the goodwill-to-book ratio estimated through the parsimonious method is substantially higher compared to the sophisticated method.

5.3. Evaluation of Investment Returns

In this section, the returns from the investment strategies – the base case and the indicator variable strategy – are evaluated using the return metrics presented in section 3.5. A ‘perfect foresight strategy’ (in the spirit of Ball and Brown, 1968) is also included as a benchmark. The investment criteria are similar to the base case strategy, but foreknowledge of the outcome of ROE is used instead of the prediction model. In the case of the indicator variable strategy, each return metric is presented for both the sophisticated method and the parsimonious method when estimating horizon values. By comparing the returns of the indicator variable strategy between the two methods, the usefulness of fundamental analysis in estimating horizon values can be assessed.

Table 13 (Appendix D) presents the summary statistics for the investment period. The 'historically motivated' value to book value of owners' equity is consistently below the price-to-book ratio, indicating that the RIV model considers the market to be overvalued on average. The adjusted probability of an increase in ROE using the calibration formula (Equation 8) has an average and median value of above 0.5, indicating that the prediction model tends to indicate an increase in ROE on average.

5.3.1. Abnormal CAPM Returns

Table 6 presents the monthly abnormal CAPM returns for the base case and perfect foresight strategies. The base case strategy does not generate a statistically significant monthly abnormal return to the hedged portfolio, while the perfect foresight strategy generated an average monthly abnormal return of 1.0% to the hedged portfolio, although driven entirely by the long positions. Since each investment position is evaluated over a 36-month holding period and the investment period covers 36 years, a total of 1,296 observations is included in the abnormal CAPM regressions for each investment strategy.

Table 6: Monthly abnormal CAPM returns over 36-month holding period (1983–2021)

Investment strategy	Position	α	β
Perfect foresight	Long	0.012	0.528
		(0.000)	(0.000)
	Short	0.002	0.500
		(—)	(0.000)
	Hedge	0.010	0.028
		(0.000)	(0.431)
Base Case Strategy	Long	0.006	0.474
		(0.000)	(0.000)
	Short	0.006	0.312
		(—)	(0.002)
	Hedge	0.000	0.162
		(—)	(0.000)

The table shows the α and β estimated according to Equation 21 for the perfect foresight strategy and the base case strategy. The α is the abnormal return and β is the beta of the position. P-values are reported below in parentheses. For the long and hedged position, the null hypothesis that α is non-positive is tested against the alternative hypothesis that α is positive. For the short position, the null hypothesis that α is non-negative is tested against the alternative hypothesis that α is negative. The p-value is omitted if the sign of α is inconsistent with the alternative hypothesis. For the β, the t-tests are two-tailed.

Table 7 reports the abnormal CAPM returns for the indicator variable strategy, using both the sophisticated method based on fundamental analysis and the parsimonious method utilizing reverse-engineering as outlined in section 3.3.1 and 3.3.2. The return to the hedged portfolio from the sophisticated method for the narrow zero interval of the indicator variable strategy is 0.3% and statistically significant. This corresponds with a 36-month abnormal CAPM return of 11.4% (calculated as $(1 + 0.003)^{36} = 1.114$). Using the parsimonious method, no statistically significant abnormal return for the entire investment period is observed. A breakdown of the abnormal CAPM returns for the two methods into two subperiods (1983–2003 and 2001–2021) is also presented in Table 14 and 15 (Appendix E and F). In the first subperiod between 1983–2003, the sophisticated method yields a higher and more statistically significant abnormal return than the parsimonious method. Furthermore, in the second subperiod between 2001–2021, the parsimonious method yielded no abnormal returns regardless of zero interval. On the other hand, the sophisticated method generated a small abnormal return although statistically insignificant (p-values of 0.114, 0.119, and 0.205 for the three variations of the indicator variable strategy). Moreover, Table 16 (Appendix G) offers a more granular breakdown of the abnormal CAPM returns when using the sophisticated method.

Table 7: Monthly abnormal CAPM returns over 36-month holding period (1983–2021)

Investment strategy	Position	Sophisticated method (1983–2021)		Parsimonious method (1983–2021)	
		α	β	α	β
Indicator variable strategy					
Zero interval for IND_0: $[-0.1 \cdot B_0, 0.1 \cdot B_0]$	Long	0.009	0.511	0.007	0.402
		(0.000)	(0.000)	(0.000)	(0.000)
	Short	0.006	0.307	0.007	0.329
		(—)	(0.002)	(—)	(0.001)
	Hedge	0.003	0.203	0.001	0.073
		(0.008)	(0.003)	(0.281)	(0.253)
Zero interval for IND_0: $[-0.2 \cdot B_0, 0.2 \cdot B_0]$	Long	0.008	0.519	0.007	0.451
		(0.000)	(0.000)	(0.000)	(0.000)
	Short	0.006	0.298	0.007	0.333
		(—)	(0.002)	(—)	(0.001)
	Hedge	0.002	0.222	0.001	0.119
		(0.030)	(0.001)	(0.283)	(0.039)
Zero interval for IND_0: $[-0.4 \cdot B_0, 0.4 \cdot B_0]$	Long	0.008	0.492	0.007	0.448
		(0.000)	(0.000)	(0.000)	(0.000)
	Short	0.006	0.302	0.007	0.327
		(—)	(0.002)	(—)	(0.001)
	Hedge	0.002	0.190	0.001	0.121
		(0.042)	(0.000)	(0.234)	(0.018)

The table shows the α and β estimated according to Equation 21 for the indicator variable strategy where the α is the abnormal return and β is the beta of the position. Both the fundamental analysis method and the parsimonious method of estimating the permanent measurement bias are included. P-values are reported below in parentheses. For the long and hedged position, the null hypothesis that α is non-positive is tested against the alternative hypothesis that α is positive. For the short position, the null hypothesis that α is non-negative is tested against the alternative hypothesis that α is negative. The p-value is omitted if the sign of α is inconsistent with the alternative hypothesis.

Notably, from Table 16 (Appendix G) a statistically significant abnormal return is generated during 1983–1997, but subsequently disappears for all succeeding years, except for 2001-2009, a period which was, however, completely dependent on the long portfolio. Furthermore, the abnormal CAPM returns have been further analyzed using the three-factor model proposed Fama and French (1992). This involves assessing the returns' sensitivity to risk and the result of this analysis is presented in Table 17 (Appendix H) for the indicator variable strategy. Overall, the abnormal CAPM returns decreased and the coefficients for the size and book-to-market ratio were statistically significant for the hedged position for all variations of the indicator variable strategy between 1983–2021. This indicates that part of the abnormal return during this period is affected by the risk proxies. In fact, the only statistically significant abnormal return for the three-factor model was between 1983–2003 for the narrow zero interval of 0.3% (p-value of 0.028).

5.3.2. Statistical Return Metric

The statistical return metric when using the sophisticated method of fundamental analysis is presented in Table 8. The average market-adjusted return for the hedged portfolio is 37.7%, 32.5%, and 24.8% for the three zero intervals, which all exceed the base case strategy of 13.0%. Interestingly, the returns to the base case strategy are almost perfectly equal between the long and short position between 1983–2021. For the indicator variable strategy, however, the long portfolio is the driver of the return during this period. Further, the returns to the long and short position are dramatically different in the first subperiod compared to the second. In the first subperiod, the return of the short portfolio is negative for all investment strategies, while all being positive in the second. This poor development for the short portfolio is ultimately outweighed by significantly more impressive returns to the long portfolios in the second subperiod, causing the hedge portfolio return to increase for all strategies (except the perfect foresight) in the second subperiod.

In contrast with the impressive returns when utilizing a sophisticated method, the parsimonious method based on reverse-engineering generated lower, although statistically significant returns. The statistical return metric yielded 15.4%, 15.4%, and 14.4% for the three variations of the indicator variable (p-value of 0.000), respectively. These returns were also affected by risk proxies, similar to the sophisticated method.

The statistical significance of the statistical return metric and its sensitivity to risk was tested through Equations 26 and 27 for the sophisticated method based on fundamental analysis of horizon values. These results are presented in Table 18 (Appendix I) for the indicator variable strategy. The return to the long and hedged portfolios were statistically significant for all investment strategies between 1983–2021. This confirms the results of the abnormal CAPM returns that there is mispricing between 1983–2021 when not considering risk proxies. When controlling for risk proxies in accordance with Equation 27, the statistical return metric seems to be sensitive to risk, similar to the abnormal CAPM returns. The coefficients for the long and hedged positions changed dramatically and the coefficients for certain risk proxies were statistically significant (earnings-to-price ratio, dividend yield, and size). These are further analyzed in section 6.

Equation 26 and 27 were also tested for the perfect foresight and base case strategies to test their statistical significance and their sensitivity to risk proxies. Both strategies had statistically significant returns to the long and hedged portfolio in the univariate regression. For the multivariate regression, only the returns for the perfect foresight strategy remained stable while the base case strategy was affected by risk proxies.

Table 8: Statistical return metric for the 36-month holding period (1983–2021)

Investment strategy	Position	No. obs	1983–2003	2001–2021	1983–2021
Perfect foresight	Long	5,043	0.187	0.494	0.291
	Short	6,480	-0.346	0.035	-0.229
	Hedge	11,523	0.533	0.459	0.519
Base case strategy	Long	6,046	-0.074	0.368	0.065
	Short	5,477	-0.179	0.172	-0.064
	Hedge	11,523	0.105	0.196	0.130
Indicator variable strategy					
Zero interval for IND_0:	Long	2,398	0.078	0.742	0.261
$[-0.1 \cdot B_0, 0.1 \cdot B_0]$	Short	3,338	-0.213	0.075	-0.116
	Hedge	5,736	0.291	0.667	0.377
Zero interval for IND_0:	Long	2,955	0.048	0.683	0.221
$[-0.2 \cdot B_0, 0.2 \cdot B_0]$	Short	3,719	-0.203	0.094	-0.104
	Hedge	6,674	0.250	0.589	0.325
Zero interval for IND_0:	Long	3,818	0.022	0.556	0.169
$[-0.4 \cdot B_0, 0.4 \cdot B_0]$	Short	4,396	-0.183	0.133	-0.079
	Hedge	8,214	0.204	0.423	0.248

The table shows the statistical return metric from Equation 23, 24, and 25. The return of the hedged portfolio is the difference between the return of the long portfolio and the short portfolio. Only firms listed throughout the 36 months are included in the statistical return metric. Number of observations refer to the period between 1983–2021.

5.3.3. Realistic Return Metric

Table 9 presents the realistic return metric which excludes non-December year-end firms and reinvests delisted firms into the market index. An average 36-month return is generated over the entire investment period of 25.8%, 20.8%, and 15.9% for the three variations of the indicator variable strategy with statistical significance when using the sophisticated method to estimate horizon values. The base case strategy, however, did not generate a statistically significant market-adjusted return. In Table 19 (Appendix J), a breakdown is presented into six smaller periods. The indicator variable strategy generated a positive return between 1983–2015 which disappeared between 2013–2021. The statistical significance, however, was weak for some periods. Further, it is observed that the returns for the short positions worsen significantly in the second subperiod. Between 2013–2021, the short positions do generate a statistically significant return, but this is also coupled with a negative return for the long positions, resulting in an overall negative return for the hedged portfolio. Furthermore, the return to the hedge portfolio in the second subperiod is significantly affected by a return-spike to the long positions between 2001-2009 and the returns between 2001–2015 are entirely dependent on the long portfolio as well. This asymmetry may hamper the reliability of any assessment of market mispricing during the second subperiod and further analysis is conducted in section 6.

For the parsimonious method based on reverse-engineering, the realistic returns between 1983–2021 for the three variations of the indicator variable strategy were 5.1%, 7.4%, and 5.7 (p-value of 0.231, 0.107, and 0.098), respectively. The difference between the two methods was also significant (p-values of 0.001, 0.002, and 0.000).

Table 9: Realistic return metric for the 36-month holding period (1983–2021)

Investment strategy	Position	No.obs	1983–2003	2001–2021	1983–2021
Perfect foresight	Long	3,021	0.166	0.366	0.266
			(0.047)	(0.006)	(0.001)
	Short	3,775	-0.347	-0.048	-0.198
			(0.002)	(0.241)	(0.002)
	Hedge	6,796	0.513	0.414	0.464
			(0.000)	(0.000)	(0.000)
Base case strategy	Long	4,295	-0.072	0.250	0.089
			(—)	(0.047)	(0.158)
	Short	3,493	-0.130	0.191	0.030
			(0.063)	(—)	(—)
	Hedge	7,788	0.058	0.059	0.058
			(0.165)	(0.258)	(0.135)
Indicator variable strategy					
Zero interval for IND_0:	Long	1,573	0.128	0.365	0.247
$[-0.1 \cdot B_0, 0.1 \cdot B_0]$			(0.127)	(0.015)	(0.007)
	Short	2,137	-0.148	0.125	-0.012
			(0.044)	(—)	(0.417)
	Hedge	3,710	0.277	0.240	0.258
			(0.008)	(0.017)	(0.001)
Zero interval for IND_0:	Long	1,961	0.064	0.350	0.207
$[-0.2 \cdot B_0, 0.2 \cdot B_0]$			(0.270)	(0.015)	(0.015)
	Short	2,380	-0.138	0.135	-0.002
			(0.051)	(—)	(0.488)
	Hedge	4,341	0.202	0.215	0.208
			(0.017)	(0.021)	(0.001)
Zero interval for IND_0:	Long	2,578	0.022	0.309	0.165
$[-0.4 \cdot B_0, 0.4 \cdot B_0]$			(0.405)	(0.022)	(0.032)
	Short	2,802	-0.144	0.156	0.006
			(0.045)	(—)	(—)
	Hedge	5,380	0.166	0.153	0.159
			(0.016)	(0.047)	(0.003)

The table shows the realistic return metric from Equation 28, 29, and 30. Only December year-end firms are included and firms that are delisted during the 36-month holding period are reinvested into the market index. The number of observations refers to the number of investment positions between 1983–2021. P-values are reported in parentheses and are based on t-tests with portfolio returns for each year as the underlying observations. For the long and hedged portfolios, the null hypotheses that the returns are non-positive is tested against the alternative hypotheses that the returns are positive. For the short portfolio, the null hypothesis that the returns are non-negative is tested against the alternative hypothesis that the returns are negative. No p-value is reported if the sign of the return is inconsistent with the alternative hypothesis.

6. ANALYSIS

This section discusses the results presented in section 5. First, the investment returns and their implication for market mispricing is discussed. Second, the reliability of estimated horizon values and the utility of fundamental analysis is assessed. Third, additional analysis related to the investment returns is conducted. Lastly, the ability to practically implement the investment strategies is scrutinized.

6.1. Investment Returns and their Implication for Market Mispricing

6.1.1. Perfect Foresight and Base Case Strategy

From Table 8, the market-adjusted 36-month return according to the statistical return metric for the perfect foresight strategy was 29.1%, -22.9% and 51.9% between 1983–2021 for the long, short and hedge portfolios, respectively. As mentioned, the statistical return metric is useful as a comparison with precedent studies, even though it is not an implementable strategy. Unsurprisingly, this strategy generated substantial market-adjusted returns, which corroborates the findings of Ball and Brown (1968) that accounting income numbers (in this case ROE) have value relevance. In comparison, the perfect foresight strategy deployed in Skogsvik (2008) generated even higher returns, although our returns were more evenly distributed between the long and short portfolios.

For the base case strategy, the market-adjusted 36-month return was 10.5% between 1983–2003. This return is inferior to the observed return in Ou and Penman (1989) over the same holding period of 36 months, and this comparatively lower return corroborates precedent research (e.g., Holthausen & Larcker, 1992) that the forecasting mispricing has decreased in the US market over time. Interestingly, the market-adjusted returns in the second subperiod between 2001–2021 for the statistical return metric is approximately twice as high, compared to the first subperiod between 1983–2003. These returns are however fully dependent on the long positions, as well as the aforementioned return-spike between 2001–2009. As for the realistic return metric, the base case strategy barely outperforms the market. Given the prediction model accuracy of 65.2% during the entire investment period, as well as the apparent value-relevance of ROE as indicated by the perfect foresight strategy, the poor performance of the base case strategy in both subperiods is somewhat puzzling.

6.1.2. Indicator Variable Strategy

Similar with findings in Skogsvik and Skogsvik (2010), the indicator variable strategy generated significantly higher returns compared to the base case strategy, regardless of zero interval, return metric, or time period. This clearly points to the superiority of the indicator variable strategy and corroborates the findings in Stober (1992) that incorporating the market's expectation is a valuable component. The statistical return metric generated a 36-month market-adjusted return of 37.7% between 1983–2021 for the indicator variable strategy when using the sophisticated method of estimating horizon values, compared to 13.0% for the base case strategy. This indicates that modelling mispricing has been of more importance than forecasting mispricing to generate the market-adjusted returns. This is in contrast to the findings in Skogsvik and Skogsvik (2010), where forecasting and modelling mispricing seemed to have been of equal importance. For the realistic return metric, the indicator variable strategy generated a 36-month market-adjusted return of 25.8% between 1983–2021, also using the sophisticated method of estimating horizon values through fundamental analysis.

Correspondingly with Skogsvik and Skogsvik (2010), the statistical return metric generated a superior return compared to the realistic return metric. This is not surprising, as the statistical return metric requires foreknowledge of future trading signals, only includes firms listed throughout the entire 36-month holding period and has therefore been argued to inflate returns (Holthausen & Larcker, 1992; Skogsvik, 2008; Skogsvik & Skogsvik, 2010). In terms of the parsimonious method, only the statistical return metric generated a statistically significant market-adjusted return, although still considerably lower compared to the sophisticated method.

As for the abnormal CAPM return metric, the indicator variable strategy using the sophisticated method to estimate horizon values generated an alpha with statistical significance during the entire investment period. Interestingly, when utilizing the parsimonious method of reverse-engineering (ceteris paribus), no alpha was generated. When analyzing more granular time-series breakdowns, it is noted that the parsimonious method indeed generates an alpha during 1983-2003, although only for the narrow zero interval, and less significant than the sophisticated method. Taken at face value, these results indicate that (1) the investment strategy has been able to generate abnormal returns over the 36-year period, and (2) that utilizing fundamental analysis when estimating horizon values was an important component to achieve the abnormal CAPM returns. Notably from Table 14 (Appendix E), the returns are however time-series dependent. In fact, no statistically significant abnormal CAPM return is generated in the second subperiod (2001–2021) regardless of what method is used to estimate horizon values. This points toward a decrease in market mispricing over time. Furthermore, upon closer inspection in Table 16 (Appendix G), the abnormal CAPM returns vanish after 1989–1997, except for the years 2001–2009.

To also investigate if the abnormal CAPM returns were sensitive to risk, the three-factor model was deployed. The results in Table 17 (Appendix H) indicate that the returns were in fact sensitive to both size and the book-to-market ratio between 1983–2021. More specifically, no statistically significant abnormal CAPM return was observed for the entire investment period when adjusting for these risk proxies. The only return that persisted after controlling for the three-factor model was between 1983–2003 for the sophisticated method and the narrow interval. This, combined with an overall weaker significance in the second subperiod, indicates that while the abnormal CAPM returns were sensitive to risk proxies, the observation of a decrease in mispricing still holds.

The market-adjusted returns' sensitivity to risk was also analyzed using the statistical return metric through the multivariate regression in Equation 27. This analysis indicates that the returns were sensitive to the earnings-to-price ratio, dividend yield, and size. Subsequently, the magnitude of these risk-effects was assessed based on Ou & Penman (1989). The sample was subsequently divided into deciles for each year and the average return for the sample was calculated for each decile and year. The market index used in the statistical return metric was then replaced with the average return per decile[3].

The risk-adjusted returns were 26.1%, 24.3%, and 19.9% for earnings-to-price ratio, dividend yield, and size, respectively. Since these returns are substantially lower compared to the market-adjusted statistical return metric of 37.7%, this further corroborates that the market-adjusted returns were affected by certain risk proxies. However, we view this discrepancy with certain skepticism. The market-adjusted returns were calculated based on the value-weighted S&P 500 index which we consider to be the most relevant (see section 4). However, when calculating the risk-adjusted returns, an equally weighted portfolio of the sample was used (equivalent to going long in all firms included in the investment strategies). This implies that part of this difference was due to the change from a value-weighted portfolio to an equally weighted portfolio, and part of it was due to the risk-adjustment. Arguably, a better comparison could be to compare the risk-adjusted returns to that of the market-adjusted returns using the average return of the sample instead of the market index, which was 27.2% between 1983–2021. Based on this analysis, the size-adjustment seems to be the most relevant when adjusting for risk.

6.2. Evaluation of Estimating Horizon Values Through Fundamental Analysis

The results indicate that using the sophisticated method of estimating horizon values through fundamental analysis has been a valuable endeavor. The returns to this method are, overall, more significant, and durable than the parsimonious method of reverse-engineering based on stock prices. This means that the modelling mispricing that was observed through the indicator variable strategy is dependent on the sophisticated method of estimating horizon values. However, the diminishing abnormal CAPM and market-adjusted returns over time as discussed in section 6.1.2 indicate that the modelling mispricing decreased after the period 1989–1997. This corroborates the findings in Skogsvik and Skogsvik (2010) which also used horizon values based on fundamental analysis, although exogenously determined. Ultimately, this highlights the importance of a rigorous method when estimating horizon values as more prolonged and statistically

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[3] Due to the high number of observations with zero dividends, the dividend yield was divided into quantiles to keep the number of observations in each split equal.

significant mispricing was observed when doing so. There are, however, two factors that could inhibit out-of-sample inferences of these findings that are discussed in section 6.3 and 6.4. First, a pervasive positive sentiment bias in the US market, especially prevalent during the second subperiod. Second, since positions were formed each year and held for 36 months, three positions were held simultaneously during most years which could have amplified the statistical significance (Skogsvik & Skogsvik, 2010).

The sophisticated method for estimating horizon values using fundamental analysis is, however, sensitive to certain assumptions that also need to be investigated further. First, the capitalization of R&D and marketing expenses is a major component of the estimated permanent measurement bias (PMB) which in turn is heavily impacted by the assumption of the useful life. The assumed useful life of seven and three years respectively for R&D and marketing is based on Runsten (1998) which is a study conducted on Swedish firms. There is indeed a possibility that this assessment could differ between US and Swedish firms. It is also possible that a shift has occurred in the useful life of R&D and marketing over the estimation period. Second, the composition of the balance sheet has changed over time. Tangible assets and inventory have decreased as a percentage of total assets which implies that the proportion of the balance sheet considered in the PMB estimation has also decreased. Therefore, it is possible that a significant component has been omitted.

6.3. Market Sentiment Bias

For the second subperiod (2001-2021), the returns to the hedged portfolio are highly dependent on the long portfolio, both for the base case strategy and the indicator variable strategy. Intuitively, a more even distribution of market-adjusted returns between the long and short portfolios is to be expected. Indeed, one explanation for this could be a discrepancy in prediction accuracy between increases and decreases in future ROE. However, since the accuracy of predicting decreases in ROE has remained rather flat over time, but the returns of the short positions have completely eroded in some periods, it is clear that this explanation does not suffice (the same observation is made in Skogsvik, 2008). The same conundrum is found for the long positions, since the prediction accuracy has decreased slightly over time, while the returns have increased significantly, especially between 2001–2009. Therefore, one would, as Skogsvik and Skogsvik (2010), want to address any possible sentiment bias at hand, particularly in the second subperiod (2001-2021) due to the significant observed return-asymmetry during these years.

The bulk of the sentiment bias discussed in Skogsvik and Skogsvik (2010) was that increases in ROE following a negative market outlook (negative indicator variable) was found to be more materialized in market reactions than in the opposite scenario (i.e. a decrease in ROE following a positive market outlook). Using the indicator variable strategy in combination with perfect foreknowledge of changes in future ROE, this analysis has been replicated. Similar to Skogsvik and Skogsvik (2010), we indeed find that increases in ROE following a negative market outlook materializes substantially more with an average return of 117.8%, compared to the opposite scenario with an average negative return of 31.3% (in the period 1983–2021 using the statistical return metric and the narrow zero interval). This points to the proposition that the significant discrepancy in market-adjusted returns can be explained by a positive sentiment bias. Arguably, this hampers the validity of out-of-sample inferences about market mispricing (Skogsvik & Skogsvik, 2010). However, the return asymmetry is substantially more prevalent in the second subperiod compared to the first, and the market-adjusted returns to the short positions outperform the long position in the first subperiod (Table 8 and 9). Therefore, we do not find any evidence that a positive sentiment bias has materially affected the result in the first subperiod between 1983–2003.

6.4. Overlapping Data Distributions

To control for the overlapping data distributions, the sample was divided into three subsamples where the investment periods were non-overlapping, following the methodology in Skogsvik and Skogsvik (2010). In each of these subsamples, investment positions were taken every three years instead of every year, so that each subsample only included non-overlapping investment returns. The first subsample included investment positions taken 1983, 1986 and so on until 2016. The second subsample included investment positions taken 1984, 1987 and so on until 2017. The third subsample included investment positions taken 1985, 1988 and so on until 2018. Each return metric was subsequently recalculated for each subsample for the indicator variable strategy.

Table 20 (Appendix K) reports the abnormal CAPM returns for the non-overlapping subsamples between 1983–2021. Ultimately, non-overlapping distributions weakened the statistical significance of the abnormal CAPM returns. In fact, only the first subsample generated a statistically significant return, and only for the narrow zero interval. This indicates that the overlapping data distributions has impacted the statistical significance of the abnormal CAPM returns. Furthermore, when also adjusting for risk proxies in the three-factor model, the statistical significance for the narrow zero interval vanishes.

Table 21 (Appendix L) reports the coefficients for the multivariate regression (Equation 27) using the statistical return metric between 1983–2021. Similar to when using the overlapping sample (results presented in Table 18 in Appendix I), the coefficients for the long and hedged portfolios changed considerably when using the multivariate compared to the univariate (the univariate model was also tested for non-overlapping subsamples and the result did not differ considerably from the overlapping sample). This indicates that the statistical return metric was still affected by risk proxies when utilizing a non-overlapping sample, more specifically the dividend yield and size. Notably, the statistical significance of the earnings-to-price ratio diminished considerably. The remaining statistical significance of the coefficient for dividend yield remains somewhat puzzling, however, given that the significance of the earnings-to-price ratio diminished substantially, and that dividends are essentially paid out earnings (Penman, 2013, p. 266).

The statistical significance of the size coefficient on the other hand, confirms the previous indication that size seems to be a relevant risk proxy for the market-adjusted returns.

Table 22 (Appendix M) reports the realistic return metric for the three non-overlapping subsamples between 1983–2021. The statistical significance is weaker compared to the overlapping sample, although still statistically significant for all subsamples of the narrow and medium zero intervals. This indicates that overlapping data distribution had limited effect on this return metric. Instead, the reduced significance is likely due to the reduced number of observations.

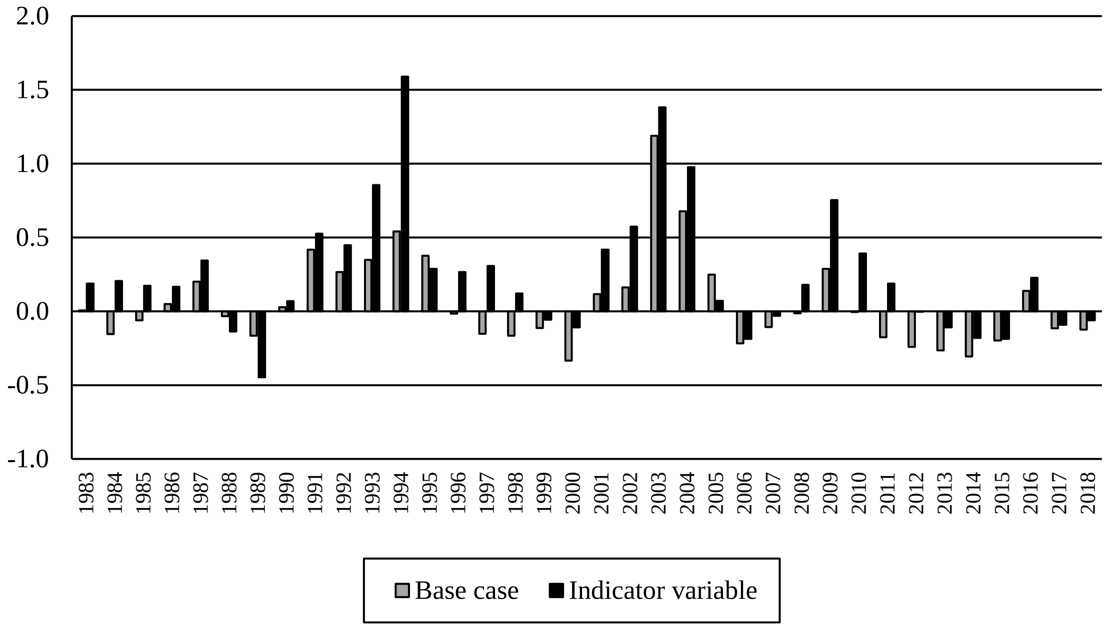
After adjusting for overlapping data distributions, the abnormal CAPM returns vanished when also controlling for the three-factor model, in all periods and for all variations of the indicator variable strategy. The statistical return metric, while still being affected by certain risk proxies, remained statistically significant. For the realistic return metric, the statistical significance diminished, but persisted for most variations of the indicator variable strategy. This indicates that any conclusions of market mispricing in the first subperiod is dependent on the choice of abnormal return metric. For the second subperiod, due to the substantial sentiment bias for the long positions as discussed in section 6.3, no mispricing can be concluded regardless of abnormal return metric.

6.5. Mispricing Due to Market Sophistication and Technical Limitations

This thesis has incorporated an investment strategy that requires a significant amount of data-gathering and statistical models. Naturally, the possibility of replicating such a strategy depends on the access to infrastructure that would make this endeavor possible. Furthermore, data collection and analysis ought to have been more complicated to conduct in earlier periods compared to later periods. Thus, it could be argued that the strategy, due to technical limitations, must have been more complicated in the years leading up to the early 1990s. Presumably, the fact that our market-adjusted and abnormal CAPM returns are higher and more statistically significant in earlier periods supports this proposition. This corroborates the analysis in Skogsvik and Skogsvik (2010) that non-trivial information and data-processing costs have hampered the replicability of an investment strategy incorporating forecasting and modelling mispricing in the early 1980s to mid-1990s, which could explain the impressive returns during this time period. Figure 1 presents the realistic return metric over time. Evidently, the market-adjusted returns to the indicator variable strategy have been periodically impressive, especially during 1991-1994. Indeed, a return spike is prevalent for positions taken between 2001-2004 as well. However, because of the return asymmetry during this period, which cannot be explained by discrepancy in prediction accuracy, this hampers any market mispricing implications.

The proposition that the US market has before the late 1990s been unable to incorporate the combination of forecasting and modelling mispricing overlaps with a large bulk of the relevant literature in the field being published around this time (e.g., Ou & Penman,

Figure 1: Realistic return metric for the hedged position over 36 months (1983–2021)



The graph displays the return to the hedged portfolio for the base case and indicator variable strategy (using the narrow zero interval) over the 36-month holding period.

1989; Holthausen & Larcker 1992; Greig 1992; Stober 1992; Setiono & Strong 1998). Furthermore, it is important to note that the methodology by Runsten (1998) that was used to estimate the PMB was not available until the late 1990s, and data-access was far scarcer during this period as well. It is therefore dubious whether the observed returns constitute market mispricing or have rather been generated as a result of an ex-post bias.

Another necessary topic of discussion relates to transaction costs, which have not been considered when calculating the investment returns. Since this study utilized a 36-month buy-and-hold portfolio, the associated transaction costs for the long positions could arguably be considered trivial. The strategy would however have been rather time-consuming, especially in the earlier periods, given the scarcer access to data as well as significant associated costs in constructing investment strategies. Presumably, this has led to a slight amplification of the investment returns during the first subperiod.

For the short positions, it should be emphasized that the calculation of the returns implicitly assumes that the availability of executing short positions over time is flawless. This may be unrealistic, since some short positions could have been difficult or even outright impossible to execute due to technical limitations, a strong demand amongst short-sellers, and/or regulation. Furthermore, while the direct transaction costs associated with the long positions can be deemed trivial, this may not be the case for the short positions. As some of these inhibiting factors would arguably be especially problematic in the first subperiod, and since the returns to the short positions were better during this time, this presumably means that the returns during earlier periods are somewhat inflated.

7. CONCLUSION

This thesis has investigated market efficiency in the United States between 1983–2021 through deploying investment strategies based on public accounting information. The main strategy, in the spirit of Skogsvik and Skogsvik (2010), has been a self-financing (hedged) portfolio incorporating an accounting-based prediction model, the market's expectation implied in stock prices using the residual income valuation model, and an estimation of horizon values based on fundamental analysis. To evaluate specifically on the usefulness of fundamental analysis to estimate horizon values, an alternative strategy has also been utilized, based on reverse-engineering horizon values through stock prices.

The returns to the strategy when using fundamental analysis to estimate horizon values have been impressive. Over the period 1983–2021, the strategy generated an average market-adjusted 36-month return of 25.8% above the S&P 500 and an abnormal CAPM return equivalent of 11.4%. Intriguingly, when instead utilizing reverse-engineering to estimate horizon values, the statistical significance of both the market-adjusted and abnormal CAPM returns vanished. Upon closer inspection, an erosion of the returns over time is however evident, regardless of method used to estimate horizon values.

Despite an observed decrease in mispricing over time, the market-adjusted returns when using fundamental analysis to estimate horizon values were still statistically significant in later years. The same could however not be observed for the abnormal CAPM returns, which vanished after 1989–1997, regardless of what method was utilized. The returns were however affected by a substantially asymmetrical return spike to the long positions in 2001–2009, which cannot be explained by discrepancy in prediction accuracy. Instead, a positive sentiment bias seems to have been prevalent, which is deemed to hamper the reliability of the market-adjusted returns' persistence and subsequently corroborates the findings in Skogsvik and Skogsvik (2010) of a decrease in market mispricing over time.

When using the three-factor model, the abnormal CAPM returns partially persisted between 1983–2003, but only when using fundamental analysis to estimate horizon values. When further testing for risk and overlapping data distributions, only the market-adjusted returns persisted. This indicates that the mispricing was sensitive to the choice of abnormal return metric. Lastly, the returns during 1983–2003 are presumed to be inflated due to transaction costs, limitations with the short positions, and an ex-post bias.

Conclusively, using a strategy of estimating horizon values through fundamental analysis has generated more significant and prolonged returns compared to a method of reverse-engineering horizon values through stock prices. Given that the mispricing seems to have vanished in later years, this casts doubt on the ability of this investment strategy to detect significant market mispricing in future periods. Nevertheless, the evidence indicates that the relevance of utilizing fundamental analysis when estimating horizon values should not be neglected in future research of market efficiency, nor amongst practitioners.

8. SUGGESTIONS FOR FUTURE RESEARCH

This thesis has investigated the ability of an investment strategy that utilizes public accounting information to generate abnormal returns. We find that a strategy of estimating horizon values through fundamental analysis has generated more significant and prolonged returns compared to a method of reverse-engineering through stock prices, as well as a discontinuance of market mispricing over time. There are, however, three areas which we consider especially intriguing for future research.

First, our findings arguably point to the importance of a rigorous method when estimating horizon values, and the evidence of superior returns compared to an alternative method is not particularly surprising, given that horizon values often account for a substantial portion of the estimated value of a firm (Francis et al., 2000; Jorgensen et al., 2011). A subsequent intriguing question, therefore, is to what degree this is recognized amongst practitioners, and whether the extent of rigorous estimations of horizon values alters depending on what valuation model is utilized. One particular advantage with the RIV model is that it incorporates both a flow-component and a stock-component. In research regarding the practitioners' perspective, however, it is commonly found that pure flow-based models are omnipresent (Demirakos et al., 2010). Furthermore, pure flow-based models may place higher emphasis on horizon values (Penman & Sougiannis, 1998; Francis et al., 2000). It might thus be interesting to investigate how rigorous fundamental analysis of horizon values might be applied in pure flow-based valuation models, such as the free cash flow model or the dividend discount model.

Second, to our knowledge, a rigorous method of estimating the accounting bias similar to Runsten (1998) has not been updated based on any change in accounting regulation and/or change in business activities during the 21st century. Consistent with our findings, this means that there could be a significant component of the PMB that future research might find utility in considering. For example, the composition of the balance sheet has changed considerably over our estimation period. As a result, a possible suggestion for future research would be to do a reassessment of Runsten's methodology to ensure its timeliness. An updated framework may subsequently be applied to an investment strategy to assess whether the mispricing in the United States investigated in this thesis or in Sweden as investigated by Skogsvik and Skogsvik (2010) is prolonged.

Third, our data sample is highly homogenous, as it is limited to manufacturing firms with further data adjustments. Regardless of the soundness behind these decisions (as outlined in section 4), there is a possibility that incorporating other sectors may have generated competing results. Any competing findings that arise as a result of incorporating other sectors would arguably inhibit the validity of any conclusions regarding market efficiency, since the efficient markets hypothesis refers to mispricing in general, and not in a particular sector. Thus, future research might find it valuable to investigate a more industry-heterogeneous sample.

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10. DEFINITIONS

Abnormal CAPM returns	a return metric that calculates the return of a strategy in excess of the risk-free rate, regressed against the market risk premium
Base case strategy	an investment strategy where positions are taken based on a prediction model used to estimate the probability of an increase in ROE
Cost matching bias	the valuation bias of owners' equity stemming from conventional accounting in relation to the book value of owners' equity
Forecasting mispricing	stock prices do not reflect the implications of fundamental analysis (tested through the base case strategy)
Goodwill-to-book ratio	the valuation bias of owners' equity in relation to the book value (comprised of business goodwill and the cost matching bias)
Indicator variable strategy	an investment strategy where positions are taken based on a prediction model and the market's expectation of the development of ROE
Modelling mispricing	stock prices do not reflect the implications of fundamental valuation (tested through the indicator variable strategy)
Parsimonious method	a method of estimating horizon values using reverse-engineering through stock prices
Perfect foresight strategy	an investment strategy where positions are taken based on foreknowledge of future development of ROE
Permanent measurement bias	the goodwill-to-book ratio that only consists of the cost matching bias
Realistic return metric	a return metric where positions are weighted equally within each year and each year is then weighted equally over time (implementable)
Sophisticated method	a method of estimating horizon values through fundamental analysis of historical financial statements
Statistical return metric	a return metric where all positions over the entire investment period are weighted equally (non-implementable)
Zero interval	an interval based on book value of owner's equity where the indicator variable is considered to be zero when determining trading signals

11. APPENDIX

Appendix A

Table 10: Model estimation for the accounting-based prediction model

Period	Years	No.obs	Constant	p-value	$\overline{ROE}_h$	p-value
I	1972–1979	1,251	2.093	(0.000)	-12.710	(0.000)
II	1975–1982	2,429	1.293	(0.000)	-10.913	(0.000)
III	1978–1985	3,178	0.781	(0.000)	-8.840	(0.000)
IV	1981–1988	3,004	0.632	(0.000)	-8.744	(0.000)
V	1984–1991	2,806	0.434	(0.000)	-7.233	(0.000)
VI	1987–1994	2,587	0.708	(0.000)	-9.028	(0.000)
VII	1990–1997	2,521	0.938	(0.000)	-9.797	(0.000)
VIII	1993–2000	2,417	1.084	(0.000)	-9.536	(0.000)
XI	1996–2003	2,191	0.304	(0.000)	-6.918	(0.000)
X	1999–2006	1,973	0.505	(0.000)	-7.692	(0.000)
XI	2002–2009	1,737	0.654	(0.000)	-7.089	(0.000)
XII	2005–2012	1,528	0.777	(0.000)	-6.732	(0.000)

The table shows the estimation results of the univariate prediction model. For the intercept, the null hypothesis that the intercept is negative is tested against the alternative hypothesis that the intercept is non-negative. For the coefficient, the null hypothesis that the coefficient is positive is tested against the alternative hypothesis that the intercept is non-positive.

Appendix B

Table 11: Dataset adjustments for the estimation period

Estimation period	I	II	III	IV	V	VI	VII	VIII	XI	X	XI	XII
Initial firm-year observations	9,744	9,829	9,348	9,108	8,899	8,903	9,060	8,892	8,030	6,860	5,849	5,175
Adjustments												
Firms with negative equity	-280	-367	-378	-499	-698	-862	-912	-996	-1,163	-1,185	-963	-728
Firms with a ROE of ± 100%	-1,067	-900	-1,171	-1,335	-1,467	-1,622	-1,644	-1,407	-978	-774	-667	-601
Firms with extreme P/B ratios	-2,766	-2,657	-2,138	-1,946	-1,815	-1,746	-2,008	-2,431	-2,527	-2,237	-2,013	-1,947
Firms with dividend share above 100%	-130	-135	-164	-220	-253	-230	-187	-120	-80	-44	-47	-46
Data not available for 13 consecutive years	-4,250	-3,341	-2,319	-2,104	-1,860	-1,856	-1,788	-1,521	-1,091	-647	-422	-325
Number of observations used in the regressions	1,251	2,429	3,178	3,004	2,806	2,587	2,521	2,417	2,191	1,973	1,737	1,528

The table shows the number of observations used in the logit regression for each estimation period. Adjustments are made in accordance with the procedure outlined in section 4.2. ROE is the return on owners' equity, P/B is the market value to book value of owners' equity, and dividend share is calculated as the dividend to market value of owners' equity. Extreme P/B ratios are defined as above or below top or bottom one-percentile in the sample.

Appendix C

Table 12: Descriptive statistics for the indicator variable strategy over the investment periods

Period	Years	No. obs	$\overline{ROE}_h$		$\overline{ds}_h$		β		r_E		$q(B)_3^{FA}$		$q(B)_3^{Parsimonious}$	
			Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
I	1983–1985	1,903	0.107	0.118	0.033	0.032	1.057	1.036	0.155	0.153	0.473	0.342	0.615	0.249
II	1986–1988	1,633	0.087	0.110	0.032	0.029	1.012	1.016	0.124	0.124	0.585	0.465	1.338	0.707
III	1989–1991	1,529	0.106	0.123	0.032	0.024	0.982	0.998	0.131	0.133	0.527	0.400	1.092	0.655
IV	1992–1994	1,568	0.071	0.084	0.035	0.025	0.843	0.878	0.088	0.089	0.648	0.480	1.210	0.573
V	1995–1997	1,521	0.112	0.118	0.031	0.019	0.681	0.700	0.095	0.098	0.764	0.586	1.790	0.907
VI	1998–2000	1246	0.136	0.140	0.032	0.021	0.778	0.769	0.097	0.097	0.714	0.497	1.298	0.703
VII	2001–2003	991	0.095	0.103	0.031	0.022	0.634	0.563	0.060	0.057	0.567	0.368	1.027	0.330
VIII	2004–2006	813	0.069	0.080	0.030	0.022	0.898	0.782	0.081	0.077	0.862	0.642	2.324	0.861
XI	2007–2009	669	0.142	0.143	0.034	0.026	1.411	1.347	0.101	0.096	0.746	0.553	1.874	1.294
X	2010–2012	634	0.097	0.104	0.035	0.024	1.529	1.497	0.087	0.085	0.798	0.581	1.412	0.690
XI	2013–2015	569	0.131	0.130	0.036	0.027	1.415	1.382	0.080	0.078	0.944	0.751	1.432	1.113
XII	2016–2018	544	0.091	0.100	0.041	0.029	1.133	1.078	0.075	0.075	1.033	0.780	1.864	1.289
All periods		13,620	0.102	0.113	0.033	0.026	0.968	0.956	0.105	0.105	0.668	0.480	1.341	0.676

The table shows the input variables used for calculating the 'historically motivated' value of owners' equity using the residual income valuation (RIV) model for each investment period. $\overline{ROE}_h$ is the three-year average historical ROE, $\overline{ds}_h$ is the three-year average historical dividend share, β is the 48 months trailing beta, r_E is the one-year required return on equity calculated using the CAPM, $q(B)_3^{FA}$ is the estimated goodwill-to-book ratio at the horizon point in time estimated using fundamental analysis, and $q(B)_3^{Parsimonious}$ is the estimated goodwill-to-book ratio at the horizon point in time estimated using the parsimonious method. The number of observations for $q(B)_3^{Parsimonious}$ is slightly lower than what is reported for the other variables since it is derived using last year' market value of owners' equity which means there is some missing data as some firms were not yet listed (total number of observations is 12,260 between 1983–2018).

Appendix D

Table 13: Summary statistics for the investment periods

Period	Years	No. obs	P_0/B_0		$V_0^{(h)}/B_0$		$\hat{p}(\Delta(\overline{ROE}_h) \geq 0)^{adj}$	
			Mean	Median	Mean	Mean	Median	Mean
I	1983–1985	1,903	1.527	1.263	1.287	1.157	0.562	0.559
II	1986–1988	1,633	1.749	1.510	1.459	1.333	0.587	0.574
III	1989–1991	1,529	1.634	1.379	1.452	1.302	0.550	0.539
IV	1992–1994	1,568	1.986	1.650	1.590	1.354	0.587	0.591
V	1995–1997	1,521	2.218	1.862	1.873	1.623	0.500	0.494
VI	1998–2000	1,246	2.117	1.684	1.923	1.631	0.438	0.419
VII	2001–2003	991	1.875	1.475	1.778	1.461	0.527	0.524
VIII	2004–2006	813	2.464	2.024	1.860	1.528	0.602	0.616
XI	2007–2009	669	2.233	1.846	1.996	1.653	0.482	0.483
X	2010–2012	634	2.415	1.982	1.966	1.564	0.517	0.511
XI	2013–2015	569	2.707	2.322	2.311	1.852	0.461	0.459
XII	2016–2018	544	2.887	2.379	2.193	1.722	0.536	0.535
All periods		13,620	2.010	1.628	1.703	1.423	0.537	0.528

The table shows the summary statistics for each investment period. P_0 is the stock price at the end of the third month after the fiscal-year end, $V_0^{(h)}$ is the 'historically motivated' value of owners' equity when using fundamental analysis to estimate horizon values, B_0 is the book value at the end of the previous fiscal year (three months before P_0) and $\hat{p}(\Delta(\overline{ROE}_h) \geq 0)^{adj}$ is the adjusted probability of an increase in the medium-term ROE.

Appendix E

Table 14: Abnormal CAPM returns to the sophisticated method (1983–2021)

Investment strategy	Position	1983–2003		2001–2021		1983–2021	
		α	β	α	β	α	β
Indicator variable strategy							
Zero interval for IND_0:	Long	0.005	0.745	0.012	0.302	0.009	0.511
$[-0.1 \cdot B_0, 0.1 \cdot B_0]$		(0.012)	(0.000)	(0.000)	(0.069)	(0.000)	(0.000)
	Short	0.001	0.703	0.010	-0.044	0.006	0.307
		(—)	(0.000)	(—)	(0.759)	(—)	(0.002)
	Hedge	0.003	0.042	0.002	0.346	0.003	0.203
		(0.006)	(0.621)	(0.114)	(0.001)	(0.008)	(0.003)
Zero interval for IND_0:	Long	0.003	0.798	0.012	0.272	0.008	0.519
$[-0.2 \cdot B_0, 0.2 \cdot B_0]$		(0.047)	(0.000)	(0.000)	(0.110)	(0.000)	(0.000)
	Short	0.001	0.698	0.010	-0.058	0.006	0.298
		(—)	(0.000)	(—)	(0.689)	(—)	(0.002)
	Hedge	0.002	0.099	0.002	0.329	0.002	0.222
		(0.048)	(0.196)	(0.119)	(0.001)	(0.030)	(0.001)
Zero interval for IND_0:	Long	0.003	0.809	0.012	0.211	0.008	0.492
$[-0.4 \cdot B_0, 0.4 \cdot B_0]$		(0.075)	(0.000)	(0.000)	(0.200)	(0.000)	(0.000)
	Short	0.001	0.729	0.011	-0.076	0.006	0.302
		(—)	(0.000)	(—)	(0.600)	(—)	(0.002)
	Hedge	0.002	0.080	0.001	0.287	0.002	0.190
		(0.033)	(0.228)	(0.205)	(0.000)	(0.042)	(0.000)

The table shows the abnormal CAPM returns from Equation 21 split into two subperiods (1983–2003 and 2001–2021) for the indicator variable strategy when using fundamental analysis to estimate horizon values. P-values are reported in parentheses. See Table 7 in section 5.3.1 for explanation of the t-tests. The p-value is omitted if the sign of α is inconsistent with the alternative hypothesis.

Appendix F

Table 15: Abnormal CAPM returns to the parsimonious method (1983–2021)

Investment strategy	Position	1983–2003		2001–2021		1983–2021	
		α	β	α	β	α	β
Indicator variable strategy							
Zero interval for IND_0:	Long	0.004	0.718	0.011	0.122	0.007	0.402
$[-0.1 \cdot B_0, 0.1 \cdot B_0]$		(0.043)	(0.000)	(0.000)	(0.504)	(0.000)	(0.000)
	Short	0.002	0.755	0.012	-0.049	0.007	0.329
		(—)	(0.000)	(—)	(0.747)	(—)	(0.001)
	Hedge	0.002	-0.037	-0.001	0.171	0.001	0.073
		(0.047)	(0.621)	(—)	(0.093)	(0.281)	(0.253)
Zero interval for IND_0:	Long	0.003	0.767	0.011	0.171	0.007	0.451
$[-0.2 \cdot B_0, 0.2 \cdot B_0]$		(0.067)	(0.000)	(0.000)	(0.336)	(0.000)	(0.000)
	Short	0.002	0.763	0.011	-0.049	0.007	0.333
		(—)	(0.000)	(—)	(0.746)	(—)	(0.001)
	Hedge	0.001	0.004	0.000	0.220	0.001	0.119
		(0.085)	(0.951)	(—)	(0.017)	(0.283)	(0.039)
Zero interval for IND_0:	Long	0.003	0.787	0.012	0.148	0.007	0.448
$[-0.4 \cdot B_0, 0.4 \cdot B_0]$		(0.196)	(0.000)	(0.000)	(0.402)	(0.000)	(0.000)
	Short	0.002	0.751	0.011	-0.049	0.007	0.327
		(—)	(0.000)	(—)	(0.741)	(—)	(0.001)
	Hedge	0.001	0.036	0.000	0.197	0.001	0.121
		(0.178)	(0.561)	(0.392)	(0.015)	(0.234)	(0.018)

The table shows the abnormal CAPM returns from Equation 21 split into two subperiods (1983–2003 and 2001–2021) for the indicator variable strategy when using reverse-engineering to estimate horizon values. P-values are reported in parentheses. See Table 7 in section 5.3.1 for explanation of the t-tests. The p-value is omitted if the sign of α is inconsistent with the alternative hypothesis.

Appendix G

Table 16: Abnormal CAPM returns to the sophisticated method (1983–2021)

Investment strategy	Position	1983-1991		1989-1997		1995-2003		2001-2009		2007-2015		2013-2021	
		α	β	α	β	α	β	α	β	α	β	α	β
Indicator variable strategy													
Zero interval for IND_0:	Long	0.002	0.852	0.002	1.236	0.005	0.560	0.013	0.569	0.017	0.521	0.012	-0.442
$[-0.1 \cdot B_0, 0.1 \cdot B_0]$		(0.271)	(0.001)	(0.266)	(0.000)	(0.086)	(0.004)	(0.000)	(0.018)	(0.002)	(0.085)	(0.015)	(0.213)
	Short	-0.001	1.039	-0.004	1.289	0.002	0.376	0.008	0.365	0.015	-0.184	0.013	-0.508
		(0.407)	(0.000)	(0.096)	(0.000)	(—)	(0.044)	(—)	(0.025)	(—)	(0.480)	(—)	(0.094)
	Hedge	0.003	-0.186	0.006	-0.053	0.003	0.184	0.006	0.204	0.002	0.705	-0.001	0.065
		(0.021)	(0.075)	(0.013)	(0.801)	(0.152)	(0.209)	(0.006)	(0.163)	(0.293)	(0.000)	(—)	(0.778)
Zero interval for IND_0:	Long	0.001	0.891	0.002	1.232	0.003	0.624	0.014	0.554	0.016	0.460	0.012	-0.430
$[-0.2 \cdot B_0, 0.2 \cdot B_0]$		(0.350)	(0.000)	(0.258)	(0.000)	(0.212)	(0.001)	(0.000)	(0.021)	(0.003)	(0.143)	(0.016)	(0.235)
	Short	-0.001	1.039	-0.004	1.281	0.003	0.372	0.008	0.351	0.015	-0.208	0.013	-0.500
		(0.415)	(0.000)	(0.097)	(0.000)	(—)	(0.044)	(—)	(0.101)	(—)	(0.433)	(—)	(0.102)
	Hedge	0.002	-0.149	0.006	-0.049	0.000	0.253	0.006	0.203	0.001	0.668	-0.001	0.071
		(0.048)	(0.107)	(0.006)	(0.794)	(0.458)	(0.063)	(0.002)	(0.123)	(0.364)	(0.001)	(—)	(0.742)
Zero interval for IND_0:	Long	0.001	0.932	0.001	1.284	0.003	0.613	0.013	0.587	0.017	0.294	0.011	-0.419
$[-0.4 \cdot B_0, 0.4 \cdot B_0]$		(0.418)	(0.000)	(0.385)	(0.000)	(0.211)	(0.001)	(0.000)	(0.012)	(0.002)	(0.324)	(0.025)	(0.249)
	Short	-0.002	1.093	-0.005	1.330	0.003	0.392	0.009	0.333	0.016	-0.230	0.013	-0.501
		(0.323)	(0.000)	(0.065)	(0.000)	(—)	(0.033)	(—)	(0.116)	(—)	(0.397)	(—)	(0.097)
	Hedge	0.003	-0.161	0.005	-0.046	0.000	0.221	0.005	0.254	0.001	0.525	-0.002	0.083
		(0.011)	(0.036)	(0.005)	(0.781)	(—)	(0.058)	(0.004)	(0.029)	(0.392)	(0.000)	(—)	(0.666)

The table shows the abnormal CAPM returns from Equation 21 split into six 6-year periods between 1983–2021 for the indicator variable strategy when using fundamental analysis to estimate horizon values. P-values are reported in parentheses. See Table 7 in section 5.3.1 for explanation of the t-tests. The p-value is omitted if the sign of α is inconsistent with the alternative hypothesis.

Appendix H

Table 17: Three-factor returns to the sophisticated method (1983–2021)

Investment strategy	Position	1983–2003				2001–2021				1983–2021			
		α	β	SMB	HML	α	β	SMB	HML	α	β	SMB	HML
Indicator variable strategy													
Zero interval for IND_0:	Long	0.006	0.718	0.005	-0.001	0.009	0.499	0.007	0.012	0.007	0.651	0.009	0.004
$[-0.1 \cdot B_0, 0.1 \cdot B_0]$		(0.001)	(0.000)	(0.000)	(0.125)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Short	0.003	0.600	0.002	-0.003	0.008	0.111	0.010	0.005	0.005	0.392	0.006	0.002
		(—)	(0.000)	(0.000)	(0.000)	(—)	(0.358)	(0.000)	(0.000)	(—)	(0.000)	(0.000)	(0.000)
	Hedge	0.003	0.118	0.003	0.002	0.002	0.388	0.001	0.002	0.002	0.259	0.002	0.002
		(0.028)	(0.151)	(0.000)	(0.000)	(0.162)	(0.000)	(0.028)	(0.003)	(0.071)	(0.000)	(0.000)	(0.000)
Zero interval for IND_0:	Long	0.005	0.765	0.005	-0.001	0.009	0.481	0.012	0.008	0.006	0.667	0.009	0.004
$[-0.2 \cdot B_0, 0.2 \cdot B_0]$		(0.006)	(0.000)	(0.000)	(0.069)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Short	0.003	0.606	0.003	-0.002	0.008	0.103	0.011	0.006	0.005	0.390	0.007	0.002
		(—)	(0.000)	(0.000)	(0.000)	(—)	(0.395)	(0.000)	(0.000)	(—)	(0.000)	(0.000)	(0.000)
	Hedge	0.001	0.158	0.003	0.001	0.002	0.379	0.002	0.002	0.001	0.277	0.003	0.002
		(0.111)	(0.034)	(0.000)	(0.001)	(0.182)	(0.000)	(0.000)	(0.000)	(0.109)	(0.000)	(0.000)	(0.000)
Zero interval for IND_0:	Long	0.004	0.773	0.005	-0.001	0.009	0.432	0.013	0.008	0.006	0.648	0.010	0.004
$[-0.4 \cdot B_0, 0.4 \cdot B_0]$		(0.011)	(0.000)	(0.000)	(0.051)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
	Short	0.003	0.656	0.003	-0.002	0.008	0.088	0.011	0.006	0.005	0.404	0.007	0.003
		(—)	(0.000)	(0.000)	(0.002)	(—)	(0.463)	(0.000)	(0.000)	(—)	(0.000)	(0.000)	(0.000)
	Hedge	0.002	0.117	0.002	0.001	0.000	0.343	0.002	0.002	0.001	0.245	0.003	0.002
		(0.053)	(0.068)	(0.017)	(0.106)	(0.354)	(0.000)	(0.000)	(0.000)	(0.173)	(0.000)	(0.000)	(0.000)

The table shows the three-factor model from Equation 22 returns split into two subperiods (1983–2003 and 2001–2021) for the indicator variable strategy when using fundamental analysis to estimate horizon values. P-values are reported in parentheses. The t-tests for the intercept (α) and the beta value (β) are the same as in table 7. The t-tests for SMB and HMB are two-tailed. The p-value is omitted if the sign of α is inconsistent with the alternative hypothesis.

Appendix I

Table 18: Estimated coefficients for the statistical return metric to the sophisticated method (1983–2021)

Investment strategy	β_0	β_1	β_2	β_3	β_4	β_5	Adj. R^2	No. obs
Indicator variable strategy								
Zero interval for IND_0:	0.261	-0.377					1.93%	5,736
$[-0.1 \cdot B_0; 0.1 \cdot B_0]$	(0.000)	(0.000)						
	0.574	-0.905	-0.603	0.219	-3.514	-0.025	5.83%	5,526
	(0.000)	(0.000)	(—)	(0.040)	(0.000)	(0.010)		
Zero interval for IND_0: $[-0.2 \cdot B_0; 0.2 \cdot B_0]$	0.221	-0.325					1.47%	6,674
	(0.000)	(0.000)						
	0.472	-0.745	-0.562	0.267	-3.298	-0.032	5.18%	6,436
	(0.000)	(0.000)	(—)	(0.011)	(0.000)	(0.001)		
Zero interval for IND_0: $[-0.4 \cdot B_0; 0.4 \cdot B_0]$	0.169	-0.248					0.89%	8,214
	(0.000)	(0.000)						
	0.348	-0.530	-0.489	0.306	-2.978	-0.044	3.96%	7,929
	(0.000)	(0.000)	(—)	(0.001)	(0.000)	(0.000)		

The table shows the estimated coefficients for Equations 26 and 27 when using fundamental analysis to estimate horizon values. The dependent variable is the market-adjusted buy-and-hold return calculated for each individual stock ($MJBH_{i;36} = \prod_{z=1}^{36}(1 + R_{i;z}) - \prod_{z=1}^{36}(1 + R_{m;z})$). The top-half of each investment strategy shows the univariate regression model $MJBH_{i;36} = \beta_0 + \beta_1 \cdot D_{i;0}^{Str(.)} + \tilde{\varepsilon}_i$ (Equation 26) and the bottom-half shows the multivariate regression model $MJBH_{i;36} = \beta_0 + \beta_1 \cdot D_{i;0}^{Str(.)} + \beta_2 \cdot \overline{\ln((B/M)_{i;0})} + \beta_3 \cdot \overline{(E/P)}_{i;0} + \beta_4 \cdot \overline{(D/P)}_{i;0} + \beta_5 \cdot \overline{\ln(MV_{i;0})} + \tilde{\varepsilon}_i$ (Equation 27). The variables are explained in section 3.5.2. P-values are reported in parentheses. For the intercept, $\overline{\ln((B/M)_{i;0})}$, and $\overline{(E/P)}_{i;0}$, a one-sided t-test is conducted where the null hypotheses that the coefficient is non-positive is tested against the alternative hypotheses that the coefficient is positive. For $D_{i;0}^{Str(.)}$ and $\overline{\ln(MV_{i;0})}$, a one-sided t-test is conducted where the null hypotheses that the coefficient is non-negative is tested against the alternative hypotheses that the coefficient is negative. The p-value is omitted if the sign of a coefficient is inconsistent with the alternative hypothesis. For $\overline{(D/P)}_{i;0}$, two-tailed tests are carried out.

Appendix J

Table 19: Realistic return metric to the sophisticated method (1983–2021)

Investment strategy	Position	1983-1991	1989-1997	1995-2003	2001-2009	2007-2015	2013-2021
Indicator variable strategy							
Zero interval for IND_0:	Long	0.086	0.470	-0.170	0.905	0.336	-0.147
$[-0.1 \cdot B_0, 0.1 \cdot B_0]$		(0.173)	(0.046)	(—)	(0.021)	(0.019)	(—)
	Short	-0.061	-0.060	-0.324	0.366	0.089	-0.080
		(0.052)	(0.227)	(0.108)	(—)	(—)	(0.033)
	Hedge	0.147	0.529	0.155	0.539	0.247	-0.067
		(0.036)	(0.060)	(0.058)	(0.035)	(0.046)	(—)
Zero interval for IND_0:	Long	0.045	0.385	-0.239	0.889	0.305	-0.144
$[-0.2 \cdot B_0, 0.2 \cdot B_0]$		(0.304)	(0.040)	(—)	(0.014)	(0.047)	(—)
	Short	-0.052	-0.069	-0.294	0.383	0.101	-(0.079)
		(0.076)	(0.170)	(0.129)	(—)	(—)	(0.041)
	Hedge	0.097	0.454	0.055	0.505	0.204	-0.065
		(0.090)	(0.049)	(0.231)	(0.024)	(0.111)	(—)
Zero interval for IND_0:	Long	0.012	0.274	-0.220	0.828	0.289	-0.189
$[-0.4 \cdot B_0, 0.4 \cdot B_0]$		(0.433)	(0.039)	(—)	(0.015)	(0.046)	(—)
	Short	-0.070	-0.086	-0.276	0.408	0.145	-(0.085)
		(0.083)	(0.105)	(0.145)	(—)	(—)	(0.024)
	Hedge	0.082	0.360	0.056	0.420	0.143	-0.105
		(0.100)	(0.038)	(0.302)	(0.034)	(0.103)	(—)

The table shows the realistic return metric from Equation 28, 29, and 30 over six 6-year periods between 1983–2021 when using fundamental analysis to estimate horizon values. P-values are reported in parentheses. See Table 9 in section 5.3.3 for explanation of the t-tests. No p-value is reported if the sign of the return is inconsistent with the alternative hypothesis.

Appendix K

Table 20: Abnormal CAPM returns to the sophisticated method for non-overlapping subsamples (1983–2021)

Investment strategy	Position	Subsample I		Subsample II		Subsample III	
		α	β	α	β	α	β
Indicator variable strategy							
Zero interval for IND_0: $[-0.1 \cdot B_0, 0.1 \cdot B_0]$	Long	0.009	0.599	0.007	0.627	0.009	0.324
		(0.002)	(0.001)	(0.007)	(0.001)	(0.002)	(0.075)
	Short	0.005	0.403	0.005	0.310	0.007	0.216
		(—)	(0.019)	(—)	(0.076)	(—)	(0.177)
	Hedge	0.004	0.196	0.002	0.317	0.002	0.108
		(0.036)	(0.126)	(0.117)	(0.008)	(0.125)	(0.329)
Zero interval for IND_0: $[-0.2 \cdot B_0, 0.2 \cdot B_0]$	Long	0.008	0.646	0.008	0.544	0.009	0.381
		(0.007)	(0.001)	(0.007)	(0.003)	(0.002)	(0.036)
	Short	0.005	0.390	0.005	0.298	0.007	0.212
		(—)	(0.022)	(—)	(0.089)	(—)	(0.188)
	Hedge	0.002	0.257	0.002	0.246	0.002	0.170
		(0.143)	(0.040)	(0.107)	(0.021)	(0.170)	(0.096)
Zero interval for IND_0: $[-0.4 \cdot B_0, 0.4 \cdot B_0]$	Long	0.008	0.559	0.007	0.524	0.008	0.403
		(0.005)	(0.003)	(0.010)	(0.004)	(0.004)	(0.026)
	Short	0.006	0.395	0.005	0.311	0.008	0.209
		(—)	(0.018)	(—)	(0.076)	(—)	(0.202)
	Hedge	0.002	0.164	0.002	0.213	0.001	0.194
		(0.089)	(0.103)	(0.130)	(0.013)	(0.317)	(0.027)

The table show the abnormal CAPM returns from Equation 21 for subsample I–III when using fundamental analysis to estimate horizon values. Subsample I considers positions formed in 1983, 1986, and so on until 2016. Subsample II considers positions formed in 1984, 1987, and so on until 2017. Subsample III considers positions formed in 1985, 1988, and so on until 2018 P-values are reported in parentheses. See Table 7 in section 5.3.1 for explanation of the t-tests. The p-value is omitted if the sign of α is inconsistent with the alternative hypothesis.

Appendix L

Table 21: Estimated coefficients for the statistical return metric to the sophisticated method for non-overlapping subsamples (1983–2021)

Investment strategy	Subsample	β_0	β_1	β_2	β_3	β_4	β_5	Adj. R^2	No. obs
Indicator variable strategy									
Zero interval for IND_0:	I	0.435	-0.686	-0.453	0.137	-1.996	-0.018	5.67%	1,976
$[-0.1 \cdot B_0; 0.1 \cdot B_0]$		(0.000)	(0.000)	(—)	(0.213)	(0.025)	(0.093)		
	II	0.600	-0.956	-0.671	0.113	-5.247	-0.026	7.00%	1,812
		(0.000)	(0.000)	(—)	(0.302)	(0.000)	(0.084)		
	III	0.694	-1.088	-0.700	0.364	-3.846	-0.033	5.38%	1,738
		(0.000)	(0.000)	(—)	(0.073)	(0.029)	(0.082)		
Zero interval for IND_0:	I	0.397	-0.616	-0.459	0.202	-2.425	-0.029	5.24%	2,264
$[-0.2 \cdot B_0; 0.2 \cdot B_0]$		(0.000)	(0.000)	(—)	(0.115)	(0.005)	(0.013)		
	II	0.466	-0.749	-0.601	0.349	-4.759	-0.033	5.72%	2,113
		(0.000)	(0.000)	(—)	(0.041)	(0.000)	(0.024)		
	III	0.550	-0.868	-0.623	0.238	-3.061	-0.033	4.52%	2,059
		(0.000)	(0.000)	(—)	(0.150)	(0.033)	(0.058)		
Zero interval for IND_0:	I	0.316	-0.459	-0.425	0.269	-2.089	-0.045	4.20%	2,763
$[-0.4 \cdot B_0; 0.4 \cdot B_0]$		(0.000)	(0.000)	(—)	(0.043)	(0.013)	(0.000)		
	II	0.316	-0.527	-0.489	0.418	-4.453	-0.036	4.64%	2,612
		(0.000)	(0.000)	(—)	(0.008)	(0.000)	(0.007)		
	III	0.409	-0.601	-0.551	0.225	-2.764	-0.049	3.47%	2,554
		(0.000)	(0.000)	(—)	(0.131)	(0.027)	(0.003)		

The table shows the regression from Equation 27 for subsample I–III when using fundamental analysis to estimate horizon values. Subsample I considers positions formed in 1983, 1986, and so on until 2016. Subsample II considers positions formed in 1984, 1987, and so on until 2017. Subsample III considers positions formed in 1985, 1988, and so on until 2018. P-values are reported in parentheses. The independent variables and t-tests are explained in Table 18. The p-value is omitted if the sign of a coefficient is inconsistent with the alternative hypothesis.

Appendix M

Table 22: Realistic return metric to the sophisticated method for non-overlapping subsamples (1983–2021)

Investment strategy	Position	Subsample I	Subsample II	Subsample III
Indicator variable strategy				
Zero interval for IND_0: $[-0.1 \cdot B_0, 0.1 \cdot B_0]$	Long	0.210	0.164	0.367
		(0.071)	(0.085)	(0.073)
	Short	-0.017	-0.043	0.026
		(0.400)	(0.326)	(—)
	Hedge	0.227	0.207	0.341
		(0.020)	(0.017)	(0.042)
Zero interval for IND_0: $[-0.2 \cdot B_0, 0.2 \cdot B_0]$	Long	0.154	0.137	0.329
		(0.127)	(0.142)	(0.079)
	Short	-0.006	-0.032	0.034
		(0.463)	(0.365)	(—)
	Hedge	0.160	0.170	0.295
		(0.047)	(0.031)	(0.043)
Zero interval for IND_0: $[-0.4 \cdot B_0, 0.4 \cdot B_0]$	Long	0.146	0.097	0.253
		(0.106)	(0.222)	(0.123)
	Short	0.009	-0.031	0.041
		(—)	(0.374)	(—)
	Hedge	0.138	0.128	0.212
		(0.050)	(0.045)	(0.070)

The table show the realistic return metric from Equation 28, 29, and 30 for subsample I–III when using fundamental analysis to estimate horizon values. Subsample I considers positions formed in 1983, 1986, and so on until 2016. Subsample II considers positions formed in 1984, 1987, and so on until 2017. Subsample III considers positions formed in 1985, 1988, and so on until 2018. P-values are reported in parentheses. See Table 9 in section 5.3.3 for explanation of the t-tests. No p-value is reported if the sign of the return is inconsistent with the alternative hypothesis.