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Do Mechanical Value Investing Strategies Beat The Market In The Nordics?

By:

Erik Årstad Gilje

Andreas Kindem

Supervisor: Carsten Bienz

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NORWEGIAN SCHOOL OF ECONOMICS

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Abstract

In this thesis, we study whether three mechanical value investing strategies consistently generate excess risk-adjusted returns (alpha) on the Nordic exchanges for a Norwegian investor (returns are reflected in NOK). We backtest: 1) Piotroski (2000)'s selection method, 2) Greenblatt (2006)'s "magic formula", and 3) a mechanical strategy employed by the new Norwegian mutual fund First Veritas (FV). We employ the CAPM, Fama and French's three-factor model (FF3F), and Carhart's four-factor model (C4F) to measure alpha. The data coverage allows for backtests from July 2008 to the end of 2021. Before accounting for transaction costs, the "magic formula" generates statistically significant alpha (on the 5% level) with the C4F, and the FV strategy generates significant alpha with all models. The Piotroski method's alpha is statistically indistinguishable from zero with all models. When controlling for transaction costs (i.e., bid-ask spreads and commission fees), the FV strategy generates significant alpha with the CAPM and C4F, while the "magic formula" portfolio's alpha becomes insignificant with all models. Furthermore, when assessing the FV strategy in a mutual fund setting where we exclude companies below 2000 MNOK market capitalization and account for fees, the alpha is statistically insignificant with all models.

Contents

1 Introduction

Contradicting the highly influential efficient market hypothesis, value investors believe the market exhibits certain biases, which creates opportunities to "beat the market." Benjamin Graham, often credited as "the father of value investing," proposes three reasons why the market occasionally behaves irrationally; 1) exaggerated responses to changes in earnings, dividends, and mergers, 2) oversimplification, and 3) neglect, particularly with "secondary" or little-known issues (Graham & Dodd, 2009, chapter 50). Similarly, some argue that the "value premium" exists because the market is overly excited about industries dealing with new technologies and companies with high growth prospects, while mature and "boring" companies are more likely to be undervalued (Chan & Lakonishok, 2004).

To capitalize on these proposed inefficiencies, some academics and professional investors advocate strategies that mechanically screen stocks on valuation multiples and quality parameters to identify companies that are undervalued compared to their fundamentals. In this study, we explore whether a Norwegian investor (returns are reflected in NOK) can apply three such strategies on the Nordic exchanges to consistently generate excess risk-adjusted returns. We test the following strategies: 1) Piotroski (2000)'s selection method 2) Greenblatt (2006)'s "magic formula," and 3) a mechanical strategy employed by the Norwegian mutual fund, First Veritas (FV).

We replicate the strategies and compute monthly returns from July 2008 to December 2021. Risk-adjusted returns are measured with the CAPM, Fama French three-factor model (FF3F), and Carhart's four-factor model (C4F). Furthermore, we account for transaction costs (i.e., bid-ask spreads and commission fees), which significantly affect our results. Only the FV strategy generates statistically significant positive alpha net of transaction costs (it is significant on the 5% level with the CAPM and the C4F). However, the FV portfolio's alpha is insignificant in a "mutual fund scenario" where we exclude companies with a market capitalization below 2 billion NOK and account for fees.

Value investors commonly believe the market is prone to human error, which occasionally causes irrational prices and, accordingly, opportunities to "beat the market" (Graham & Dodd, 2009, chapter 50). The "tech bubble" between the late 90s and the early 2000s is often used as evidence of herd behavior in financial markets and investors' excessive optimism about companies dealing with new technologies (Chan & Lakonishok, 2004). To capitalize on these biases, value investors try to identify stocks whose prices differ from a "fair" value. Among the methods of identifying such stocks is mechanically screening the market by valuation multiples and quality parameters to identify high-quality companies whose stocks are priced "cheaply." By committing to a pre-developed selection process and "tying themselves to the mast," investors seek to remedy their psychological biases and go against the herd[1].

Despite the implicit contradiction to the seemingly robust efficient market hypothesis, some academics and investors believe such strategies can "beat the market." Piotroski (2000) tests a portfolio that selects companies on the book-to-market ratio and a financial robustness proxy (i.e., the "F_SCORE") and concludes that it is able to "beat the market." Furthermore, Joel Greenblatt, a former hedge fund manager and professor at Columbia University, proposes a "magic formula" in his book *"The Little Book That Beats The Market,"* which selects stocks on return on capital employed and earnings yield. He claims that the "magic formula" would achieve a 30.8% annual return in the period between 1988-2004 in the U.S. Moreover, a recent Norwegian mutual fund, First Veritas, employs a mechanical model that selects stocks on price-over-earnings and other quality- and risk parameters that utilize normalized fundamental data back to 2011.

According to Damodaran (2010), academics and practitioners wrongly advocate mechanical strategies by pointing to evidence from inflated backtests, and accordingly, "*a money making strategy is born.. books are written.. mutual funds are created.*" He argues that the backtests do not account for transaction costs and, therefore, money managers have been unable to "beat the market" in practice with mechanical methods that seem to do well on paper.

[1]Thomas Nielsen, portfolio manager of First Veritas, uses this expression (FIRST Fondene, 2022). Furthermore, Greenblatt (2006) argued that the "magic formula" works because it is free of psychological biases.

Thus, we add to the literature by backtesting the abovementioned strategies and accounting for transaction costs. Furthermore, there is less empirical literature on the Nordic exchanges. There is some empirical literature covering Piotroski's strategy, while studies on the "magic formula" are limited. Moreover, there are no peer-reviewed studies on the First Veritas model, seemingly due to its recent inception and local nature. Furthermore, we test how well the First Veritas strategy performs in a "mutual fund scenario" where we exclude companies with a market capitalization below 2 billion NOK (which are seemingly more likely to be neglected) and assess alpha net of fees. Corresponding to the proposed strategies, we focus on long-only portfolios.

We use data from Compustat, which includes delisted companies. Hence the sample is free of survivorship bias[2]. To avoid look-ahead bias[3], we use non-restated figures and form portfolios at the end of June the year preceding the fiscal period. We exclude non-common equity and non-primary securities. Moreover, we adjust closing prices for stock splits, cash equivalent distributions and convert to NOK when computing returns. Portfolios are rebalanced yearly to limit transaction costs. Since Nielsen currently employs accounting data starting from 2011 (he previously employed data starting from 2006), we use ten-year trailing accounting data when replicating the First Veritas model. We have sufficient data to start the test from 2008. Transaction costs accounted for include commission fees and bid-ask spreads. Portfolio turnover accounts for yearly portfolio formation, rebalancing, and reinvesting proceeds when companies are delisted during the holding period. Furthermore, we construct the HML (high-minus-low book-to-market), SMB (small-minus-big market capitalization), and WML (winner-minus-loser 1-year return) variables to measure risk-adjusted performance with the CAPM, Fama French three-factor model, and the Carhart four-factor model.

In our sample period from July 2008 to December 2021, we estimate an annual average gross return of 16.3% for the First Veritas model, 16.9% for the "magic formula," 14.1% for Piotroski's strategy, while the Nordic index achieved 12.8% (VINX All-Share Index represented

[2]Survivorship bias refers to excluding companies that went bankrupt ex-ante.

[3]Look-ahead bias refers to using information not yet available to investors when forming portfolios.

in NOK). With gross returns, the Piotroski strategy's alpha is not significantly different from zero with all models. Moreover, the "magic formula" portfolio's alpha is only statistically significant with the C4F, while the First Veritas portfolio generates significant positive alpha in all models. When accounting for transaction costs, the "magic formula" portfolio's alpha in the C4F becomes insignificant, while the First Veritas portfolio generates significant alpha with the CAPM and C4F. Moreover, when excluding companies with a market capitalization below 2 billion NOK and accounting for First Veritas' fee structure, the alpha is statistically indistinguishable from zero with all models.

For the Piotroski strategy, our evidence suggests that the selection of high book-to-market stocks is causing the poor performance, while the F_SCORE is able to predict returns. This is in line with recent evidence from other markets suggesting that the book-to-market premium has disappeared (e.g., Fama and French (2021) and Park et al. (2019)). For the First Veritas model, our evidence suggests that most firms in the investment universe (i.e., stocks with sufficient ten-year historical accounting data) outperform the market. Thus, the weighted average rank on the parameters is seemingly unimportant for the strategy's performance, which does not fit well with the strategy's hypothesis. However, companies with ten years of historical accounting data may be endogenous with other value or quality characteristics. Moreover, the "magic formula" successfully separates winners from losers.

In part 2, we review relevant theory and literature about market efficiency, market equilibrium models, and measuring portfolio performance. In part 3, we discuss the "value premium" and whether it is compensation for risk or caused by irrational investors. Furthermore, we present the three value strategies tested in this study. Part 4 describes the methodology and analysis employed in the study. In part 5, we present the results. Finally, in part 6, we conclude the study and discuss our results.

2 Theoretical background and literature review

2.1 The Efficient Market Hypothesis (EMH)

Fama (1970) reviewed literature related to the idea of an efficient market. The EMH suggests that stock prices reflect all available information. Thus, according to this theory, selecting stocks based on easily available information such as valuation ratios and financial quality parameters should not generate excess risk-adjusted returns. Fama points out that this theory is difficult to test because of the joint hypothesis problem. This problem occurs because any test of the EMH relies on a correct model for predicting equilibrium prices, which economists cannot be certain they have. Thus, any discoveries that contradict equilibrium models could prove that economists have the wrong model and do not necessarily prove that markets are inefficient. Furthermore, due to the extreme null hypothesis of the EMH (i.e., all information is reflected in the market), Fama studied three levels of informational efficiency.

Weak Form:

This level of market efficiency holds when market prices reflect all historical trading data (e.g., stock prices and trading volume) for a given stock at any point in time. If this form of EMH does not hold, one could predict future stock prices using technical analysis and statistics. The empirical evidence supports weak-form EMH (Fama, 1965). However, some research has shown that historical price patterns may not be reflected in market prices. Jegadeesh and Titman (1993) found short-term momentum effects, while De Bondt and Thaler (1985) found reversal tendencies in long-term returns.

Semi-strong Form:

This level of market efficiency holds when all public information is fully reflected in the market. In addition to the weak form of efficiency, the semi-strong form of EMH includes all information available to the public (e.g., future dividends and historical earnings). The empirical evidence from Fama (1970) suggests that the reactions to public announcements were consistent with the efficient market model. However, Rendleman Jr et al. (1982) find evidence that market prices can take several days to adjust for publicly announced information.

Strong Form:

This level of market efficiency holds when all public and inside information is fully reflected in stock prices at any point in time. Inside information refers to information exclusively available to certain people (e.g., management and advisors). The empirical evidence presented by Fama (1970) indicates that the strong form of EMH is unlikely to hold. On the other hand, Keown and Pinkerton (1981) found some evidence of a market reaction before the announcement of takeovers, suggesting that some trades were made by insiders. However, the market reaction to the public information was complete the day after the announcement, consistent with the semi-strong EMH.

Despite strong evidence that the semi-strong EMH generally holds, numerous empirical studies have discovered the existence of market anomalies. French (1980) finds a calendar effect in which stock returns are lower on Mondays than on other weekdays. A possible explanation for the "Monday effect" could be that institutional investors are less active on Mondays due to strategic planning (Wang & Walker, 2000). Saunders (1993) discovered that the New York Stock Exchange index often is negative when New York is cloudy. Hirshleifer and Shumway (2003) show that stock market returns correlate positively with sunshine in most countries studied. Another study investigating the relationship between investors' moods and stock prices was done by Edmans et al. (2007). They show that a country's stock exchange return was significantly lower after losing important football matches. The effect on stock returns the following day was magnified by the importance of the football game. These studies suggest that the market is not completely efficient as it can seemingly be affected by mood.

Furthermore, Grossman and Stiglitz (1980) argued that a state in which all information is reflected in the markets could not be an equilibrium. Paradoxically, if there are no arbitrage opportunities, investors have no incentives to gather information, which would lead to inefficient markets and create arbitrage opportunities. They also argue that an investor should not be able to generate excess returns above the cost of gathering the informational advantage.

From the research discussed above, it seems unlikely that the market is efficient if one defines it as an all-knowing and entirely rational market. However, with the evidence documenting that an active investing strategy rarely beats a passive investing strategy (Malkiel, 2003), it seems efficient if one defines it as efficient to a degree where investors are unable to exploit market mistakes.

2.2 Market Equilibrium Models

Capital Asset Pricing Model (CAPM)

In the empirical literature related to the EMH, the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), Lintner (1965), and Mossin (1966) is often considered the foundation for predicting asset returns. If the assumptions for the CAPM holds, the only risk an investor is rewarded for in the form of higher returns is the systematic risk (also known as the market risk). This risk cannot be eliminated by holding a well-diversified portfolio since it affects all assets (e.g., business cycles). The CAPM defines the expected return of an asset i as:

$$R_i = R_F + \beta_i[E(R_M) - R_F] \tag{2.1}$$

Where β_i measures the asset's sensitivity to the market returns. R_f is the return on a risk-free investment, and $E(R_m) - R_f$ reflects the spread between the expected market return and the risk-free return. This difference is also known as the market risk premium.

Arbitrage Pricing Theory (APT)

APT was developed by Ross (1976) as an alternative to the CAPM. APT differs from the CAPM because it allows multiple macroeconomic factors to capture systematic risk. APT assumes that markets can temporarily misprice assets, but these opportunities are exploited quickly by arbitrageurs, such that the price is corrected back to its fair value. The APT can be described with the following equation (Chen, 1983):

$$R_i = \lambda_0 + \lambda_{i1}b_1 + ... + \lambda_{ik}b_k + \epsilon_i \tag{2.2}$$

Where R_i is the return of asset i, λ_0 is the risk-free rate, $b_{i1}, \ldots b_{ik}$ represent various macroeconomic factors, while $\lambda_1, \ldots \lambda_k$ reflects the corresponding sensitivity to the macroeconomic factor, and ϵ_i is the idiosyncratic risk component. Ross does not specify how many or which risk factors should be included in the model. However, Chen (1983) uses factor analysis to estimate five risk factors (the number of factors was prespecified to avoid overfitting the model) and find evidence that APT performs well empirically.

Fama & French Three-Factor Model

In the 80s, papers had been accumulating showing that the CAPM struggled when researchers sorted data on different variables[4]. Arguing that this was evidence of the CAPM's failure to capture all relevant risk factors, Fama and French (1992) and Fama and French (1993) put these discoveries together and created the three-factor model, which also accounts for size and the book-to-market ratio. The formula for the Fama and French three-factor model for the return of an asset i at time t can be shown as:

$$R_{it} - R_{Ft} = a_i + b_i(R_{mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + e_{it} \tag{2.3}$$

$R_{it} - R_{Ft}$ is the return of asset i at time t in excess of the risk-free rate, and b_i measures the sensitivity of asset i to the market volatility, similar to the CAPM. SMB is the return of small companies minus the return of big companies, HML is the return of high book-to-market firms over low book-to-market firms, and s_i and h_i are the respective coefficients that measure the asset i's sensitivity to these factors. a_i is a constant term ($alpha$) that measures the average excess return of an asset i that cannot be explained by the sensitivity to the risk factors.

The SMB (small-minus-big) factor reflects the size premium, which is the excess returns generated by smaller firms. SMB is constructed by ranking the companies by size and calculating the spread of returns from the smallest and largest firms. Arbel and Strebel (1982) discuss the possibility that investors require a risk premium on small firms since there is less information available on them (e.g., research coverage by analysts). Moreover, Amihud and Mendelson (1986) proposed a liquidity discount for smaller firms as they tend to have lower trading volumes than larger companies.

[4] Banz (1981) documented the (so-called) market capitalization anomaly, Bhandari (1988) documented the relationship between debt/equity and returns, controlling for beta, and Rosenberg, Reid, and Lanstein (1985) documented the (so-called) book-to-market anomaly.

The HML (high-minus-low) factor, often called the value premium, is constructed by calculating the spread of returns between high and low book-to-market firms. Fama and French (1995) and Chen and Zhang (1998) argued that firms with high book-to-market ratios often struggle financially, and accordingly, investors require higher returns for value firms. We will discuss possible explanations for the value premium further in section 3.

Carhart Four-Factor Model

Carhart (1997) builds further on the three-factor model created by Fama and French by including a factor to capture the 1-year momentum effect (i.e., last year's winning stocks tend to have higher preceding returns) discovered by Jegadeesh and Titman (1993). Literature preceding Carhart's paper documented that mutual funds that had generated alpha in the past were more likely to outperform in the short-term future and argued that this was evidence of short-term stock-picking talent (i.e., the "hot hands effect"). On the other hand, Carhart argued the 1-year momentum effect drove the short-term persistence. He found evidence that because some mutual funds happened to hold last year's winners by chance, they were more likely to outperform in the short-term future. Thus, he adds a fourth variable to Fama and French's three-factor model, namely the momentum effect, to assess whether performance can be attributable to following a momentum strategy. The Carhart four-factor model can be shown as:

$$R_{it} - R_{Ft} = a_i + b_i(R_{mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + w_i WML_t + e_{it} \tag{2.4}$$

The model consists of the same variables as the Fama and French three-factor model but includes a momentum factor, WML (winner-minus-loser), and its respective coefficient w_i. The factor is constructed by taking the ex-post returns of the firms with the highest ex-ante one-year returns minus the ex-post returns of firms with the lowest ex-ante one-year return. Carhart only employs the model to explain the returns of assets and does not discuss interpretations of risk. Daniel et al. (1998) argue that the momentum anomaly is a result of a delayed overreaction caused by overconfidence and self-attribution bias. On the other hand, Ruenzi and Weigert (2018) propose a risk-based explanation as they find evidence of momentum stocks having higher tail-risk exposure (i.e., crash sensitivity).

Fama & French Five-Factor Model

Preceding Fama and French (1993), related studies have documented other "anomaly" variables explaining returns the three-factor model fails to capture. Thus, Fama and French (2015) extend their three-factor model with two additional factors to better explain returns empirically. The formula can be shown as:

$$R_{it} - R_{Ft} = a_i + b_i(R_{mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \quad (2.5)$$

The model includes two additional factors to their three-factor model, RMW (robust-minus-weak) and CMA (conservative-minus-aggressive), as well as r_i and c_i, which measures the sensitivity to the factors, respectively. RMW, also known as the profitability factor, measures the difference in the returns of firms with stable margins versus firms with volatile margins. CMA, also known as the investment factor, measures the difference in returns of firms with low investment levels versus firms that invest heavily. The CMA factor suggests that firms with a more conservative investment strategy tend to outperform firms with aggressive investment levels, as they tend to over-invest. Fama and French find that including these two additional factors makes the HML factor redundant, seemingly due to the high correlation between CMA and HML.

2.3 Risk-Adjusted Performance

Since investors are compensated for risk exposure through higher returns, they should assess risk-adjusted performance. In the following, we will discuss various measures to evaluate risk-adjusted performance.

Jensen's Alpha

Jensen (1968) employed theory from market equilibrium models to assess the performance of mutual funds. Jensen's alpha measures the excess risk-adjusted return of a portfolio based on the CAPM and is obtained from the following equation:

$$\alpha^{CAPM} = R_P - [R_F + (R_M - R_F)\beta_P] \quad (2.6)$$

α measures the excess return which cannot be attributed to systematic risk for a portfolio P. The first joint on the right side of the equation, R_P, is the portfolio's actual return. The second joint on the right side of the equation measures the expected return according to the CAPM.

Later studies (e.g., Davydov et al. (2016); Gorman and Weigand (2008)) have built upon this methodology by tweaking Jensen's alpha to control for other variables that could capture risk like those described in 2.2. By isolating the alpha on the left side of the equation, we get the following expressions:

$$\alpha^{FF3F} = R_P - [R_F + \beta_P(R_M - R_F) + s_P SMB + h_P HML] \tag{2.7}$$

$$\alpha^{C4F} = R_P - [R_F + \beta_P(R_M - R_F) + s_P SMB + h_P HML + w_P WML] \tag{2.8}$$

$$\alpha^{FF5F} = R_P - [R_F + \beta_P(R_M - R_F) + s_P SMB + h_P HML + r_P RMW + c_P CMW] \tag{2.9}$$

Similar to Jensen's alpha, the multi-factor models measure α as the excess returns that cannot be explained by market risk but also control for additional potential risk variables like size, book-to-market, and momentum. A positive and statistically significant alpha indicates that the portfolio has generated excess returns that cannot be attributed to the factors capturing risk in the models.

Sharpe Ratio

A common measure for evaluating risk-adjusted performance is the Sharpe (1964) ratio. The Sharpe ratio can be expressed as:

$$\text{Sharpe Ratio} = \frac{R_P - R_F}{\sigma_P} \tag{2.10}$$

R_P is the return of a portfolio P, R_F is the return of a risk-free asset, and σ_P is the standard deviation of portfolio P. The Sharpe ratio measures the portfolio's excess return above the risk-free rate, relative to the volatility of the portfolio.

Sortino Ratio

Sortino and Price (1994) criticized The Sharpe ratio for punishing large positive returns as they increase the standard deviation. The Sortino ratio addresses this issue by only accounting for the downside in the standard deviation. The Sortino ratio can be shown using the following equation:

$$\text{Sortino Ratio} = \frac{R_P - R_F}{\sigma_{P_d}} \tag{2.11}$$

Where:

$$\text{Downside Deviation} = \sigma_{P_d} = \sqrt{\left(\frac{\sum_{i=1}^{N}[MIN(\mathrm{R}_P - MAR;0)]^2}{N-1}\right)} \tag{2.12}$$

The Sortino Ratio is similar to the Sharpe ratio except that the denominator only considers the downside deviation. The downside deviation is measured by the square root of the sum of the squared differences between the return of portfolio P and the minimum acceptable return (MAR) when the portfolio return is lower than the MAR.

Information Ratio

The Information ratio (IR) is another risk-adjusted performance measure developed by Treynor and Black (1973). The IR measures the portfolio's ability to generate returns above its benchmark and accounts for the additional idiosyncratic risk which occurs from selecting assets and being less diversified. The IR is expressed through the following equation:

$$IR = \frac{\overline{R}_P - \overline{R}_B}{\sigma_{(R_P - R_B)}} \tag{2.13}$$

Where $\overline{R}_P - \overline{R}_B$ is the average return spread between portfolio P and its benchmark B. $\sigma_{R_P - R_B}$ is the standard deviation of the return spread between portfolio P and benchmark B, also known as the tracking error (Gjølberg & Johnsen, 2003).

Positive IR can occur from 1) generating positive alpha or 2) a difference in systematic risk between the portfolio and the benchmark (also known as beta tilting). Gjølberg and Johnsen (2003) decompose the IR into two underlying components by employing the CAPM and re-writing the equation as:

$$IR = \frac{\alpha + (\beta - 1)(\overline{R}_M - \overline{R}_F)}{\sqrt{\sigma_\epsilon^2 + (\beta - 1)^2 \sigma_{(R_M - R_F)}^2}} \tag{2.14}$$

Where σ_ϵ measures the idiosyncratic risk (i.e., the standard deviation of the residuals in the CAPM). If the alpha is positive and the beta is one, then the IR is equal to the Appraisal Ratio (AR), which measures how much alpha is generated per unit of idiosyncratic risk.

$$IR = \frac{\alpha}{\sigma_\epsilon} = AR \tag{2.15}$$

If the alpha (α) and idiosyncratic risk (σ_ϵ) are equal to 0, the beta is different from 1, and assuming the standard deviation in the risk-free returns is 0, the return of the portfolio is equal to the benchmark's Sharpe ratio:

$$IR = \frac{(\overline{R}_M - \overline{R}_F)}{\sigma_{(R_M - R_F)}} = \text{Sharpe Ratio of benchmark} \tag{2.16}$$

3 Value investing

The philosophy of value investing is often credited to Graham and Dodd (2009) in their book *"Security Analysis"* which was first published in 1934. Graham and Dodd advocate buying profitable firms which appear "cheaply" priced by the market. They argue that since the market is made up of groups of individuals, it is prone to human error. They believe the most common mistakes are: 1) exaggerated responses to changes in earnings, dividends and mergers, 2) oversimplification, and 3) neglect, particularly with "secondary" or little-known issues (Graham & Dodd, 2009, chapter 50). The famous value investor Warren Buffet employed a strategy he called "cigar-butt-investing" in his early days as a value investor (The Economic Times, 2020). He compared the companies he invested in with used cigar butts left on the street that no one wanted with "one free puff" left in them. However, this method became increasingly difficult as his fund grew in size. In general, value investors have a shared belief that some companies are neglected, often because they are "boring" or less known to the public. Furthermore, value investors often argue that investors are overly excited about companies with high growth prospects in new industries. The "tech bubble" in the early 2000s is often used as evidence for the latter (Chan & Lakonishok, 2004).

Value investing can be broadly defined as investing in firms trading below their intrinsic value. Graham and Dodd (2009) estimate intrinsic value by projecting the business's future cash flows and computing its net present value with an appropriate discount rate. They also discuss mechanical methods that use accounting figures such as the book value of equity or earnings as proxies for fundamental value and advocate buying companies priced low relative to these measures. Some also add quality conditions in addition to valuation multiples.

The value premium is addressed by the academic literature through the book-to-market anomaly discovered by Rosenberg et al. (1985) and later embraced by Fama and French's three-factor model. Although the existence of the book-to-market anomaly has been uncontroversial, there is disagreement between academics about the reason for its existence. Similar to Graham and Dodd (2009), some argue that the phenomenon is caused by irrational investors, which contradicts the efficient market hypothesis. On the other hand, some argue that it is not evidence of market inefficiency as high book-to-market firms tend to be riskier. Hence, rational investors require higher returns for high book-to-market firms. Fama and French (1996) argued that the value premium is caused by the relationship between high book-to-market ratios and financial distress. Piotroski (2000) argues that high book-to-market ratios can be related to depreciating or low margins, profits, cash flow, liquidity, and increasing and/or high leverage. Cooper (2006), Li et al. (2009), and Gulen et al. (2011) suggested that the value premium could be explained by traditional value firms having less operational flexibility than growth stocks when adjusting to worsening market conditions.

Chan and Lakonishok (2004), on the other hand, questioned the financial distress argument. They exemplified the discussion using internet stocks in the 90s and struggled to see why internet stocks in the 90s with low book-to-market ratios would be regarded as a safer investment than traditional firms with high book-to-market ratios. They also found evidence that value stocks outperformed growth stocks in both bull and bear markets, suggesting a lower fundamental risk. Furthermore, they analyzed the outperformance of growth over value stocks in the 90s. They concluded that the difference in performance was unlikely caused by patterns in fundamentals and that the most plausible explanation was exaggerated levels of optimism by investors. Moreover, they suggest that agency costs can explain the value premium. They argue that analysts have an interest in promoting stocks with financial growth and that growth stocks typically operate in more exciting industries, which simplifies the advertising process for investment banks. This build-up of hype around growth stocks then strengthens the argument why investors overestimate growth stocks' performance. Their beliefs are shared by several academics (Pätäri & Leivo, 2017).

Piotroski (2000) documents that firms with robust fundamentals yield higher returns than financially weak firms in the top 20% of book-to-market firms. This contradicts the argument that the high book-to-market return is compensation for risk related to financially distressed companies. Moreover, Chan and Lakonishok (2004) argue that searching for a way to rationalize a finding ex-post is a bias and questioned why value stocks were not associated with higher risk before the discovery of the value premium.

Black and Fraser (2003) also mention that the value premium found in the literature could be random and not attributed to rational or irrational behavior in the market. However, this seems relatively unlikely given the extensive evidence across markets and time periods. Furthermore, Chan and Lakonishok (2004) discuss the possibility that the value premium is an artifact of data snooping, a statistical bias that appears when searching for a statistically significant pattern that lacks predictive power (Lo & MacKinlay, 1990). However, they believe it is more likely that the value premium is caused by investors' tendency to extrapolate from the past and become overly excited about new technologies.

With the arguments presented above, there is a strong case that the market exhibit the biases in which the value investing philosophy is grounded. However, recent studies find evidence that the value premium (i.e., book-to-market anomaly) has deteriorated over time and is statistically indistinguishable from zero. Thus, some have questioned whether value investing no longer works (Moore, 2021). Fama and French (2021) revisit their model and show that the average monthly value premium is lower in the second half of their 1963-2019 sample period in the U.S. However, due to large volatility in the monthly value premium, one can not conclude that it is significantly lower than the first half. Fama and French (2021) point out that if the book-to-market ratio is not capturing risk as originally believed, one would expect that the discovery and increased awareness of the value premium would lead to its demise. Thus, these findings could suggest that the value premium was not compensation for risk but rather a product of irrational investors.

Park et al. (2019) argue that intangible assets have become a more central part of companies' balance sheets and conservative accounting biases in capitalization and valuation of intangibles cause the book value of equity to be a bad proxy for fundamental value. Park et al. (2019) find evidence that a value premium still exists when accounting for unrecorded intangible assets. Goncalves and Leonard (2021) find similar evidence by constructing another proxy for fundamental value and find that its correlation with the book value of equity has declined over time. The value premium remains constant for later periods when defining value stocks as companies priced low compared to their proxy for fundamental value.

F_SCORE - Joseph D. Piotroski

In wake of the discussion about the book-to-market ratio's relation to financial distress, Joseph D. Piotroski wrote in his paper "*Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers*" (2000) about nine proxies for companies' financial condition to separate financially robust vs. weak value stocks. His study finds evidence that financially robust firms achieve higher returns than the weaker firms with high book-to-market ratios.

The first step in Piotroski's value strategy is to rank firms based on the book-to-market ratio, where he eliminates the companies outside the highest quintile. In other words, he only keeps the top 20% of firms with the highest book-to-market ratio in the investment universe. To separate the "good" value companies from the "bad" ones, Piotroski uses nine metrics that cover (1) profitability, (2) financial development, and (3) operating efficiency. Every factor is a binary variable, which means that if a firm fulfills the requirement of a factor, the firm receives one point and zero otherwise. If a firm meets all criteria, it accomplishes the maximum F_SCORE of nine.

Piotroski uses four variables to measure a firm's profitability: ROA, CFO, ΔROA, and $ACCRUAL$, which are defined as:

$$ROA = \frac{\text{Net income before extraordinary items}}{\text{Total Assets}} \tag{3.1}$$

$$CFO = \frac{\text{Cashflow From Operations}}{\text{Total Assets}} \tag{3.2}$$

$$\Delta ROA = ROA_t - ROA_{t-1} \tag{3.3}$$

$$ACCRUAL = CFO - ROA \tag{3.4}$$

If the company's ROA is larger than zero, the firm receives an F_ROA score of one and zero otherwise. Similar to ROA, a company will receive an F_CFO score of one if CFO is positive and zero otherwise. Moreover, if ROA has increased, the company receives an F_ΔROA score of one and zero otherwise. $ACCRUAL$ reflects the difference between a firm's CFO and ROA. If $CFO > ROA$, the company receives an $F\_ACCRUAL$ score of one and zero otherwise. Piotroski argues that positive accrual is a sign of accounting quality and that it is important for value companies as their incentive to manipulate earnings is high.

Furthermore, Piotroski developed three indicators to evaluate firms' financial development and risk: $\Delta LEVER$, $\Delta LIQUID$, and EQ_OFFER, which are defined as:

$$\Delta LEVER = LEVER_t - LEVER_{t-1} \tag{3.5}$$

$$\Delta LIQUID = LIQUID_t - LIQUID_{t-1} \tag{3.6}$$

Where:

$$LEVER = \frac{\text{Net Long-Term Debt}}{\text{Total Assets}} \tag{3.7}$$

$$LIQUID = \frac{\text{Current Assets}}{\text{Current Liabilities}} \tag{3.8}$$

If the firm's leverage decreases, the company receives an $F\_\Delta LEVER$ score of one and zero otherwise. Drawing from Myers and Majluf (1984), Piotroski argued that firms seeking external financing signal that they either lack internal funds or are overvalued. An increase in leverage also leads to less flexibility due to creditor restrictions. If a firm improves its liquidity, it is a positive signal and receives an F_$\Delta LIQUID$ score of one and zero otherwise. Moreover, EQ_OFFER shows if a firm has issued common equity during the last year. Since raising external capital is considered a negative signal, the firm receives an EQ_OFFER score of one if they did not issue equity and zero otherwise. Piotroski states that similar to raising debt, issuing equity signals that the firm is overvalued.

Furthermore, operating efficiency is measured by two indicators, $\Delta MARGIN$ and $\Delta TURN$, which are defined as:

$$\Delta MARGIN = MARGIN_t - MARGIN_{t-1} \tag{3.9}$$

$$\Delta TURN = TURN_t - TURN_{t-1} \tag{3.10}$$

Where:

$$MARGIN = \frac{\text{Gross Margin}}{\text{Revenue}} \tag{3.11}$$

$$TURN = \frac{\text{Revenue}}{\text{Total Assets}} \tag{3.12}$$

Piotroski's rationale is that these metrics reflect two important underlying elements in the return on assets (ROA). If the firm has improved its gross margin ratio, the firm receives an $F\_\Delta MARGIN$ score of one and zero otherwise. Furthermore, increasing the asset turnover ratio implies that the firm has become more efficient. Thus, improving efficiency gives an $F\_\Delta TURN$ score of one and zero otherwise.

Finally, the strategy ranks firms on nine dummy variables, where the maximum F_SCORE possible is nine. The formula for the F_SCORE can be shown as:

$$\begin{aligned} F\_SCORE = {} & F\_ROA + F\_\Delta ROA + F\_CFO + F\_ACCRUAL + F\_\Delta MARGIN \\ & + F\_\Delta TURN + F\_\Delta LEVER + F\_\Delta LIQUID + EQ\_OFFER \end{aligned} \tag{3.13}$$

Piotroski argued that the higher F_SCORE a firm has, the more suited the firm is to grow and be profitable in the future.

Following the Piotroski (2000) paper, other studies have investigated the performance of his value strategy. Pätäri et al. (2018) analyzed the Piotroski strategy in the German stock market during the 2000-2015 period. They found that the F_SCORE with the highest decile of book-to-market firms generated a positive but insignificant alpha in the Carhart four-factor model. They also found that the F_SCORE without the book-to-market ratio criteria (e.g., "plain F_SCORE") was able to generate a positive and significant alpha in the Carhart four-factor model. The F_SCORE also boosts the performance when combined with the top decile of other valuation ratios. Hyde (2018) finds that the Piotroski method does not generate significant alpha with the Carhart four-factor model in the Australian market. Ng and Shen (2020) examined the F_SCORE in Asian markets from 2000 to 2016. They found that a long-short F_SCORE portfolio can generate positive and significant alpha in Hong Kong, Japan, Singapore, and Taiwan with the Fama and French three-factor model. Furthermore, Walkshäusl (2020) found strong empirical evidence that firms with a high F_SCORE generate excess returns in international markets outside the U.S.

The Magic Formula - Joel Greenblatt

Greenblatt published his bestseller "*The Little Book That Beats the Market*" in 2006. The book received excellent critics for its ability to explain the financial theory easily and understandably. Greenblatt has several years of experience in the finance industry, both as a hedge fund manager at Gotham Capital and as an adjunct professor at Columbia University. In his book, he proposes a "magical formula," which aims to find good companies at a low price. Greenblatt claims that his fund, which is partially based on the "magical formula," has achieved a 40% annualized return since 1985. He also claimed that backtests of the "magical formula" in the American market, where the investment universe included the 3500 and 1000 largest companies, yielded an average geometric return of 30.8% and 22.9% in the period 1988-2004, respectively.

The "magic formula" excludes firms related to finance, utility, and firms with a market capitalization below $50 million. It excludes the finance sector primarily due to its complex and unique audit measures. He excludes the utility sector because it is highly regulated in the U.S. He also sets a minimum requirement on the market capitalization of a firm to be at least $50 million (real figure per 2003) to ensure liquidity. After filtering out companies with these characteristics, he ranks the remaining companies based on two variables, (1) Earnings yield and (2) Return on Capital Employed (ROCE).

$$\text{Earnings Yield} = \frac{EBIT}{\text{EV}} \tag{3.14}$$

Earnings yield aims to find companies that are cheaply priced relative to the operating income of the company. The higher the earnings yield is, the more attractive the pricing of the firm seems.

$$\text{ROCE} = \frac{EBIT}{\text{Net Fixed Assets + Working Capital}} \tag{3.15}$$

Greenblatt believes that ROCE is a great indicator of how well a firm is operated as it measures how effective the firm is at utilizing its invested capital. Capital employed (net fixed assets and working capital) is an estimate of how much capital a firm utilizes for its operations to maintain and improve operations.

Furthermore, the companies in the investment universe are ranked on the two metrics. Greenblatt then combines the relative rank of the two variables for each company and advocates investing in the top 20-30 best companies. To exemplify, if there exist 100 firms in the investment universe, and a firm is ranked number 85 and 95 for earnings yield and ROCE, respectively, the company's overall score is 90.

Since Greenblatt published his book in 2006, several studies have investigated his results. Bill Alpert (2006) critiqued Greenblatt's result for being overly optimistic and database dependent. Alpert claimed that backtesting the "magic formula" between 1997-2002 on the databases of Bloomberg and Compustat prompted 16% and 10% annualized returns, respectively. Davydov et al. (2016) compare the "magic formula" to other value strategies in the Finnish market between 1991-2013. They found that the "magic formula" was able to consistently outperform the market portfolio. Blackburn and Cakici (2017) also documented that the "magic formula" outperformed the market in Europe, but not in North America, Asia, or Japan, in the period between 1991-2016.

First Veritas - Thomas Nielsen

First Veritas is a Norwegian mutual fund established in August 2019 and is managed by Thomas Nielsen. The fund invests in the Nordic markets and has a long investment horizon. The fund's investment philosophy is: *"To own the 12-18 stocks in the Nordic which at any time has the most optimal combination of high quality and low risk"* (First Fondene, 2021b). Since its inception, the fund has generated an accumulated return of 92.8% and an annualized return of 32.3% as of December 30th, 2021 (First Fondene, 2021b). Over this period, the fund has outperformed its benchmark (VINX Benchmark CAP NI in NOK), as illustrated in figure 3.1 (First Fondene, n.d.).

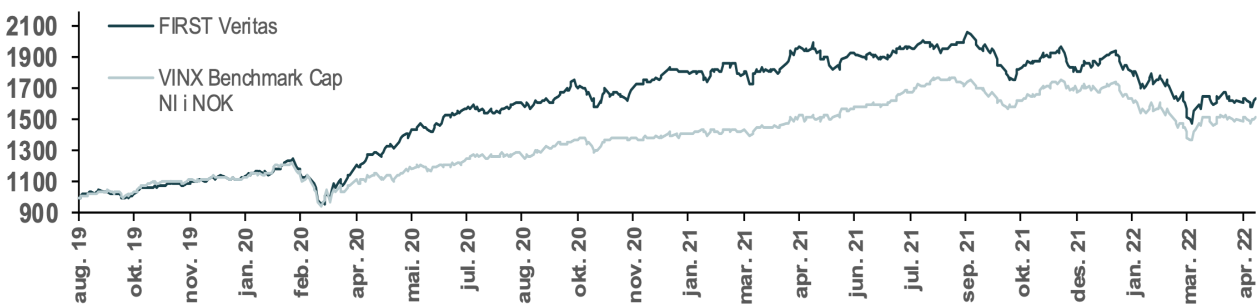

Figure 3.1: First Veritas' HPR (actual after fees) vs. benchmark from Aug. 19 to Apr. 22

The fund screens firms based on a model that generates an overall score depending on a company's relative rank on seven parameters. The variables can be divided into two categories, quality and risk. Furthermore, Nielsen does not invest in banks, insurance, and debt collectors, claiming they have high leverage, complex balance sheets, a cyclical nature, and generally marginal value creation (First Fondene, 2021c). The fund does not have a specified size restriction, but Nielsen claims that firms with sufficient historical accounting data tend to be large enough to be considered.

In the following, we describe how he defines the parameters based on information provided by Nielsen himself [5]. Nielsen employs quarterly data. The quality parameters are (1) revenue

[5]Nielsen sent us an excel sheet that includes the formulas for the parameters.

growth, (2) return on equity (ROE), (3) cash conversion, and (4) margin variance.

$$\text{Revenue Growth}_{2011-dd} = \left(\frac{\text{Revenue}_{LTM}}{\text{Revenue}_{2011}}\right)^{1/N} - 1 \tag{3.16}$$

$$ROE_{2011-dd} = \frac{\sum_{i=2011}^{dd} \text{Net Income}}{\sum_{i=2011}^{dd} \text{Book Value of Equity}} * 4 \tag{3.17}$$

$$\text{Cash Conversion}_{2011-dd} = \frac{\sum_{i=2011}^{dd} \text{Free Cash Flow}}{\sum_{i=2011}^{dd} \text{Net Income}} \tag{3.18}$$

$$\text{Margin Variance}_{2011-dd} = \frac{\text{Standard dev.(EBIT-margin)}_{2011-dd}}{\overline{\text{EBIT-margin}}_{2011-dd}} \tag{3.19}$$

Where:

$$\overline{\text{EBIT-margin}}_{2011-dd} = \frac{\sum_{i=2011}^{dd} \text{EBIT}}{\sum_{i=2011}^{dd} \text{Revenue}} \tag{3.20}$$

Revenue growth is, according to Nielsen, one of the most important value drivers, as revenues can grow indefinitely and thus have no long-term restrictions. He argues that this factor has also been common among the companies in the S&P 500 with the highest returns over the last 15 years. ROE assesses the business idea and how well it is executed. Similar to Piotroski's accrual variable, cash conversion serves as a proxy for accounting quality. Furthermore, Nielsen uses it to penalize companies that have grown by investing heavily. Margin variance measures the volatility in a firm's EBIT margin and indicates a firm's robustness.

Moreover, the risk variables are (5) solidity, (6) valuation (P/E), and (7) cyclical phase.

$$\text{Solidity} = \frac{\text{Book Value of Equity}}{\text{Book Value of Equity + Net Debt}} \tag{3.21}$$

$$\text{Valuation (P/E)} = \frac{\text{Price}}{\text{Earnings}}, \qquad (0 \leq P/E \leq 200) \tag{3.22}$$

$$\text{Cyclical Phase} = \frac{\text{EBIT-margin}_{LTM}}{\frac{1}{2}(\overline{\text{EBIT-margin}}_{2011-dd} + \overline{\text{EBIT-margin}}_{3y\ rolling\ avg.})} \tag{3.23}$$

Where:

$$\overline{\text{EBIT-margin}}_{3y\ rolling\ avg.} = \frac{\sum_{i=dd-2}^{dd} \text{EBIT}}{\sum_{i=dd-2}^{dd} \text{Revenue}} \tag{3.24}$$

Solidity is included to penalize firms with high leverage. Furthermore, Nielsen includes P/E to assess the market's valuation of the business. He believes "expensive" stocks are prone to a high risk of repricing. Moreover, Nielsen acknowledges that no company is so great that it cannot end up as a bad investment if it is overvalued. He exemplifies with Intel and Cisco, which have not been able to deliver positive returns since their highest valuation in 2000, despite showing a strong development in key financial parameters. Nielsen also excludes firms with a P/E above 200. Cyclical phase is the last parameter and is a counter-cyclical element that limits investments in companies when they are able to generate super-profits.

As mentioned, the fund selects companies based on the relative rank of the seven variables. Similar to the "magic formula," companies are ranked on each variable, and a final score is given by the weighted average of the ranks on the seven variables. The current weights are as follows:

(1) Valuation (P/E) - 20%
(2) Revenue growth - 17.5%
(3) ROE - 17.5%
(4) Margin Variance - 17.5%
(5) Cash-Conversion - 10%
(6) Cyclical Phase - 10%
(7) Solidity - 7.5%

This means that the twelve to eighteen companies with the highest weighted average relative rank are selected for the portfolio. To illustrate this, an excerpt from the backtest portfolio is shown in tables 7.2 and 7.3 in the appendix.

Nielsen makes some "exceptions" to the model, which cannot be captured by a backtest. In Nielsen's model, fundamentals are normalized to reflect the underlying profitability of a firm better. These adjustments are based on subjective evaluations (e.g., changing "milestone payments" in BioGaia to a "one-off-effect" (Nielsen, 2021)). Furthermore, Some firms that recently went public (e.g., Paradox in 2016 and Fjordkraft in 2018) have sufficient historical data as private firms and are included in the fund. Moreover, Nielsen sometimes uses projections in accounting figures which can change the companies in the portfolio before figures are published (e.g., Nielsen dropped H&M from the portfolio before a quarterly report based on his own future estimates). Furthermore, he has previously changed the parameters and their respective weights and the number of firms in the fund between 12 and 18. Nielsen has also made exceptions to the exclusion of financial companies by investing in ABG Sundall Collier and Avanza (investment banks).

4 Methodology and analysis

We use the Compustat database for annual fundamental data and daily securities prices data. We download data for Norway, Sweden, Denmark, and Finland. Compustat has been used by acknowledged researchers (e.g., Fama and French (1993) and Carhart (1997)) and is a global database with standardized financial accounting data and market data for more than 80 000 active and inactive publicly traded companies (Wharton Research Data Services, n.d.-c). The database provides fundamentals data from 1986 for global companies and securities data from 1984. Moreover, using Compustat does not limit the use by others at NHH due to data downloading limits (e.g., datastream).

It is important to note that the choice of the database can have a significant impact on results from studies using fundamental data to explain returns due to different coverage between data sources. Tobek and Hronec (2018) test the statistical significance of a set of anomalies (e.g., F_SCORE, book-to-market) on data from Compustat and Datastream, which are often used in studies of this kind. When they allow for unmatched samples (difference in coverage between data sources), the dissimilarity in results between data sources is substantial. Out of the 74 anomalies they tested in the 1990-2016 period, 41 are significant at the 5% level with Compustat, 39 anomalies are significant in Datastream, and only 29 are significant in both.

The Compustat database separates fundamental data for banks and non-financial firms (Wharton Research Data Services, n.d.-c). We do not have access to the global database for banks' fundamentals through NHH. However, the three strategies in this study exclude banks from their investment universe. The securities market data consists of all sectors, including banks.

Furthermore, the Compustat database includes inactive firms, which makes the study free of survivorship bias. Backtesting an investment strategy on a database without inactive firms implies that firms going bankrupt or are delisted for other reasons are excluded from the investment universe ex-ante (Garcia & Gould, 1993). Moreover, the Compustat database provides "as-first-reported" fundamental data to avoid look-ahead bias. Look-ahead bias can be described as using data that was not yet available to the public when forming portfolios (Goldman & Johny, 2021). If restated figures were used, information that was not available at the given point in time would have been used and reduced the credibility of the study.

In line with Fama and French (1993) we filter out all the security types that are not common equity (e.g., preferred equity, warrants, ETFs) with Compustat's "Issue Type Code" (TPCI) variable. Moreover, since companies can have multiple listed securities simultaneously, we need to filter out the non-primary issues. We use the "Primary Issue Tag" (PRIROW) variable in Compustat to do this. Compustat defines the Primary issue as: *the issue whose monthly market data is used to represent market data for the company as a whole* (Wharton Research Data Services, n.d.-a). Furthermore, to compute the market value of common equity, we take the total number of common shares outstanding times the closing price for the primary issue. This is in line with Compustat's user guide (Wharton Research Data Services, 2020).

To compute returns, we adjust the monthly closing stock price for stock splits and cash equivalent distributions (e.g., dividends). For this, Compustat provides two separate cumulative adjustment factors for stock splits (AJEXDI) and cash equivalent distributions (TRFD). In line with Compustat's manual, we use the formula below to compute adjusted closing prices (Wharton Research Data Services, n.d.-b).

$$\text{Adj. Price Close} = \frac{\text{Price Close}}{\text{AJEXDI}} * \text{TRFD} \tag{4.1}$$

Since we look at the strategies for a Norwegian investor, we also adjust prices to Norwegian currency (NOK). We identify the currencies that are present in the dataset and download exchange data from Norges Bank and Macrobond, and match stock prices and exchange rates by the last available trading day of the month. A list of the currencies is presented in table 7.1 in the Appendix. Furthermore, Compustat tracks the reason for deletion through the variable "Research Company Reason for Deletion" ("DLRSN"). We set returns equal to -100% at the end of the month following the last observation for the companies going bankrupt.

In line with Compustat's guidelines, we link the fundamental and securities market data through Compustat's proprietary GVKEY-variable. This is a permanent unique identifier for each company that is never reused or never changed throughout the company's lifespan regardless of name changes (Stanford Graduate School of Business, n.d.). The Plot in figure 4.1 illustrates the data coverage by year.

In line with Fama and French (1993), we construct portfolios at the end of June, the year following the fiscal year, for all strategies to mitigate look-ahead bias. For companies with deviating reporting periods, we define the fiscal year as the year the reporting period ends. For example, fundamental data for companies ending the reporting period in March will not be accounted for in the formation of the portfolios before June next year. Portfolios are rebalanced to equal weights at the end of June each year to limit transaction costs. Thus, we account for the changes in weights occurring from price movements during the holding period when calculating the portfolio's monthly weighted average returns. Furthermore, when a company is delisted during the holding period, it is assumed that the proceeds are reinvested in the remaining companies in the portfolio by their corresponding weights at the time of the delisting (except for bankrupt companies).

Furthermore, to ensure sufficient liquidity, we remove companies with a market capitalization below 100 MNOK, which represent about 20-25% of companies in the dataset, depending

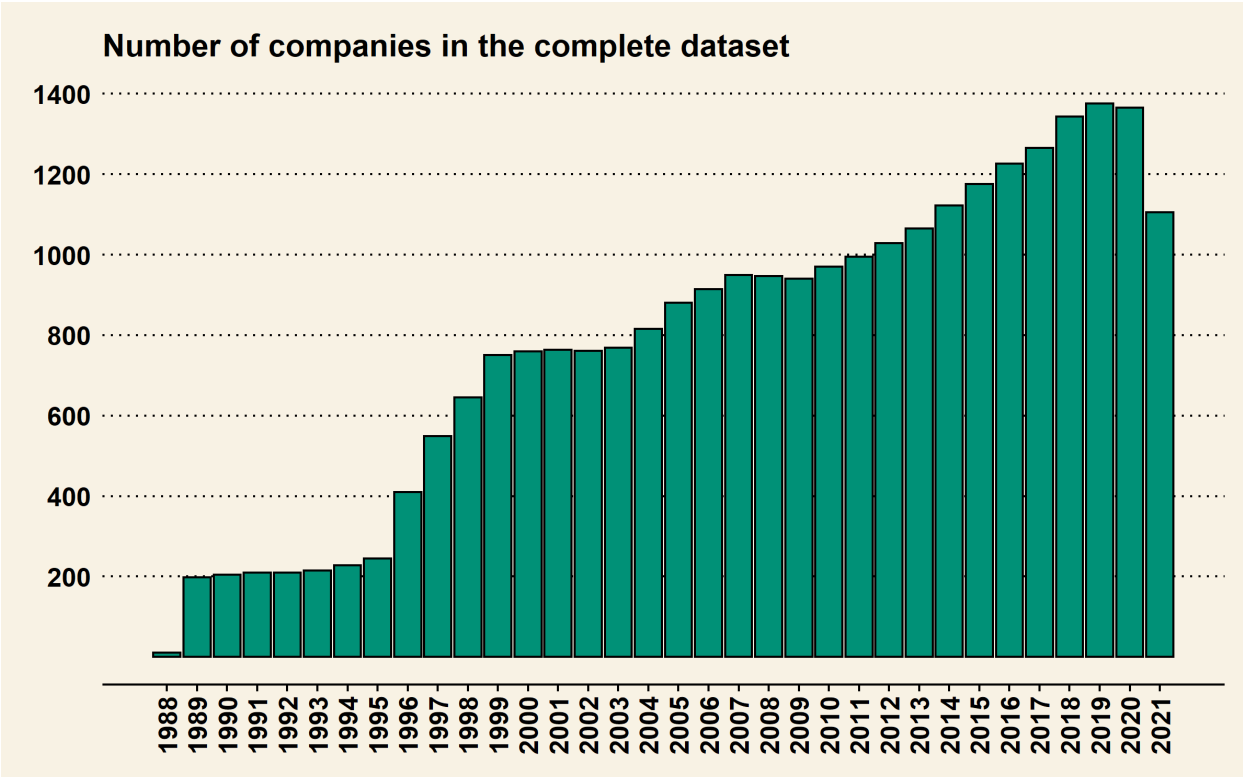

Figure 4.1: Number of firms in the dataset each year between 1988 and 2021

on the time period. Greenblatt (2006) suggested excluding companies with a market capitalization below \$50 million. However, this restriction was meant for the U.S., which has a larger pool of companies. Since First Veritas manages around 900-1000 MNOK, we also test the First Veritas strategy in a "mutual fund scenario," which requires at least 2000 MNOK in market capitalization. Thus, assuming equal weights, the fund invests around 55-83 MNOK per company, corresponding to 2.75%-4.15% ownership for 2000 MNOK market capitalization. Larger companies are seemingly more covered by analysts and available to professional investors and, accordingly, more likely to be correctly priced. Thus, it is interesting to test whether the size requirement affects results. There are sufficient companies above 2000 MNOK with 10-year fundamental data to test the strategy in the same period.

Replicating First-Veritas' model

In the First Veritas model, Thomas Nielsen uses historical data starting from 2011 when measuring the parameters. He previously employed data starting from 2006, and argued that he can not hold the "start year" fixed forever (First Fondene, 2021a). Thus, we use 10-year rolling data in our study (e.g., 10-year average ROE). Thus, to be included in the First Veritas universe, companies must have 10-year continuous historical data on revenue, ROE, cash conversion, and EBIT margin. P/E and solidity are supposed to capture the current situation of a firm and are therefore measured in the respective year.

Moreover, we adjust financial figures for companies that have changed the currency they report their financial statements in. For example, in 1999, Finland changed their official currency from FIM to EUR, which caused several companies to switch from reporting in FIM to EUR (European Commission, n.d.). Adjustments are important to measure revenue growth correctly. Also, due to how Nielsen estimates the average ROE, cash conversion, and EBIT margin, it is also necessary to adjust these variables. For example, implicit in how Nielsen defines the average EBIT margin, each period's margin is not equally weighted but weighted on the respective period's absolute sales figure. Table 4.1 shows how many companies have changed their reporting currency.

Table 4.1

The table shows the number of companies with the number of changes in accounting currency.

Changes	**Number of companies**
0	1916
1	219
2	14
3	2

Compustat does not have a function to convert reporting currency automatically but tracks the currency of financial statements. Thus, we use exchange rate data from Norges Bank and Macrobond and link it with the dataset from Compustat. To limit the manipulation of original data, we convert the companies' financial figures to the most used reporting currency (i.e., the mode currency). For example, PGS ASA reported financials in NOK for five years from 1991 to 1995 but has reported in USD for 26 years from 1996 to 2021. Thus the financial figures in 1991-1995 are converted to USD.

To make the processing of data feasible, we download all the spot exchange rate quotes in NOK (for example, NOK per EUR and NOK per DKK) and use them to proxy exchange rates for other quotes (for example, DKK per EUR). We use the last available trading day spot rates for the respective years in the calculations. A yearly average for all quotes and base currencies would seemingly be more accurate. However, we believe it is a reasonable compromise to make computing easier. The formula below shows how we adjust revenue, net income, the book value of equity, cash flow from operations, cash flow from investments, and EBIT for changes in reporting currency:

$$\text{Currency adjustment factor}_{it} = \frac{(\text{Reported Currency/NOK})_t}{(\text{Mode Currency}_i/\text{NOK})_t} \tag{4.2}$$

Furthermore, we define the seven parameters in the model using annual data on Compustat's variables as shown below, where financial figures denoted with a * are multiplied with the currency adjustment factor in equation 4.2:

$$\text{Revenue Growth}_{10y\ rolling\ avg.} = \left(\frac{\text{Revenue}^*_t}{\text{Revenue}^*_{t-9}}\right)^{1/9} - 1 \tag{4.3}$$

$$ROE_{10y\ rolling\ avg.} = \frac{\sum_{i=t-9}^{t} \text{Net income}^*}{\sum_{i=t-9}^{t} \text{Book value of equity}^*} \tag{4.4}$$

$$\text{Cash Conversion}_{10y\ rolling\ avg.} = \frac{\sum_{i=t-9}^{t} (\text{CFO}^* + CFI^*)}{\sum_{i=t-9}^{t} \text{Net income}^*} \tag{4.5}$$

$$\text{Margin Variance}_{10y\ rolling\ avg.} = \frac{\text{Standard dev.}(\text{EBIT-margin})_{10y}}{\overline{\text{EBIT-margin}}_{10y}} \geq 0 \tag{4.6}$$

$$\text{Solidity} = \frac{\text{Book value of equity}}{\text{Total assets - Cash}} \tag{4.7}$$

$$\text{Valuation (P/E)} = \frac{\text{Market capitalization}}{\text{Net income}}, \qquad (0 \leq P/E \leq 200) \tag{4.8}$$

$$\text{Cyclical Phase} = \frac{\text{EBIT-margin}_t}{\frac{1}{2}(\overline{\text{EBIT-margin}}_{10y} + \overline{\text{EBIT-margin}}_{3y})} \tag{4.9}$$

Where:

$$\overline{\text{EBIT-margin}}_N = \frac{\sum_{i=t-N+1}^{t} \text{EBIT*}}{\sum_{i=t-N+1}^{t} \text{Revenue*}} \tag{4.10}$$

Since Nielsen uses cash conversion to account for companies' level of investments, we include cash flow from operations (CFO) and investments (CFI). Furthermore, to avoid rewarding firms with negative average EBIT margins in the "margin variance" and "cyclical phase" variable, we filter out companies with negative 10-year-average EBIT margin. P/E is measured as the market capitalization at the end of the reporting period divided by net income for the corresponding period. The market capitalization is converted to the corresponding currency of the reported earnings. Firms with P/E greater than 200 or below zero are also filtered out. Cyclical phase is measured as the EBIT margin in year t divided by the average of the 10-year- and 3-year rolling average EBIT margin. Companies with missing data are filtered out, and we compute companies' relative rank on respective parameters every year. The model favors low Margin Variance, P/E, and Cyclical phase and high Revenue Growth, ROE, Cash Conversion, and Solidity.

As mentioned, the strategy requires a lot of historical data to be evaluated for its portfolio. Since we have fundamental data from 1987, the earliest possible time for the portfolio formation is June 1997. However, some figures are not available until later (e.g., cash flow figures). Figure 4.2 illustrates how many companies have adequate data on all parameters for each fiscal year. For the 2007 fiscal year, there are enough companies with sufficient data to make the selection of the top 12-18 companies meaningful. Thus, we start the backtest from July 2008. The same figure for the "mutual fund scenario" is shown in figure 7.1 in the appendix.

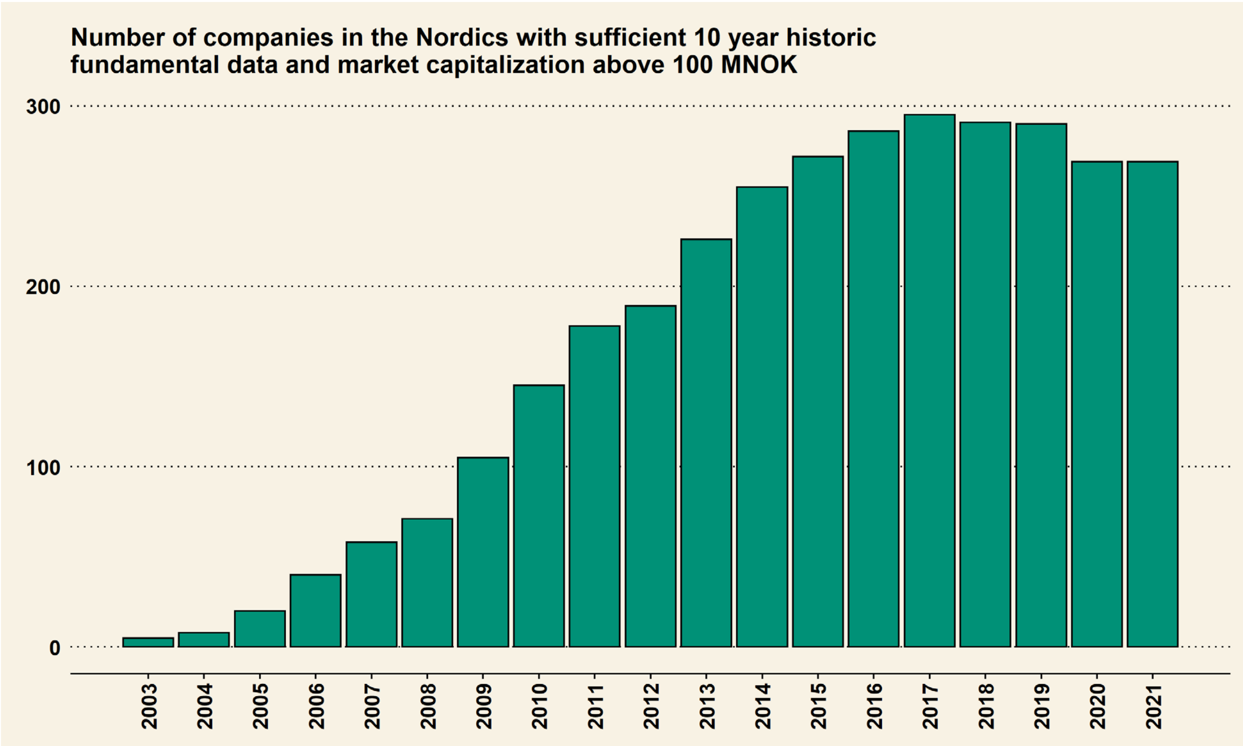

Figure 4.2

Since Nielsen invests in the top 12-18 companies, we select the top 15 companies with the highest weighted-average rank on the seven parameters each year. We use the weights as defined in part 3. As previously discussed, there are several conditions with the First Veritas fund that cannot be replicated in our "mutual fund scenario" backtest. However, we are confident that our results are a close approximation to the original strategy as several of the same companies are present in the back-tests portfolio (e.g., H&M AB, Bouvet ASA, Novo Nordisk A/S, G5 Entertainment AB, Bahnhof AB, Betsson AB, Pandora AS, Orion Corp, Simcorp A/S). The portfolios formed in June 2021 are shown in tables 7.2 and 7.3 in the appendix.

The "Magic Formula" by Greenblatt

In line with Greenblatt's strategy, we remove utilities from the investment universe by filtering on NAICS code 22 "Utilities." Using variables available from Compustat, we define Greenblatt's two variables as:

$$\text{Earnings Yield} = \frac{EBIT}{\text{Long-term Debt - Cash + Market Capitalization}} \tag{4.11}$$

$$\text{ROCE} = \frac{EBIT}{\text{Total Assets - Current liabilities}} \tag{4.12}$$

The market capitalization corresponds to the end of the reporting period and is converted to the currency of the financial statements. All companies' relative rank on these variables is computed at the end of June each year. Since Greenblatt suggests investing in the top 20-30 companies, we select the 25 companies with the highest equal-weighted rank on the two parameters each year.

Piotroski's F_SCORE

The first step in Piotroski's F_SCORE strategy is to select the top 20% of firms with the highest book-to-market ratio. However, in our investment universe, limiting the number of firms to the top 20% of firms with the highest book-to-market ratio leads to multiple years with few firms in the winner-portfolio (firms with an $F\_SCORE \geq 8$). To reduce this problem, we select the top 30% of firms with the highest book-to-market ratio. This increases the number of firms in the portfolio without deviating significantly from the initial strategy. This is also where Fama and French (1993) separate firms with high book-to-market ratios.

To measure the F_SCORE, we define $LEVER$, $LIQUID$, $MARGIN$, and $TURN$ using Compustat's variables as:

$$LEVER = \frac{\text{Long-term debt - Cash}}{\text{Total Assets}} \tag{4.13}$$

$$LIQUID = \frac{\text{Current Assets}}{\text{Current Liabilities}} \tag{4.14}$$

$$MARGIN = \frac{\text{Revenue - COGS}}{\text{Revenue}} \tag{4.15}$$

$$TURN = \frac{\text{Revenue}}{\text{Total Assets}} \tag{4.16}$$

For $LEVER$, Net long-term debt is defined as long-term debt less cash, and gross margin in $MARGIN$ is defined as revenue less COGS (Cost of goods sold). Thus, Piotroski's variables used to compute the dummy variables, except EQ_OFFER, are defined below:

$$ROA = \frac{\text{Net income}}{\text{Total Assets}} \tag{4.17}$$

$$CFO = \frac{\text{Cashflow From Operations}}{\text{Total Assets}} \tag{4.18}$$

$$\Delta ROA = ROA_t - ROA_{t-1} \tag{4.19}$$

$$ACCRUAL = CFO - ROA \tag{4.20}$$

$$\Delta LEVER = LEVER_t - LEVER_{t-1} \tag{4.21}$$

$$\Delta LIQUID = LIQUID_t - LIQUID_{t-1} \tag{4.22}$$

$$\Delta MARGIN = MARGIN_t - MARGIN_{t-1} \tag{4.23}$$

$$\Delta TURN = TURN_t - TURN_{t-1} \tag{4.24}$$

Compustat does not provide a variable for EQ_OFFER to track if the firm has issued equity. However, we can track if the number of shares outstanding has increased after controlling for stock splits and use this as a proxy. Using the Compustat variable $AJEXDI$, we subtract the difference in shares caused by stock splits. The proxy for shares offered at time t is defined as:

$$\text{Shares offered}_t = \text{Shares outstanding}_t - \text{Shares outstanding}_{t-1} * \frac{AJEXDI_{t-1}}{AJEXDI_t} \tag{4.25}$$

Since exercised warrants could cause small increases in shares outstanding, we assume that an increase in shares outstanding by 5% or more is due to equity offerings. Thus, EQ_OFFER is equal to one if the shares offered proxy is less than 5% of shares outstanding and zero otherwise. After computing the nine dummy variables with the same criteria as in part 3, we compute the F_SCORE using equation 3.13. Also, a firm must have available data for all the components in the F_SCORE to be included in the portfolio.

Computing the Carhart four-factor model's explanatory variables

We employ the Carhart (1997) four-factor model to assess whether performance can be attributed to four elementary strategies or risk factors; high vs. low beta (market return sensitivity), small vs. large firms, high vs. low book-to-market stocks, and 1-year winners vs. losers. In line with Carhart (1997), the ex-post returns of the winner (loser) portfolio are the equal-weighted average of firms with the 30% highest (lowest) eleven-months returns ex-ante. Portfolios of stocks are formed monthly. Since Carhart (1997) obtains SMB and HML from Fama and French's website for US-listed stocks, we construct the variables for the Nordics using the methodology by Fama and French (1993).

Due to the correlation between market capitalization and the book-to-market ratio, Fama and French (1993) limit the influence between the two variables by employing a methodology in which they divide the dataset into six portfolios, which is described in figure 4.3:

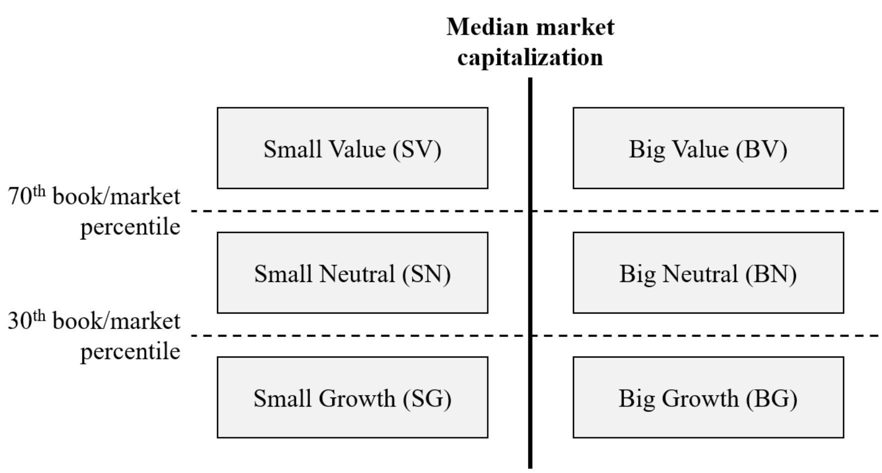

Figure 4.3: Fama & French's six portfolios for the construction of SMB and HML.

For each year, the dataset is first split by the median market capitalization. Then, the two groups are split by the 30th and 70th percentile book-to-market ratio. The portfolios are formed in June for the year preceding the year in which the companies' reporting period ends to avoid look-ahead bias. Then, value-weighted returns are calculated monthly.

The returns of the SMB portfolio are the simple average between the three small stock portfolios minus the simple average between the three large stock portfolios, as illustrated below:

$$SMB = 1/3\ (\text{Small Value} + \text{Small Neutral} + \text{Small Growth}) - \\ 1/3\ (\text{Big Value} + \text{Big Neutral} + \text{Big Growth}) \tag{4.26}$$

The returns of the HML portfolio are the simple average between the two high book-to-market portfolios minus the simple average between the two low book-to-market portfolios, as illustrated below:

$$HML = 1/2\ (\text{Small Value} + \text{Big Value}) - 1/2\ (\text{Small Growth} + \text{Big Growth}) \tag{4.27}$$

This ensures that both small and big firms are represented in the high- and low book-to-market portfolios.

We use the market capitalization at the end of the financial reporting period in the two variables (i.e., size and book-to-market) used for forming the six portfolios the following June. When ranking the companies by size, we convert market prices to NOK using the end of the corresponding month's exchange rate. For the construction of the book-to-market ratio, when a company's primary issue trades at a different currency than the book values are reported in, the market capitalization's currency is adjusted to that of the financial reports by using the end of the corresponding month's exchange rates. Moreover, the book value of equity and the market capitalization represents common equity, and negative book-to-market firms are removed in line with Fama and French (1993).

Due to data availability limits at NHH for the Compustat database as described earlier, the dataset for constructing the SMB and HML portfolios does not include banks. However, this is not expected to significantly impact the SMB and HML returns as the majority of the Nordic companies are represented, and there is a large variation in size and book-to-market ratios in the dataset.

For the market portfolio, we use the value-weighted VINX all share index GI in NOK, which includes every share listed on the Nordic exchanges. We use the gross total return index (GI), which assumes 100% of the gross dividends are reinvested and does not deduct withholding tax on dividends received from foreign exchange investments (Oslo Børs, 2020). This is the most appropriate benchmark to compare the returns computed from Compustat with, as these returns do not account for withholding tax on dividends received from foreign exchange investments. For the "mutual fund scenario," we use First Veritas' benchmark (VINX Benchmark Cap NOK) with gross returns as the market portfolio. This index includes the largest and most traded stocks in the Nordics. Switching between the two indexes does not impact results significantly. Indexes are downloaded from Nasdaq Nordic (2022).

Furthermore, we use the one-month NIBOR (converted from annual to monthly returns) obtained from Macrobond as a proxy for the risk-free rate as we look at monthly returns in NOK.

Transaction Costs

Lesmond et al. (2004) suggest that transaction costs consist of the bid-ask spread, commissions, impact costs, and taxes. Impact costs and bid-ask spreads are believed to be the most important (Damodaran, 2010). However, there is no clear-cut answer to how much indirect costs (i.e., bid-ask spread and impact costs) one should account for, and it depends on how much money one is managing.

Since impact costs are hard to measure, we focus on bid-ask spreads. The bid-ask spread reflects the cost of instantaneously buying and selling a stock. However, crossing the entire bid-ask spread requires two trades. Thus, in line with Hyde (2018), we assume that a single trade crosses half of the bid-ask spread. Furthermore, since the magnitude of the bid-ask spread depends on how many shares the investor trades, and we do not account for impact costs, we also run the regressions when crossing the full bid-ask spread per trade. The latter scenario is more accurate for a larger investor and seemingly conservative for a small investor. Lastly, we assume a brokerage fee (commission cost) of 0.05% (Brockfield (2011), Nordnet (n.d.)).

An investor will also incur foreign exchange costs when trading stocks denominated in different currencies. However, we do not account for this as it is seemingly of little impact since this cost is low and the exchange turnover is lower than the portfolio turnover if the investor holds a foreign currency account. For example, selling stocks denominated in SEK and using the proceeds to buy stocks denominated in SEK does not incur currency exchange costs. Thus, the turnover of currencies incurred by transactions will always be lower than the turnover of traded stocks unless 100% of the portfolio converts to currencies that the portfolio did not hold initially. Moreover, a Norwegian investor can create a foreign currency account with Nordnet, which charges only 0.075% per exchange (Nordnet.no, 2022).

The Compustat database does not track bid/ask prices. However, it tracks daily high and low prices, which can be used to estimate the bid-ask spread with the model developed by Corwin and Schultz (2012), which achieves a 0.9 correlation with actual bid-ask spreads in the U.S. The model has two important underlying assumptions: (1) the high price is buyer-initiated (ask-price) while the low price is seller-initiated (bid-price), and (2) the bid-ask spread and the one-day price volatility are constant over a two-day interval. With this, the spread between the daily high and low prices is a function of the bid-ask spread and the one-day volatility in prices, which is a function of time. Thus, by comparing the highest and lowest price over one and two days, we can estimate the bid-ask spread. The bid-ask spread S is defined as:

$$S = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}} \tag{4.28}$$

where:

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \tag{4.29}$$

$$\beta = \left(ln \left(\frac{H_t}{L_t} \right) \right)^2 + \left(ln \left(\frac{H_{t+1}}{L_{t+1}} \right) \right)^2 \tag{4.30}$$

$$\gamma = \left(ln \left(\frac{Max[H_t; H_{t+1}]}{Min[L_t; L_{t+1}]} \right) \right)^2 \tag{4.31}$$

H_t and L_t are the respective high- and low prices at time t. Also, in accordance with Corwin and Schultz (2012), high- and low prices are adjusted for overnight returns at time $t+1$ with the following equations:

$$H^A_{t+1} = H_{t+1} + Max[0; C_t - H_{t+1}] - Max[0; L_{t+1} - C_t] \tag{4.32}$$

$$L^A_{t+1} = L_{t+1} + Max[0; C_t - H_{t+1}] - Max[0; L_{t+1} - C_t] \tag{4.33}$$

C_t is the closing price at time t, while H^A_{t+1} and L^A_{t+1} are the adjusted high- and low prices. Overnight returns are controlled for by replacing H_{t+1} and L_{t+1} in (4.30) and (4.31) with H^A_{t+1} and L^A_{t+1}. If the bid-ask estimator is negative at a given date, the bid-ask spread for the given date is set to zero, similar to Corwin and Schultz (2012). Also, if a firm does not have data on high or low prices at time t, the bid-ask spread is "NA" for day t and $t+1$.

After taking samples of the estimator for various stocks, we find that the model seemingly has a downward bias for highly illiquid firms. The model requires at least two trades per day (one buyer-initiated and one seller-initiated) to provide appropriate estimates. However, illiquid firms sometimes only have one trade a day (e.g., Integrated Wind Solutions ASA). Then, the daily high price is equal to the daily low price, which leads to very low bid-ask spread estimates. Thus, to mitigate this issue, we ignore bid-ask spread estimates for day t and $t+1$, when the closing price is equal to the high- and low price on the same day ($C_t = H_t = L_t$). The adjustment does not impact the results materially. Finally, we estimate the monthly average bid-ask spread per security and aggregate the securities market data into monthly observations.

For summary statistics of the bid-ask estimates, see tables 7.4 and 7.5 in the appendix. As expected, there is a negative relationship between market capitalization and bid-ask spreads.

5 Results

Figure 5.1 illustrates the holding period returns of the selected strategies in the Nordics from July 2008 to the end of 2021, indexed at 100. First Veritas and Greenblatt's "magical formula" generate higher returns than the VINX, especially after the market decline early in

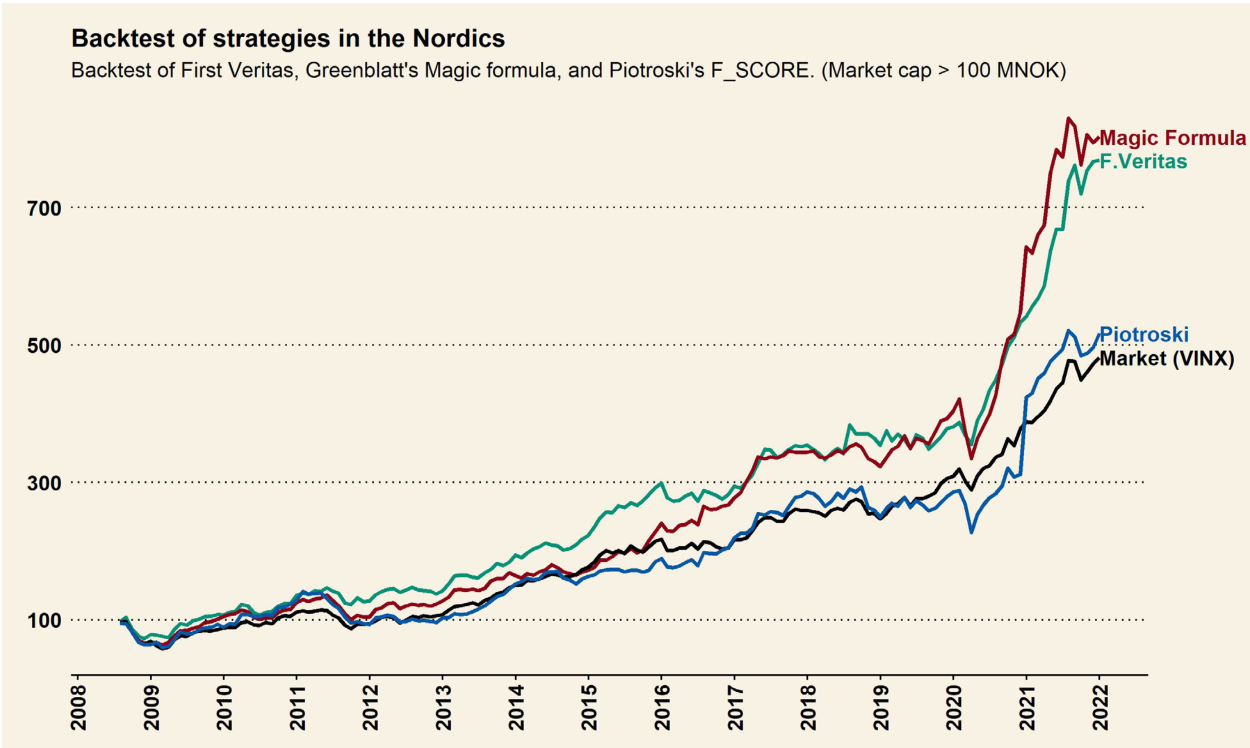

Figure 5.1: HPR for the strategies and the market from July 2008 to December 2021

2020. This is consistent with First Veritas' actual returns, illustrated in figure 3.1. Piotroski's F_SCORE delivers slightly higher returns than the VINX due to a strong 2020 and 2021.

Table 5.1 presents the holding period returns for the portfolios between the time of formation and selected performance measures. The results indicate that the FV model and the "magic formula" "beat the market" in the sample period, while the Piotroski strategy's performance seems relatively equal to the market. First Veritas and the "magic formula" have a higher geometric and arithmetic average annual return than the VINX, but they also have a higher standard deviation. However, they both have a higher Sharpe ratio than the market, which implies that the investor receives higher return per unit of risk. The Sortino ratio for First Veritas and the "magic formula" is higher than for the VINX.

Table 5.1

The table reports yearly HPR between the time of portfolio formation and performance measures for the benchmark (VINX) and the three strategies (First Veritas, Magic Formula, and Piotroski). The performance measures are computed with monthly data and are annualized. The standard deviation, Sharpe ratio, Sortino ratio, and information ratio are annualized by multiplying by $\sqrt{12}$. Numbers in red indicate negative HPR, while blue cells show where the strategies' HPR are higher than the VINX.

Holding period	**VINX**	**First Veritas**	**Magic Formula**	**Piotroski**
July 2008 - June 2009	-23.7%	-7.6%	-15.0%	-20.3%
July 2009 - June 2010	20.3%	16.1%	18.5%	31.5%
July 2010 - June 2011	16.5%	32.3%	27.6%	16.6%
July 2011 - June 2012	-7.0%	0.6%	-6.8%	-20.1%
July 2012 - June 2013	22.2%	12.8%	18.7%	18.8%
July 2013 - June 2014	37.4%	29.5%	26.6%	46.5%
July 2014 - June 2015	17.8%	26.2%	9.3%	-0.1%
July 2015 - June 2016	3.4%	3.5%	21.2%	5.3%
July 2016 - June 2017	22.4%	27.2%	41.3%	44.0%
July 2017 - June 2018	4.3%	-1.4%	1.7%	7.5%
July 2018 - June 2019	6.5%	8.1%	6.1%	-1.3%
July 2019 - June 2020	17.3%	17.3%	9.6%	1.6%
July 2020 - June 2021	37.1%	54.1%	94.2%	77.8%
July 2021 - Dec. 2021	8.3%	15.0%	3.7%	4.6%
Arithmetic average	12.8%	16.3%	16.9%	14.1%
Geometric average	12.4%	16.3%	16.7%	12.9%
Standard deviation	14.8%	15.0%	16.5%	20.0%
Sharpe ratio	0.75	0.98	0.92	0.63
Sortino ratio ($MAR = Rf$)	0.97	1.42	1.32	0.95
Information ratio		0.39	0.41	0.09

Furthermore, we investigate if the performance of the strategies can be attributed to the four fundamental strategies or risk factors covered by the Carhart four-factor model. Table 5.2 presents the regression output of monthly returns for First Veritas, the "magic formula," and the Piotroski strategy from July 2008 to December 2021. First Veritas generates a positive and significant alpha at the 5% level, which is robust when controlling for SMB, HML, and WML. First Veritas has the highest and most significant alpha of the respective strategies, generating an annualized alpha between 5.0- and 5.5%, depending on the model. First Veritas also has the lowest beta, which is between 0.83 to 0.86. This is likely a result of the strategy incorporating risk factors such as solidity and margin variance. Furthermore, First Veritas is significantly tilted towards the SMB strategy, which is surprising given that the strategy requires ten years of historical fundamental data, which we expect is more available for larger and more mature companies. Furthermore, the strategy excludes firms with a market capitalization below 100 MNOK. However, other parameters may drive the tilt towards SMB as P/E may favor lower market capitalization in the numerator. Moreover, First Veritas is not significantly tilted towards value stocks despite having a positive sign on the coefficient, which may suggest a weak correlation between firms with high book-to-market ratios and low P/E.

The "magic formula" only generates significant positive alpha when employing the Carhart four-factor model. The "magic formula" has a higher beta than the FV portfolio. Thus, the higher information ratio than the FV portfolio in table 5.1 is partially attributable to a higher beta. The "magic formula" also tilts towards SMB but more than First Veritas, and has no tilt towards value stocks which could imply a weak correlation between EBIT-to-EV and book-to-market.

For the Piotroski portfolio, the alpha is statistically indistinguishable from zero with all models. The portfolio has a beta between 0.95 and 1.02 and also tilts positively towards SMB. The Piotroski strategy has a significant tilt toward HML, which is expected due to the selection of firms with high book-to-market ratios.

Table 5.2: Regression results on gross returns

The table reports the regression results for the three strategies (First Veritas, Magic Formula, and Piotroski) for the CAPM, FF3F- and the C4F-model using monthly returns. The data period is from July 2008 until December 2021. Furthermore, the alpha and standard error of residuals (SE) are annualized by multiplying with 12 and $\sqrt{12}$, respectively. P-values (two-tailed test) are in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First Veritas			**Magic Formula**			**Piotroski**		
	CAPM	FF3F	C4F	CAPM	FF3F	C4F	CAPM	FF3F	C4F
Alpha	5.4%**	5.0%**	5.5%**	5.2%*	4.5%*	5.5%**	1.9%	0.7%	1.9%
	(2.6%)	(3.4%)	(2.3%)	(6.1%)	(8.5%)	(3.7%)	(63.4%)	(84.6%)	(59.9%)
Market	0.83***	0.86***	0.84***	0.90***	0.95***	0.93***	0.95***	1.02***	0.99***
	(0.0%)	(0.0%)	(0.0%)	(0.0%)	(0.0%)	(0.0%)	(0.0%)	(0.0%)	(0.0%)
SMB		0.197***	0.195***		0.358***	0.355***		0.583***	0.579***
		(0.2%)	(0.2%)		(0.0%)	(0.0%)		(0.0%)	(0.0%)
HML		0.067	0.053		0.005	-0.025		0.283***	0.247**
		(28.5%)	(41.7%)		(94.1%)	(72.0%)		(0.3%)	(1.0%)
WML			-0.035			-0.072*			-0.085
			(32.7%)			(6.5%)			(11.1%)
Adj. R^2	67.0%	68.8%	68.8%	64.1%	69.0%	69.5%	49.3%	61.2%	61.6%
SE	8.7%	8.4%	8.4%	10.0%	9.3%	9.2%	14.3%	12.5%	12.4%
N	162	162	162	162	162	162	162	162	162

To better understand which steps in the stock screening process are driving the results, we assess high and low-ranked companies by the three strategies. The results are shown in tables 7.6 and 7.7 in the appendix. Our results indicate that most companies with sufficient 10-year historical data to be considered for the FV-model generate alpha, suggesting that the relative rank on the parameters is less important for performance. This does not fit well with the reasoning behind the model. However, it seems likely that long available data on fundamentals is endogenous with other value characteristics as such companies are seemingly in a more mature stage in the archetypal business life cycle. Moreover, our results indicate that the poor performance of the Piotroski strategy is attributable to the selection of high book-to-market stocks, while the F_SCORE predicts winners from losers. This fits well with other studies discussed in part 3, which document that the book-to-market premium has declined over the years and that the book value of equity has become a poor proxy for fundamental value.

Adjusting for transaction costs

To test the robustness of the positive alpha for the "magic formula" and the FV model, we estimate the portfolio's turnover and average bid-ask spread for corresponding months. The portfolio turnover accounts for yearly portfolio formation, rebalancing, and reinvesting proceeds for companies that are delisted during the holding period. It does not account for reinvestment of dividends which are expected to have a small impact.

Table 5.3

The table reports the average bid-ask spread using the Corwin and Schultz (2012) bid-ask spread estimator for the First Veritas and "magic formula" portfolios and all securities in the dataset from July 2008 until December 2021. The annual portfolio turnover accounts for annual portfolio formation, annual rebalancing, and reinvestment of proceeds from delisted firms during the holding period.

Strategy	Avg. bid-ask spread	Annual portfolio turnover		
		Avg.	**Min**	**Max**
First Veritas	0.76%	47%	25%	67%
Magic Formula	0.95%	69%	54%	100%
Full dataset	1.39%			

Table 5.3 summarizes the turnover and bid-ask spreads. The turnover of the FV portfolio is lower than the "magic formula," which is likely caused by new fiscal periods having a lower impact on ranking due to the use of longer historical data. Furthermore, the average bid-ask spread for the First Veritas and the "magic formula" portfolios are 0.76% and 0.95%,

respectively. The average bid-ask spread for the entire dataset in the same period is 1.39%.

The returns of the portfolios are adjusted for transaction costs in the months they are incurred, which is mainly at the end of June each year and some during the holding period when firms are delisted. To simplify, we use the monthly equal-weighted average bid-ask spread for the companies in the portfolio. As discussed in part 4, we assume an investor must cross half of the bid-ask spread per trade. Furthermore, the turnover has to be multiplied by two to account for both selling and buying stocks. Thus, the returns net of transaction costs are calculated as follows:

$$\text{Adj. return} = (1+\text{return})*[1-2*\text{turnover}*(\text{bid-ask spread}/2 + \text{commission fee})]-1 \quad (5.1)$$

However, since the magnitude of the bid-ask spread depends on the amount of money an investor is managing and we do not account for impact costs, we also show results when crossing the full bid-ask spread, which we believe is a conservative measure for a small investor.

Table 5.4 shows the alpha of the same regressions as in table 5.2 with returns net of transaction costs. When crossing half of the bid-ask spread, the alpha for the FV portfolio is significant at the 5% level for the CAPM and C4F model and has a p-value of 5.5% for the FF3F model. Thus, it seems likely that the model is able to generate alpha after accounting for transaction costs for a small investor. However, when crossing the full bid-ask spread, the alpha is insignificant in all models. For the "magic formula," the alpha is still positive on average, but we fail to reject the null hypothesis that the alpha equals zero at the 5% significance level for all models.

This analysis is seemingly a conservative measure if one defines "beating the market" as generating excess returns compared to holding a portfolio with an equal loaded mix of the four risk factors, since one can not invest in the risk factors without incurring transaction costs. This "bias" is seemingly most at play in the FF3F and the C4F model as the HML, SMB, and WML portfolios are formed monthly. The market factor, on the other hand, is

Table 5.4: Results net of transaction costs

The table reports the alpha from the regression results for the First Veritas and "magic formula" portfolios after transaction costs (i.e., bid-ask spread and commission fees) when crossing half and the full bid-ask spread. Portfolios are rebalanced yearly. The portfolios' returns are regressed on the CAPM, FF3F-model, and C4F-model using monthly returns from July 2008 until December 2021. Furthermore, the alpha's are annualized, while the p-values (two-tailed test) are shown in parenthesis. The other factors from the regressions are not included for the sake of brevity. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		First Veritas			**Magic Formula**		
		CAPM	FF3F	C4F	CAPM	FF3F	C4F
Crossing half the	Alpha	5.0%**	4.5%*	5.1%**	4.5%	3.7%	4.8*%
bid-ask per trade	P-value	(4.2%)	(5.5%)	(3.6%)	(10.8%)	(15.1%)	(6.8%)
Crossing the full	Alpha	4.6%*	4.1%*	4.7%*	3.8%	3.1%	4.2%
bid-ask per trade	P-value	(6.2%)	(8.1%)	(5.3%)	(17.4%)	(24.1%)	(11.3%)

a value-weighted index, which prompts less portfolio turnover (less rebalancing) and high liquidity (most weighted on the most liquid stocks). Thus, an investor would seemingly be able to replicate the market index with lower transaction costs than the HML, SMB, and WML portfolios. If we exclusively assess the alpha with the CAPM, it does not change the conclusions made above.

Mutual Fund Scenario - First Veritas

For the First Veritas strategy, we also test how well the strategy performs in a mutual fund setting where we exclude companies below 2000 MNOK market capitalization and account for fees. Since we only consider the largest companies, we assume there is sufficient liquidity such that the fund must only cross half the bid-ask spread per trade. This assumption does not affect results materially. Furthermore, it is important to note that our study cannot replicate all the work put in by the portfolio manager, which fees should compensate for (e.g., adjusting financial statements, employing quarterly data, retrieving fundamental data from before companies were taken public). Nonetheless, it is interesting to assess the model's performance with larger stocks since they are seemingly less neglected, and how much of the potential alpha is reduced by fees.

According to the First Veritas prospect, the management fee equals 1.25% annually and is expensed monthly (First Fondene, 2022). Thus, we subtract 1.25%/12 from monthly returns. In addition, the variable performance-based fee equals 20% of the return (net of management fees) above the benchmark and is expensed annually. However, this cannot exceed 2.5% or be less than 0%. Also, if the fund underperforms the benchmark for a year, the fund will not expense a performance fee until it has caught up with past percentage returns under the benchmark (i.e., "high-water mark"). The performance fee is calculated annually with the equation below:

$$\text{Variabel Fee} = MIN[0.2 * MAX[r_t - HWM_{t-1}; 0]; 0.025] \tag{5.2}$$

Where:

$$HWM_t = MAX[HWM_{t-1} - r_t; 0] \tag{5.3}$$

$$r_t = \text{Return net of management fee above the benchmark} \tag{5.4}$$

HWM_t represents the "high-water mark," which tracks the accumulated underperformance the fund must catch up with before variable fees can be expensed. To simplify, we calculate and subtract the performance fee from the returns net of management fees at the end of June each year (December for 2021). However, this is not completely accurate. For example, if the fund achieves a 10% return net of management fee above the benchmark in February, the actual return for an investor is slightly less than 10% due to an increase in the NPV of the expected variable fee. This effect would be complicated to compute and seemingly does not affect the results materially. Furthermore, the variable performance-based fee accounts for about 1/4 of the total estimated fees.

Table 5.5 shows the regression results for gross returns, net of transaction costs, and net of transaction costs and fees when excluding companies with a market capitalization below 2000 MNOK. In this setting, the First Veritas model does not generate significant alpha, even on gross returns. A possible explanation for this is that the market for larger stocks could be more efficient. Professional investors (e.g., mutual funds) are more able to participate in the market for larger stocks which increase competition and seemingly prompt more "correct" prices. Larger stocks are also more covered by analysts.

Table 5.5: First Veritas mutual fund scenario

The table reports regression results for First Veritas for the CAPM, FF3F- and the C4F-model using monthly returns. The portfolio is analyzed before- and after transaction costs, and also after transaction costs and fees. In contrast to table 5.4, the minimum market capitalization is 2000 MNOK. Also, the market factor is the excess return of the VINX Benchmark CAP NOK GI. The data period is from July 2008 until December 2021. Furthermore, the alpha and standard error of residuals (SE) are annualized by multiplying with 12 and $\sqrt{12}$, respectively. P-values (two-tailed test) are in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Gross			**Net of t. costs**			**Net of t. costs & fees**		
	CAPM	FF3F	C4F	CAPM	FF3F	C4F	CAPM	FF3F	C4F
Alpha	3.3%	2.9%	3.4%	3.0%	2.6%	3.1%	1.4%	1.0%	1.5%
	(14.9%)	(19.5%)	(14.1%)	(19.5%)	(25.2%)	(18.2%)	(55.4%)	(67.4%)	(51.4%)
Market	0.85***	0.88***	0.87***	0.85***	0.88***	0.87***	0.86***	0.88***	0.87***
	(0.0%)	(0.0%)	(0.0%)	(0.0%)	(0.0%)	(0.0%)	(0.0%)	(0.0%)	(0.0%)
SMB		0.149**	0.147**		0.150**	0.148**		0.161***	0.158**
		(1.5%)	(1.5%)		(1.5%)	(1.5%)		(0.8%)	(1.0%)
HML		0.057	0.042		0.056	0.040		0.059	0.041
		(34.2%)	(49.5%)		(35.5%)	(51.8%)		(33.6%)	(51.8%)
WML			-0.034			-0.036			-0.040
			(32.3%)			(30.1%)			(24.9%)
Adj. R^2	71.0%	71.9%	71.9%	71.0%	71.9%	71.9%	71.1%	71.9%	71.9%
SE	8.2%	8.1%	8.1%	8.2%	8.1%	8.1%	8.3%	8.2%	8.2%
N	162	162	162	162	162	162	162	162	162

6 Conclusion

In this study, we have tested whether the three mechanical value strategies: 1) the First Veritas model, 2) Greenblatt's "magic formula," and 3) Piotroski's selection method beat the market in the Nordics from July 2008 to December 2021. Before accounting for transaction costs, the First Veritas model generates statistically significant alpha with all models, while the "magic formula" only generates statistically significant alpha with the Carhart four-factor model. The Piotroski portfolio performs the worst of the strategies and does not generate significant alpha on any models with gross returns. Our results are sensitive to transaction costs, and after accounting for the bid-ask spread and commission fees, the "magic formula" portfolio's alpha in the four-factor model becomes insignificant, while the First Veritas model still generates significant alpha with the CAPM and the four-factor model and has a p-value of 5.5% in the three-factor model. The First Veritas model has a low portfolio turnover and select stocks with low bid-ask spreads. It is important to note that transaction costs depend on how much money the investor manages. Since we do not account for impact cost and assume an investor crosses half of the bid-ask spread per trade, these results are seemingly more accurate for a small investor. A larger investor is more likely to impact prices and cross more of the bid-ask spread.

So, does the alpha's for the FV model suggest that markets are inefficient? As with any test on market efficiency, we run into the dual hypothesis problem, which occurs because we cannot be certain we have the true market equilibrium model. With recent evidence documenting a declining relevance of the book-to-market variable, the HML variable may not be able to capture the same risk as when Fama and French presented their three-factor model. Thus, the HML variable might be due for an update. However, with the strong evidence presented by Piotroski against the argument that the book-to-market premium is compensation for risk related to financially weak companies, it is not evident that the HML variable was necessary in the first place.

Furthermore, considering that "everyone" can apply mechanical strategies and they do not require accumulated knowledge or wisdom, it may seem surprising if they can beat the market. However, there are many strong arguments supporting the value investing philosophy and the idea that the market can neglect or be overly pessimistic towards certain "boring" or little-known companies.

Moreover, it seems unlikely that our results are a product of data snooping as we test the strategy in the Nordic markets, which are less covered in the literature. Thus, it seems unlikely that the selection of the First Veritas model is based on previously identified statistically significant patterns.

Furthermore, it depends on how one defines market efficiency and "beating the market." If one defines beating the market as providing a better alternative than what an investor can achieve in practice by constructing a portfolio with an equal loaded mix of the risk factors (e.g., through ETFs), we might have been too "strict" with the mechanical strategies since an investor cannot replicate the risk factors without incurring transaction costs. To conclude, it seems likely that a non-institutional investor can apply the FV model and "beat the market."

We have also assessed the First Veritas strategy in a mutual fund scenario by excluding companies with a market capitalization below 2000 MNOK and accounting for fees. The model does not generate statistically significant alpha on gross returns. After fees and transaction costs, the portfolio generates an annualized alpha between 1.0-1.5% depending on the model, but it is highly insignificant (p-value above 50% in all models). This may suggest that the market for larger companies is more competitive and efficient, as discussed by Arbel and Strebel (1982). Thus, it seems probable that it is harder for mutual funds to reap the potential benefits of mechanical strategies since they operate in more competitive markets. Furthermore, fees remove a significant part of the potential alpha, and it seems unlikely that the mutual funds' investors can achieve excess returns. It seems reasonable that potential alpha would be distributed to the fund manager as investors only deploy capital which is seemingly less scarce than the fund manager's hard work and accumulated knowledge.

It is important to note that there are some elements of the First Veritas mutual fund's strategy that fees should compensate for that we cannot replicate. For example, Nielsen normalizes accounting figures and employs quarterly data. Furthermore, he occasionally makes exceptions to some criteria (e.g., excluding banks or requiring accounting data from 2011) where he deems it appropriate. Moreover, his portfolio formation is more dynamic, whereas we only form portfolios once a year. However, among thousands of companies in the dataset, many of the same 12-18 stocks that First Veritas actually holds end up in the backtest portfolios.

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7 Appendix

Table 7.1: Number of companies in the dataset for respective currencies

Currency	Securities market data	Fundamental data
ARS	1	0
CHF	2	0
DKK	389	267
EUR	406	297
FIM	1	115
GBP	9	1
HRK	1	0
MXN	1	0
NOK	626	418
PLN	1	0
SEK	1383	1150
SGD	1	0
AED	0	1
AUD	0	1
EEK	0	1
INR	0	1
ISK	0	1
USD	0	135
N/A	389	0

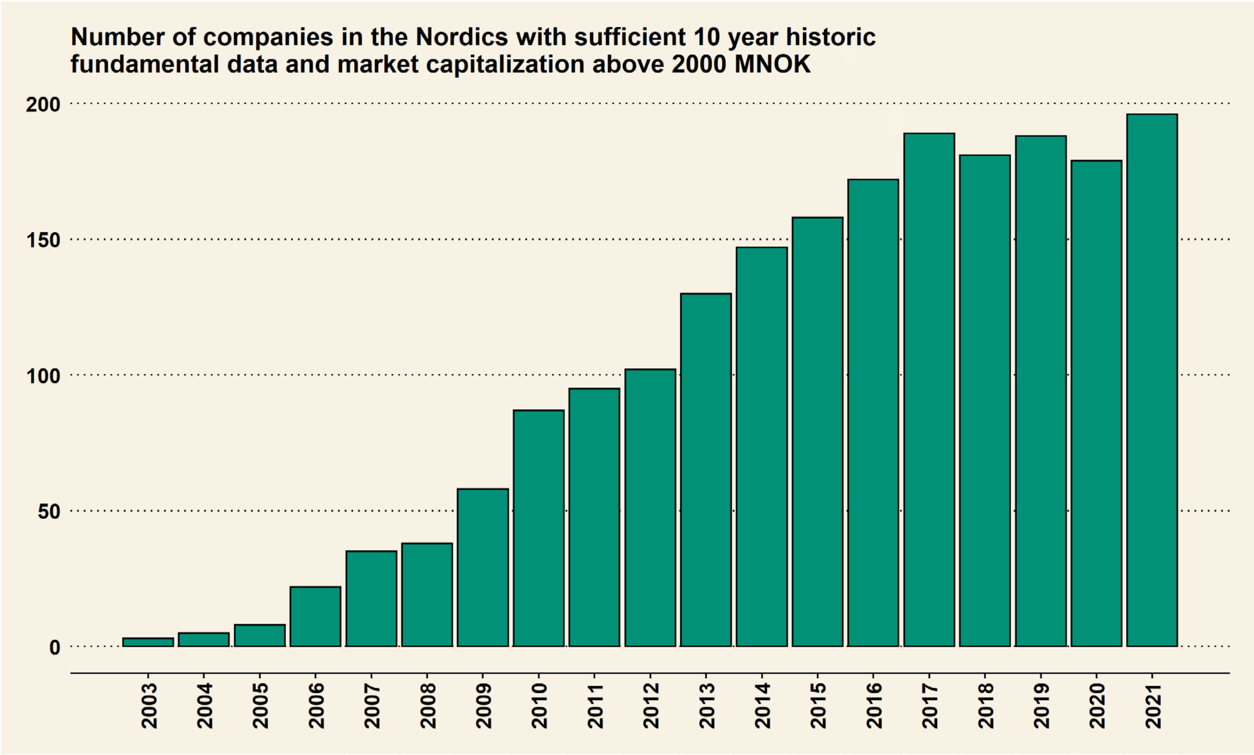

Figure 7.1:

Table 7.2

A list of the firms included in the portfolio formed in June 2021 for First Veritas (based on the 2020 fiscal year data). It also includes their relative rank on the seven parameters and the weighted average score. The market capitalization limit is 100 MNOK.

			Rank							
F Year	Name	N	Growth	ROE	CCR	Margin var	Solidity	PE	C. Phase	Total score
2020	BETSSON AB	284	242	228	122	191	198	250	202	212.93
2020	BAHNHOF AB	284	249	253	190	233	207	165	146	210.75
2020	JOBINDEX	284	213	267	178	227	124	160	171	199.93
2020	DEDICARE AB	284	183	256	203	120	111	255	214	198.85
2020	NOVO NORDISK A/S	284	161	266	179	252	115	170	158	195.15
2020	OEM-INTERNATIONAL AB	284	173	232	142	256	235	175	112	193.70
2020	ORION CORP	284	72	252	191	262	242	173	168	191.20
2020	AF GRUPPEN ASA	284	244	255	215	140	12	157	205	186.13
2020	PANDORA AS	284	223	264	196	213	85	70	231	185.58
2020	OGUNSEN AB (PUBL)	284	131	257	180	141	240	144	259	183.28
2020	SCANFIL OYJ	284	222	141	118	176	166	231	179	182.68
2020	ADDTECH AB	284	215	243	55	257	51	174	127	181.95
2020	BOUVET ASA	284	217	263	224	207	169	86	70	179.50
2020	BEIJER ALMA AB	284	114	202	101	261	182	177	188	178.93
2020	SIMCORP A/S	284	196	261	168	259	194	32	152	178.25

Table 7.3

A list of the firms included in the portfolio formed in June 2021 for First Veritas (based on the 2020 fiscal year data). It also includes their relative rank on the seven parameters and the weighted average score. The market capitalization limit is 2000 MNOK.

			Rank							
F Year	Name	N	Growth	ROE	CCR	Margin var	Solidity	PE	C. Phase	Total score
2020	BAHNHOF AB	186	166	172	136	144	146	120	96	142.50
2020	BETSSON AB	186	160	150	90	108	137	171	140	140.63
2020	NOVO NORDISK A/S	186	98	179	130	163	82	124	107	131.65
2020	ORION CORP	186	42	171	137	173	164	127	116	130.55
2020	OEM-INTERNATIONAL AB	186	107	154	104	167	161	129	65	129.68
2020	PANDORA AS	186	145	178	141	128	61	53	159	124.10
2020	AF GRUPPEN ASA	186	162	173	149	71	7	114	141	123.38
2020	ADDTECH AB	186	138	163	38	168	38	128	78	122.13
2020	BEIJER ALMA AB	186	67	128	72	172	126	131	130	120.08
2020	KONE OYJ	186	97	170	145	177	41	62	121	119.78
2020	SIMCORP A/S	186	124	175	122	170	134	25	101	119.43
2020	BOUVET ASA	186	140	177	158	122	118	65	34	117.88
2020	SCANFIL OYJ	186	144	81	86	94	115	162	124	117.85
2020	PONSSE OYJ	186	100	145	91	132	152	87	139	117.78
2020	HEXPOL AB	186	96	137	63	149	132	108	120	116.65

Table 7.4

Average bid-ask spreads estimated with the Corwin and Schultz (2012) model by size quartiles (market capitalization) in Norway and Sweden.

	NOR				SWE			
Year	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
2008	1.7%	1.2%	1.2%	1.1%	3.2%	1.2%	1.0%	1.0%
2009	2.0%	1.2%	1.0%	1.0%	4.6%	1.5%	1.1%	0.9%
2010	2.1%	2.2%	1.1%	0.9%	5.8%	1.6%	1.0%	0.7%
2011	2.9%	2.0%	1.1%	0.9%	4.7%	1.8%	1.1%	0.8%
2012	3.3%	1.7%	1.0%	0.8%	5.7%	2.1%	1.1%	0.7%
2013	2.2%	1.3%	0.9%	0.6%	4.3%	1.8%	1.1%	0.6%
2014	1.8%	1.2%	0.9%	0.7%	3.1%	1.6%	1.0%	0.6%
2015	1.9%	1.3%	1.0%	0.7%	2.8%	1.8%	1.1%	0.7%
2016	1.8%	1.3%	1.1%	0.7%	2.6%	1.6%	1.1%	0.7%
2017	1.6%	1.3%	0.8%	0.6%	2.3%	1.5%	1.1%	0.6%
2018	1.6%	1.2%	0.8%	0.7%	2.6%	1.6%	1.1%	0.7%
2019	2.1%	1.3%	0.9%	0.7%	2.4%	1.7%	1.2%	0.7%
2020	2.7%	1.6%	1.3%	0.9%	2.6%	2.0%	1.4%	1.0%
2021	1.8%	1.5%	1.2%	0.9%	2.3%	1.7%	1.3%	0.8%
Average	2.1%	1.5%	1.0%	0.8%	3.5%	1.7%	1.1%	0.8%

Table 7.5

Average bid-ask spreads estimated with the Corwin and Schultz (2012) model by size quartiles (market capitalization) in Denmark and Finland.

	DNK				FIN			
Year	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
2008	2.0%	1.5%	1.0%	0.9%	3.2%	1.2%	1.1%	1.1%
2009	2.9%	1.6%	1.2%	0.9%	3.0%	1.4%	0.9%	0.9%
2010	3.1%	1.5%	1.0%	0.7%	3.3%	0.9%	0.7%	0.6%
2011	2.9%	1.6%	1.0%	0.7%	2.4%	1.1%	0.8%	0.8%
2012	3.8%	1.5%	1.0%	0.6%	2.6%	1.1%	0.8%	0.7%
2013	3.5%	1.1%	0.8%	0.5%	2.7%	0.9%	0.7%	0.6%
2014	2.8%	1.1%	0.9%	0.5%	2.5%	0.8%	0.7%	0.5%
2015	1.7%	1.1%	0.8%	0.6%	1.3%	0.7%	0.7%	0.6%
2016	1.7%	0.9%	0.8%	0.6%	1.2%	0.6%	0.7%	0.6%
2017	1.5%	0.8%	0.6%	0.4%	1.1%	0.6%	0.6%	0.5%
2018	1.9%	0.8%	0.7%	0.6%	1.9%	0.8%	0.8%	0.6%
2019	1.8%	1.0%	0.7%	0.6%	1.6%	0.8%	0.8%	0.6%
2020	1.7%	1.3%	1.0%	0.8%	1.7%	1.1%	0.9%	0.8%
2021	1.7%	1.3%	0.9%	0.7%	1.2%	0.9%	0.8%	0.6%
Average	2.4%	1.2%	0.9%	0.6%	2.1%	0.9%	0.8%	0.7%

Table 7.6

The table shows the gross performance (before transaction costs) of portfolios split by quartile ranks by the strategies. The first quartile (1Q) represent the 25% lowest ranked stocks. Portfolios are formed in the end of June each year and we calculate monthly equal-weighted returns (contrary to portfolios in table 5.1) for simplicity which assumes monthly rebalancing. Companies with market capitalization under 100 MNOK are excluded. The performance measures are calculated using monthly returns from July 2008 until December 2021 and are annualized and calculated as in table 5.1. The alpha and its respective p-value (two-tailed test) are obtained from the C4F-model.

	First Veritas				**Magic Formula**			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Geometric average	16.1%	19.5%	17.0%	18.0%	1.1%	13.6%	18.1%	17.4%
Sharpe ratio	0.90	1.00	0.96	1.04	0.07	0.76	0.97	0.98
Information ratio	0.43	0.90	0.60	0.66	-0.77	0.17	0.75	0.69
Carhart 4F Alpha	3.9%	6.2%	5.3%	5.9%	-10.0%	1.6%	5.4%	5.1%
P-value alpha	5.9%	0.1%	0.6%	0.4%	0.0%	37.1%	0.2%	0.2%

Table 7.7

The table presents the gross performance (before transaction costs) of high and low book-to-market stocks, split by low-, medium- and high F_SCORE. Portfolios are formed in the end of June each year and we calculate monthly equal-weighted returns (contrary to portfolios in table 5.1) for simplicity which assumes monthly rebalancing. Companies with market capitalization under 100 MNOK are excluded. The performance measures are calculated using monthly returns from July 2008 until December 2021, and are annualized and calculated as in table 5.1. The alpha and its respective p-value (two-tailed test) are obtained from the C4F-model.

Book-to-market	**Top 30%**			**Bottom 30%**		
F_SCORE	low	medium	high	low	medium	high
	(0-3)	(4-6)	(7-9)	(0-3)	(4-6)	(7-9)
Geometric average	1.0%	11.6%	11.8%	4.3%	12.3%	18.8%
Sharpe ratio	0.10	0.53	0.65	0.23	0.67	1.05
Information ratio	-0.41	0.02	-0.03	-0.29	0.03	0.73
Carhart 4F Alpha	-9.8%	-0.1%	1.2%	-4.5%	0.4%	6.4%
P-value alpha	7.1%	96.0%	61.5%	34.0%	85.5%	0.2%