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COMBINING VALUE AND MOMENTUM STRATEGIES WITH FUNDAMENTALS

Empirical evidence from the returns of the combined investment strategies in US equities

Master´s Thesis
in Accounting and Finance

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1 INTRODUCTION

1.1 Background

One of the most studied capital market phenomenon relates to abnormal returns earned by various investment strategies. According to the efficient market hypothesis (EMH), if markets are semi-form efficient, the current stock prices would timely reflect all publicly available information including historical prices and financial statement information (Fama 1970, 383). Consequently, investors would not be able to continually achieve abnormal returns using investment strategies based on ex ante return time-series and fundamental information. Various studies have, however, found empirical evidence that contradicts with the EMH. There seems to be several persistent anomalies that are associated with economically significant returns, which have become central to the efficient market debate. The proponents of the EMH argue that these anomalies are compensation for higher risk whereas the opponents believe that these anomalies reflect mispricing. Whether these anomalies are compensation for bearing higher systematic risk or due to investors irrationality, there are various strategies based on style, market capitalisation and fundamentals that try to take advantage of these anomalies.

The two most studied and persistent firm-level characteristics associated with excess returns are value and momentum. The value effect (or value premium) is generally the tendency of value stocks to outperform growth stocks. One of the most commonly used relative value measure to capture the value premium is the book-to-market ratio (*B/M*). Several studies including Fama and French (1992 & 1998), Chen et al. (2008) and Asness et al. (2013) have documented a significant and long-lasting value premium in stock returns across the globe using *B/M*. In other words, high *B/M* stocks ("value stocks") tend to on average outperform low *B/M* stocks ("growth stocks"). Approach in the momentum effect differs from the value effect as focus is on the relation between historical and future stock returns. The evidence supporting the strong intermediate-term momentum effect seems to be even more robust than the value effect. Various studies including Jegadeesh and Titman (1993), Rouwenhorst (1998) and Fama and French (2012) have found that stocks with high past 3- to 12-month returns ("high momentum") outperform stocks with low past 3- to 12-month returns ("low momentum") over the next 3- to 12-month period across various markets after controlling for risk. Hence, stocks that have performed well in the past tend to on average produce excess returns in the short- and intermediate-term, whereas past losers continue to perform poorly. Whether the value and momentum premium are compensation for higher systematic risk or due to mispricing continues to be one of the central debates in asset pricing. Given the abundance of evidence for both risk and mispricing, it is difficult to conclude that neither of the two prominent explanations is the sole cause for value and momentum premium. As there is evidence that the valuation of value stocks is incongruent with fundamentals, momentum premium is too large to be explained with systematic risk factors, and even sophisticated institutional investors have behavioural biases, it seems difficult to conclude that the value and momentum premium are solely driven by higher risk at least in the short- and intermediate-term

The empirical evidence also shows that fundamental information can be used to construct investment strategies. Fundamentals-based investment strategies often take a more holistic view and focus on stock's fundamental strength based on current profitability, cash flow generation, solvency and liquidity. Therefore, the key idea is to separate undervalued stocks from overvalued stocks using relative valuation metrics and ex ante fundamental information that is not fully reflected in prices. According to Piotroski (2000), the fundamental analysis is particularly useful when applied to high *B/M* stocks. Although *B/M* strategy produces on average excess returns, less than 44% of the high *B/M* stocks produce excess returns in a one- and two-year period following portfolio formation. Hence, the return distribution of value strategy tends to be skewed and relies on the superior performance of certain value stocks. (Piotroski 2000, 2.) To overcome this issue, Piotroski (2000) uses nine ex-ante financial signals to separate fundamentally strong value stocks from weak ones. These signals are aggregated into one composite measure known as the *FSCORE*, which measures the stock's overall fundamental strength. The results are impressive as value stocks with high *FSCORE* (strong fundamentals) outperform value stocks with low *FSCORE* (weak fundamentals) in 18 out of 21 years. Further, the high *FSCORE* firms earn a mean market-adjusted annual return of 13.4% compared to -9.6% for low *FSCORE* firms – an economically and statistically significant difference of 23.0% annually. Novy-Marx (2013) also finds that value strategy's returns can be improved by controlling profitability. Using gross profit-to-assets as a profitability measure, more profitable value stocks outperform less profitable value stocks. Similar results have also been found in recent working papers by Asness, Frazzini and Pedersen (2014) and Novy-Marx (2014). Both working papers find that fundamentally strong value firms earn on average higher risk-adjusted returns than fundamentally weak value stocks. Thus, it seems that there is some kind of premium towards higher fundamental strength and/or quality in the value framework.

Compared to value stocks, fundamentals are still rarely used together with momentum strategies. However, if momentum strategies are driven by investors' expectation errors and produce higher returns in low information dissemination environment like value stocks, it could be that fundamentals are also useful in momentum investing framework. Very recently fundamentals have also been used together with momentum strategy by Chen et al. (2016). They use *FSCORE* together with intermediate-term momentum and results are exceptional; strategy that goes long for stocks with highest momentum and highest *FSCORE* and short for stocks with lowest momentum and lowest *FSCORE* produces abnormal returns that outperform traditional momentum strategy irrespective of the length of short-term holding period.[1] Overall, it seems that fundamentals could be successfully combined both with value and momentum strategies, opening a new interesting framework to study fundamental value and momentum strategies.

1.2 Motivation and research questions

Traditional value and momentum strategies have been studied extensively. In contrast, studies on fundamental value and particularly fundamental momentum are still at an early stage. The interest towards the relation between fundamental strength or quality and stock returns is however growing. By studying the combination of style and fundamentals-based investment strategies, we can improve our understanding of how investors can potentially construct portfolios with better risk-adjusted performance using fundamental signals. Hence, the main purpose is to examine whether fundamentals can be used to enhance traditional value and momentum strategies in order to earn abnormal returns.

We form value and momentum portfolios with well-known measures, *B/M* and the past 12-month cumulative total raw return (skipping the most recent month). To measure fundamental strength of value and momentum stocks, we use the *FS_SCORE* introduced by Gray and Carlisle (2013) to separate winners from losers. The *FS_SCORE* is very close to the original *FSCORE* by Piotroski (2000), but makes some key improvements. As Piotroski (2000, 10) points out, *FSCORE* variables have been chosen quite ad hoc, leaving room for further enhancement. Like Piotroski (2000) and Chen et al. (2016), we expect portfolios with fundamentally strong value and momentum stocks to outperform against (1) portfolios with value and momentum stocks that have weak fundamentals and (2) all value and momentum stocks. In other words, we assume that ex ante fundamental information is not fully reflected in prices and that strong (weak) fundamentals should be positively (negatively) related to future stock returns.

To test these hypotheses, we use several portfolio's risk and return measures. Like Piotroski (2000), we use market-adjusted returns to measure the abnormal performance of fundamental value and momentum portfolios. However, in order to get a more thorough view of the risk-adjusted performance, we will also use the Sharpe ratio, the CAPM, the Fama-French three-factor and Carhart four-factor model. Therefore, in addition to testing the one-year buy-and-hold returns from pooled firm-year observations like Piotroski (2000), we will also test portfolio returns to see whether portfolios produce statistically significant alpha after controlling for well-known risk factors.

[1] Chen et al. (2016) also use the *GSCORE* tailored for growth stocks by Mohanram (2005), but the results are more robust using *FSCORE*.

The empirical part focuses on US equities between 1997 and 2015. We use stocks listed in the S&P Composite 1500 index, which combines three different indices: The S&P 500, S&P MidCap 400 and S&P SmallCap 600. The S&P Composite 1500 index covers approximately 91% of the US market capitalization as at the end of November 2016, giving a broad and comprehensive sample of the US stock market. The reason why we include both mid-cap and small-cap stocks besides large-cap stocks is supported by the previous research. Firstly, both value and momentum effect have been documented to be stronger among smaller stocks (see Loughran 1997; Hong et al. 2000; Fama & French 2012). Secondly, fundamental analysis tends to produce higher returns in low information dissemination environment, which typically includes smaller stocks that are not actively followed by analysts (see Piotroski 2000). Additionally, although there are several limitations to investing in small- and mid-sized stocks, including these stocks in the sample can provide useful information for a broader investor community.

1.3 The scope and limitations

The theoretical framework and empirical part in this thesis focuses on value effect, momentum effect and fundamentals-based investment strategies. These three topic areas form the core of the investment strategy tested in the empirical part. In the literature review we provide comprehensive evidence for value and momentum premium as well as risk- and mispricing-based explanations. Additionally, we try to emphasize value and momentum specific information reported in previous studies that could be used to enhance both strategies. The literature review on fundamentals-based investment strategies focuses on the concept of fundamental analysis and well-known investment strategies that use information from financial statements to take advantage of accounting-based anomalies. It is also important to notice that as the focus the empirical part is on combining value, momentum and fundamentals from more a pragmatic approach, we exclude the literature on more sophisticated portfolio optimization techniques such as the modern portfolio theory (MPT).

There are also several limitations in our thesis. The first limitations relate to our data sample. Firstly, the focus is solely on one asset class, namely equities. Even though value and momentum have been found in other asset classes such as bonds and currencies, we narrow our scope to stocks as we are interested in the usefulness of fundamentals in the value and momentum framework. However, studying cross-asset value and momentum strategies could provide a more comprehensive view and would also be likely to provide significant diversification benefits. Secondly, we limit our geographical scope only to the US. Although there is evidence that value, momentum and fundamental strategies can produce abnormal returns also outside the US, most of the studies are still conducted using data from the US stock market. Thus, providing out-of-sample evidence from other markets would probably add more value. However, as we study whether an enhanced version of the original *FSCORE* can produce abnormal returns in value and momentum framework, our results should still provide value-adding information using US data. Further, availability of data is far better for US stocks. Thirdly, our data requirements cause selection bias at some level. If a stock delists within one-year of portfolio formation, it is assumed that the delisting return is the last return provided by Thomson Reuters Datastream. Consequently, as Datastream uses a constant total return value equal to the last valid data point after the stock delists, we assume that the delisting return of the stock is zero after the month the stock ceases trading. This is likely to cause a delisting return bias of some kind, which can be particularly problematic if the stock is delisted for performance-related reasons as it exaggerates returns. Our large sample size should, however, partly mitigate this concern.

The investment strategy applied in the empirical part also has its limitations. Firstly, we only use simple value and momentum measures to form portfolios. It could be that other measures would produce better results either separately or jointly. For example, we could use other value measures such as earnings to price and cash flow to price ratios when forming value portfolios. Additionally, as we use 12-month holding period and rebalancing frequency both for fundamental value and fundamental momentum portfolios, it is possible that higher gross returns could be achieved with a more frequent rebalancing frequency. This is particularly a concern among momentum stocks, where higher rebalancing frequency and shorter holding period tend to produce higher returns. Nevertheless, excessive trading costs are not likely to be an issue for our strategy. Secondly, *FS_SCORE* is backward-looking by nature and is unlikely to be the optimal portfolio formation technique. It relies on historical financial statements, making possible that all alpha-relevant information has already been arbitraged away, and does not try to optimize portfolio’s risk and return characteristics. Instead, it is more like a first-stage tool for screening undervalued and overvalued stocks. In addition, *FS_SCORE* is based on an aggregate score from ten binary variables which can potentially eliminate useful information. Thirdly, it is possible that a single fundamental measure such as the gross profit-to-assets by Novy-Marx (2013) could subdue the majority of other variables used in *FS_SCORE*. *FS_SCORE* is, however, very intuitive by nature and the original *FSCORE* has produced significant abnormal returns also in more recent studies such as by Piotroski and So (2012). Consequently, we believe that *FS_SCORE* provides a profound and efficient way to examine whether traditional value and momentum strategies can be enhanced using fundamental information.

1.4 The structure of the thesis

The rest of this thesis is structured as follows. In the second chapter, we review the previous literature on value effect, momentum effect and fundamental-based investment strategies. In addition to reviewing value, momentum and fundamentals separately, we present joint evidence from these strategies. As the focus on this thesis is in fundamental value and momentum strategies, the second chapter will broadly introduce two well-known fundamental strategies, namely *FSCORE* and *GSCORE*. In the third chapter, the data and methodology for the empirical part are presented. When introducing the methodology, focus is on presenting the *FS_SCORE* and its modifications relative to *FSCORE*, portfolio formation and measurement, hypotheses and statistical methods used to test the hypotheses. In chapter four, we present our main findings from the empirical part and conduct robustness tests for fundamental value and momentum strategies. The fifth chapter summarizes our thesis and presents our main conclusions of tested hypotheses. We also highlight briefly potential follow-up research ideas.

2 LITERATURE REVIEW

2.1 The value effect

2.1.1 Book-to-market ratio in valuation

Price multiples are one of the most popular valuation tools used by investors. Price multiple is a ratio that compares share price to some fundamental measure such as earnings, cash flow and book value. The same applies when using enterprise multiples, which compare the firm's enterprise value to unlevered metrics such as earnings before interest and taxes (*EBIT*). Thus, a price or enterprise multiple enables investors to evaluate the stock's relative worth and can be used as a screening tool when selecting stocks to the portfolio. Price multiples are often related to fundamental analysis through discounted cash flow analysis, which drives growth and profitability forecasts. In addition, a common way in practice is the method of comparables, which is based on the law of one price for similar assets. (Pinto et al. 2010, 258–260.) In the method of comparables investors compare the relative value of a stock to selected benchmark price multiples, which are often companies operating in the same industry with similar key business characteristics and financial profile such as size, growth prospects and capital structure.

Price multiples are a crucial part of value investment strategies. In general, value stocks are considered to have high relative value measures such as book-to-price, earnings to price, cash flow to price and dividend yield.[2] In contrast, growth stocks usually have low relative value measures which can reflect various aspects, including higher expected growth and profitability, lower risk profile and even mispricing. The most popular value measure used in the academic literature is by far the book-to-market ratio (*B/M*), which is calculated as firm's book value of shareholders' common equity (*BE*) divided by firm's market value of equity (*ME*), or

$$B/M = \frac{BE}{ME} \tag{1}$$

which is the inverse of price-to-book ratio. Thus, roughly speaking, the higher (lower) the *B/M* ratio is, the stronger (weaker) the value signal as lower share price implies higher expected return.

[2] Inverse price ratios are often used in portfolio selection as it enables a consistent ranking (Pinto et al. 2010, 271).

The advantage of using *B/M* ratio is that it often captures the value premium better than other value measures and it is a more stable measure than earnings or cash flows. According to Fama and French (2011), this stability is also important as is it lowers the turnover of value portfolio. There is also a clear relation between the stock's *B/M* ratio and fundamentals. According to Harris and Marston (1994, 24), there is a statistically significant positive relation between *B/M* ratio and beta (i.e. systematic risk) once forecasted growth is controlled. Further, there is a clear negative relation between *B/M* ratio and growth prospects, and this seems to explain cross-sectional variation in *B/M* ratios better than beta. Fairfield's (1994, 26) results also show that *B/M* ratio correlates negatively with the current and the future level of profitability measured as return on equity (*ROE*). Although *B/M* ratio is related to fundamentals, it is also often criticized as a value measure particularly among non-financial companies. For example, as book value of equity merely reflects historical value of shareholders' investments, it may not be an accurate measure of company's current value of equity. The key strengths and weaknesses of using *B/M* ratio as a relative valuation measure are summarized in table 1 below (Pinto et al. 2010, 295–296).

Table 1 Advantages and drawbacks for using book-to-market ratio in equity valuation

Advantages	Drawbacks
• As book value of equity is generally positive, whereas earnings per share (EPS) can often be negative, book-to-market ratio can be used in valuation even if EPS was negative unlike earnings to price ratio	• Book value of equity does not take into account off-balance sheet value drivers such as human capital and company reputation that can sometimes be more important than physical capital
• Book value of equity is more stable than other fundamental measures such as earnings, which makes book-to-market ratio a less noisy valuation measure	• Book-to-market ratio can be a misleading valuation tool when the level of assets differ significantly across companies
• Particularly useful for valuing companies with liquid and market-valued assets such as financial companies	• Book-to-market ratio does not take into account different accounting effects across companies relating to capitalisation of intangible assets such as R&D and marketing expenses
• Empirical research shows that there is a connection between book-to- market ratio and fundamentals such as growth, profitability and risk	• Book value often reflects the historical value of assets, which is a poor proxy for the current value of shareholders' investment in the company
	• Share repurchases or equity issuances may distort historical comparison

2.1.2 Book-to-market ratio and value premium

Although the use of *B/M* strategy was applied already by well-known value investors Graham and Dodd at the beginning of the 20th century, the *B/M* strategy started to become more popular again in the 1980s and 1990s. One of the first studies to capture value effect using *B/M* ratio was by Rosenberg et al. (1985), who found that high book-to-market strategy produced significant abnormal returns in the US stock market. At first the *B/M* effect was seen as a contradiction to the semi-strong market efficiency as stock prices did not seem to fully incorporate all publicly available information, but the cross-sectional relation of stock returns and *B/M* was further developed by Fama and French (1992). They reported a significant positive relation between stock returns and *B/M* ratio in the US and argued that *B/M* ratio is likely to be a proxy for some systematic risk factor such as financial distress. In addition, the combination of firm's market capitalization (size) and *B/M* ratio captured the majority cross-sectional variation in average stock returns. This indicated that cross-sectional variation in stock returns could not be fully explained with exposure to market risk i.e. beta (Fama & French 1992, 445).

Value premium has also been found to be robust internationally across various markets. To provide further out-of-sample evidence, Fama and French (1998) studied the *B/M* strategy in an international context. Their results showed a strong value premium between 1975 and 1995; high *B/M* stocks outperformed local market and low *B/M* stocks in twelve out of thirteen international markets in the US, Europe, Asia and Australia. The average return of high *B/M* portfolio and value premium in the global portfolio was 14.76% and 7.68% in excess of T-bill rate respectively (both statistically significant at the 1% level).[3] Various other studies have also found evidence on a global value premium since. Asness, Moskowitz and Pedersen (2013) studied value and momentum jointly in eight international markets and asset classes including stocks, stock indices, currencies, government bonds and commodity futures. They reported a strong value premium and correlation across all markets and asset classes for a long period. When looking at the long-only stock portfolios, the average raw excess returns, Sharpe ratios and alphas increase steadily when moving from low *B/M* portfolio to high *B/M* portfolio in each single market. The average raw excess returns, Sharpe ratios and alphas are between 13.2-16.7%, 0.67-0.84% and 3.1-7.3% respectively. When the high minus low and factor portfolios are included, the value premium is strongest in Japan (Asness et al. 2013, 945).[4] This seems to be due to growth stocks' exceptionally weak performance relative to value stocks in Japan compared to the other markets. There also seems to be a clear value premium in all other asset

[3] Fama and French (1998) also found similar value premiums using other value indicators including earnings to price, cash flow to price and dividend to price. However, the average value premium for the global portfolio was strongest when using book-to-market ratio.
[4] A factor portfolio is constructed by creating a long-short (hedge) portfolio that goes long for value stocks and short for growth stocks.

classes, but this is not in our focus as this thesis focuses solely on equities. In addition, measuring value in currencies, government bonds and commodity futures is not that straightforward as there is no measure of book value (Asness et al. 2013, 937).

Although there seems to be persuasive evidence for international value premium using *B/M* ratio, there are also various other value measures that have demonstrated strong positive relation with future stock returns. Hou, Karolyi and Kho (2011) apply a wide sample of over 27,000 stocks from 49 countries between 1981 and 2003 to study what factors drive global stock returns. Although their results confirm a strong value premium across markets, the results seem to be stronger for other value measures than *B/M* ratio. Like Fama and French (1992 & 1998) they construct factor portfolios for each firm-level characteristic. The average monthly return of earnings to price (*E/P*), cash flow to price (*CF/P*) and dividend to price (*D/P*) factor portfolios are between 0.63% and 0.75%, which is higher than the corresponding return of 0.55% for *B/M* factor portfolio (all statistically significant at 5% level). Additionally, *CF/P* seems to better explain the average cross-sectional variation in global stock returns as the average time-series coefficients are higher and statistically more meaningful than for *B/M* ratio. This is particularly true in the latter part of the sample period between 1992 and 2003. Besides the above-mentioned price multiples, enterprise multiples are commonly used by many practitioners. Loughran and Wellman (2011) find that enterprise value (*EV*) divided by earnings before interest, taxes, depreciation and amortization (*EBITDA*) has a strong positive relation with future stock returns in the US between 1963 and 2009. They construct high-low factor portfolios using the monthly averages of the value-weighted returns and find that the average return spread is 0.44% per month for *EV/EBITDA* factor portfolio. The factor returns are also statistically significant after controlling for Fama-French three-factor and Carhart four-factor models; the monthly alphas are 0.19% and 0.16%, both statistically significant at the 0.05 significance level. However, the factor portfolio using *B/M* ratio generates also a monthly return of 0.42% and is highly correlated with *EV/EBITDA* factor, reflecting rather similar information about the expected stock returns.

The evidence also shows that value premium can vary with firm size. Loughran (1997) finds that the *B/M* effect is significantly larger for small stocks than large stocks in the US between 1963 and 1995. While the high-low book-to-market spread is 11.25% annually for small stocks, it is only 1.80% for large stocks. Interestingly, when January is excluded from return calculation, small stocks still earn a significant value premium of 9.09% annually, but there seems to be a growth premium among large stocks as high-low spread is -0.92%. Hence, the value premium seems to be driven mainly by small stocks (around 7% of the total market value) as there is no value premium for large stocks outside of January. (Loughran 1997, 255, 257.) Fama and French (2006) find partially contrary evidence to Loughran (1997). Although their results show that the value premium is clearly higher for small stocks (0.59% per month with *t*-statistics of 4.13) than for large stocks (0.13% per month with *t*-statistics of 1.01) between 1963 and 2004 in the US, Fama and French (2006) argue that this depends on sorting stocks based on *B/M* ratio.[5] When stocks are sorted based on *E/P* ratio, the value premium is still larger for small stocks, but drops significantly; value premium for small stocks is 0.43% per month with 4.20 *t*-statistics, compared to 0.26% with 2.07 *t*-statistics for large stocks. This is due to (1) higher returns for small growth stocks and (2) higher value premium among the largest stocks when using *E/P* rather than *B/M* (Fama & French 2006, 2170). Fama and French (2006) also use an out-of-sample test outside the US. The results show that value premiums are similar among small and large cap stocks using both *B/M* and *E/P* and that the difference is not statistically significant. Thus, the higher small cap value premium could be due to randomness or the relatively low share of larger stocks (Fama & French 2006, 2172).

However, as Fama and French (2012, 460) note, their sample size in the 2006 study was limited particularly for smaller international stocks (they used only two size groups). Contrary to the original results, Fama and French (2012) report a significantly larger value premium (difference of 0.42% with *t*-statistics of 2.76) for small stocks than for large stocks between 1990 and 2011 across markets in North America, Europe, Japan and Asia-Pacific. Consequently, overall evidence seems to support that there is somewhat higher value premium among small stocks. This provides support for using fundamental analysis among small stocks that are often less followed and potentially mispriced. However, investing in small cap stocks is likely to be difficult for a majority of mutual fund and hedge fund managers due to higher illiquidity and transaction costs among small caps.

2.1.3 Risk-based explanations

Although there is an abundance of evidence showing that a portfolio of high book-to-market stocks outperforms a portfolio of low book-to-market stocks, there is still no consensus amongst researchers regarding the cause of value effect. In general, there are two major explanations for value effect. Firstly, there are risk-based explanations arguing that the outperformance of value stocks is due to compensation for higher risk. Secondly, many argue that value effect is due to investors' irrationality which causes mispricing. There seems to be a major confrontation between these two theories for value premium. Risk-based theories are in line with the efficient market hypothesis as they argue that the value premium is due to systematic risk factors priced by investors, whereas behaviourists believe that the value premium is too large to be explained by systematic risk factors.

[5] Fama and French (2006) measure the value premium slightly differently than Loughran (1997). They use monthly differences between the average returns of the two highest and lowest book-to-market and earnings-to-price portfolios instead of the simple high-low spread used by Loughran (1997).

First we look into risk-based explanations that are consistent with rational and efficient asset pricing. Fama and French (1995) and Chen and Zhang (1998) were one of the first researchers to argue that value effect relates to firm's financial characteristics such as financial distress, earnings uncertainty and financial leverage. Fama and French (1995) showed that high *B/M* stocks had persistently low earnings on book equity compared to low *B/M* stocks, indicating that value stocks are financially distressed. Interestingly, this was not just a short-term phenomenon as value stocks had low profitability for four years before and five years after the ranking. Conversely, growth stock tended to have stronger profitability. This supported the view that profitability is a common risk-based factor explaining the higher returns of value stocks. (Fama & French 1995, 132, 154.) Chen and Zhang (1998) took a slightly different approach than Fama and French (1995) as they used the standard deviation of earnings to price ratio, financial leverage defined as book value of debt divided by the book value of equity and proportion of firms that cut dividends by 25% or more to see if value stocks have common risk characteristics. The results show that value stocks have on average higher volatility of earnings, higher leverage and are more likely to cut their dividends by 25% or more. All three risk factors also seem to be correlated with each other, *B/M* ratio and stock returns, indicating that they are proxies for a similar risk and capture information relating to returns. As returns are higher for high *B/M* stocks, these three risk measures seem to capture the value effect. The risk measures are also strongest and more persistent in the US, where the value effect is clearly stronger than in other countries. (Chen & Zhang 1998, 526–532.)

Vassalou and Xing (2004) take the idea of financial distress further and study default risk premium in equity returns using data from equities instead of financial statements or bond market. They argue that financial statement data does not necessary indicate future performance and does not give a correct picture of asset volatility of stocks. Instead, they estimate the default likelihood indicators using the market value of stock's equity for each single firm, which can be though as a market-implied default indicator. The results show that default risk is indeed related to the value effect. The value stocks have higher default risk than growth stocks and the value premium is strongest among stocks with the highest *B/M* ratios and default risk. Hence, *B/M* ratio seems to be a proxy for default risk that is a systematic risk factor. (Vassalou & Xing 2004, 832, 866.)

There are also studies which connect the value effect to economic cycles, asset base adjustment costs, financial leverage and operational leverage. Zhang (2005) argues that value stocks earn higher returns than growth stocks due to asymmetric risk relating to investment and disinvestment costs. As value stocks usually have a higher asset base than growth stocks, the cost of reducing non-productive assets in economic downturns is costlier for value stocks. This results in higher variation of earnings, dividends and stock returns in downturns. In addition, as the cost of capital is usually higher in economic downturns, the value premium increases significantly. On the contrary, in periods of high economic activity, value stocks face smaller asset base adjustment costs than growth stocks and their asset base becomes productive, which results in smaller variation in earnings and dividends during the economic upturn. (Zhang 2005, 68–69.) Hence, value stocks seem to have less flexibility to adapt their asset base to changes in economic situation, which drives the value risk premium. Similar results were also found by Cooper (2006), who argues that value stocks are more sensitive to changes in economic situation than growth stocks and that value premium depends significantly on investment irreversibility. When firms face economic shocks, the option to disinvest becomes important to reduce adverse impact. This is particularly true for value stocks as value stocks tend to have higher asset base than growth stocks. If a significant part of this asset base is irreversible, it becomes more difficult for value stocks to mitigate these shocks and book value of equity stays relatively flat compared to market value of equity. Thus, the higher the degree of investment irreversibility in asset base, the higher the systematic risk and value premium should be. (Cooper 2006, 139–141.)

Recent study by Fama and French (2007) shows evidence that migration of stocks across value and growth portfolios explains a significant portion of value premium. In order to study migration across portfolios, Fama and French (2007, 48, 54) form six size-book-to-market portfolios, which they further divide into four migration groups:

- *Same*, which includes stocks that stay in the same size-book-to-market category one-year after portfolio formation.
- *Plus*, which includes stocks that move to a lower book-to-market (growth) portfolio or are acquired.
- *Minus*, which includes stocks that move to higher book-to-market (value) portfolio, are delisted or their book value becomes negative.
- *dSize*, which includes small (large) stocks that become large (small).

The results can be divided into two key parts. Firstly, migration between book-to-market categories is more common than between size categories and migration to higher (lower) book-to-market category produces significantly negative (positive) excess returns. Secondly, value premium is driven by *Same*, *Plus* and *Minus* migration groups, whereas *dSize* migration reduces the value premium across all size categories. The positive contribution to value premium by *Plus* and *Minus* migration is mainly explained by migration frequencies (Fama & French 2007, 57). *Plus* migration (which produces positive excess returns) is significantly more common for value stocks (19.6-22.5%) than for growth stocks (0.7-2.4%). Further, *Minus* migration (which produces negative excess returns) is more common for growth stocks (10.9-25.8%) than value stocks (0.1-1.0%). The third positive component to value premium is stocks that do not migrate across portfolios i.e. *Same*, which is mainly explained with positive return difference between value and growth stocks. Interestingly, these positive migration impacts are partly mitigated by small cap stocks that become big. Small stocks that migrate to big category are usually growth stocks and produce on average significant excess returns, which reduces the value premium. (Fama & French 2007, 56–57.) Although Fama and French (2007) do not provide direct evidence that the value premium due to migration is driven by risk-based explanations, they argue that there is an economic rationale behind migration. As value stocks on average improve profitability following portfolio formation, their book-to-market ratio tends to decrease due to lower risk premium. This is the opposite for growth stocks, resulting in value premium. (Fama & French 2007, 48.) However, one could also argue that both value and growth stocks are mispriced by investors and thus converge to intrinsic value in period following portfolio formation.

2.1.4 Mispricing

Behavioural theories argue that value premium is not driven by higher risk, but in fact by mispricing due to biases among investors. These biases lead to systematic errors in investors' expectations and thus cause value stocks to deviate from their fundamental (intrinsic) values. Thus, if investors underprice high *B/M* stocks, the mean-reversion could produce the value premium. In this case, value strategies would produce higher returns without additional systematic risk (Chaves et al. 2013, 3).

Lakonishok, Shleifer and Vishny (1994) argue that investors are systematically too optimistic about growth stocks and too pessimistic about value stocks as they extrapolate past historical growth rates into the future. Historically value stocks have on average lower sales and earnings growth rates than growth stocks. However, these growth rates seemed to mean-revert following portfolio formation. (Lakonishok et al. 1994, 1559.) According to Lakonishok et al. (1994) the difference in ratios between value and growth stocks is driven by differences in ex ante expected future growth rates, which is reflected as higher (lower) *B/M* and *CF/P* ratios for value (growth) stocks. Therefore, investors seem to expect that growth stocks continue to outperform value stocks in terms of growth. However, this seems to be the case only at the beginning of post formation period. Although growth stocks seem to grow faster than value stocks in the short-term (first two years), this development does not last. The growth rates for value stocks seem to reverse later in post formation period (last three years), which leads to higher returns for value stocks due to upward revisions in valuation as investors realize mispricing. Thus, investors seem to extrapolate past growth rates particularly in short-term. (Lakonishok et al. 1994, 1562–1564.) The biased growth expectations could potentially reflect overconfidence as investors overreact to private signals and underestimate forecast errors (Daniel et al. 1998, 1841). This could lead value and growth stocks to deviate temporarily from their fundamental value. Following these results, Lakonishok et al. (1994) then argue that contrarian investors who take advantage of this are not exposed to higher systematic risk.[6] This argument is supported by the evidence that value strategies on average outperform growth strategies during economic downturns and that traditional risk measures beta and volatility are not sufficient to explain the large premium.

La Porta (1996) uses survey data on five-year earnings growth forecasts by analysts to study similar hypotheses as Lakonishok et al. (1994). The results show that returns for stocks with low ex ante earnings growth forecasts outperform stocks with high ex ante earnings forecast by 20.9%, measured by a one-year holding period. Hence, investors do not seem to adjust for analysts' too high or low growth expectations, which mean revert in the subsequent period. Additionally, analysts' earnings forecast revisions and expectation errors are negatively correlated with *B/M* ratio, indicating that value premium is partially explained with mispricing. (La Porta 1996, 1729–1732.) Evidence by La Porta (1996, 1738–1739) is also similar to that of Lakonishok et al. (1994); higher returns earned by value stocks do not seem to be due to higher systematic risk as stocks with low expected growth have on average lower volatility, lower market risk and perform better when stock markets fall. The results on extrapolation hypothesis, however, are more controversial; value stocks tend to underperform stocks which are expected to underperform in the future although they have performed well in the past (La Porta 1996, 1737).

Daniel and Titman (2006, 1607) argue that past fundamental performance (tangible information), such as historical sales and earnings growth does not drive value premium. Instead, there seems to be a negative correlation between intangible information about stock's future performance (e.g. new high-tech products) and future stock returns. Thus, the value premium may be due to investors' overreaction to intangible information, which drives the value premium as intangible returns reverse. (Daniel & Titman 2006, 1638, 1640.) Similar results were also found by Jiang (2010), who studied institutional investors trading to intangible information. Surprisingly, the results show that institutional investors do not trade against intangible information to capture the value premium. Institutional investors seem to buy (sell) stocks with positive (negative) intangible information, which increases (decreases) institutional ownership in stocks with high (low) historical intangible returns. Institutional investors' historical trading volumes are also negatively related to future intangible returns as return reversals are higher among stocks with high institutional trading volumes due to positive intangible information. Hence, institutional investors also seem to overreact to intangible information, which drives value premium as stocks with low historical intangible returns (value stocks) outperform stocks with high historical intangible returns (growth stocks). (Jiang 2010, 99.) Jiang (2010, 112) then argues that stocks with low intangible returns are not fundamentally riskier than stocks with

[6] Contrarian investors tend to buy out-of-favour stocks such as value stocks as they believe that these are underpriced by other naïve market participants (Lakonishok, Shleifer & Vishny 1994, 1542).

high intangible returns, as the return spread cannot be explain with traditional asset pricing models due to significant alphas when the measure of institutional investors herding is high. Consequently, institutional investors' behaviour does not always seem to be rational, contributing to the value premium.

Piotroski and So (2012) tested the mispricing hypothesis by comparing investors' ex ante expectations to fundamentals in order to identify if there are potential expectation errors. This means that value and growth stocks are mispriced if their performance expectations are not consistent with their expected performance implied by fundamental strength (Piotroski & So 2012, 2846–2847). Piotroski and So (2012) measure investors' expectations by *B/M* ratio and use composite *FSCORE* to measure fundamental strength, which is the aggregate of nine binary financial statement signals. Firms with strong fundamentals have high *FSCORE* and firms with weak fundamentals have low *FSCORE*. The results supported the mispricing hypothesis as value and growth effect were strongest among stocks with inconsistent ex ante expectations between *B/M* ratio and *FSCORE*. Growth stocks with low *FSCORE* (score 0-3) had an average -14.38% annual size-adjusted buy-and-hold return, whereas value stocks with high *FSCORE* (score 7-9) had an average 8.26% annual size-adjusted buy-and-hold return. Further, the returns were lower for stocks with congruent expectations relative to fundamentals. Inconsistent value strategy also produced positive returns in 35 years out of 39 compared to 27 for consistent value strategies, and outperformed almost each year. (Piotroski & So 2012, 2851–2854.) Thus, it seems that investors ignore ex ante fundamental signals among high value and growth firms, resulting in mispricing and value premium. This can also be seen as a positive difference in earnings period announcement returns, analyst errors and analyst forecast revisions between growth firms with low *FSCORE* and value firms with high *FSCORE* (Piotroski & So 2012, 2861, 2863).

Many are likely to argue that if there persists mispricing among value and growth stocks, why arbitrageurs do not trade against mispricing? One plausible reason for this could be the arbitrage risk hypothesis suggested by Doukas, Kim, and Pantzalis (2010) and Ali, Hwang and Trombley (2003). Assuming that arbitrageurs are risk-averse investors that who often focus on a limited amount of stocks, arbitrage risk is closely related to idiosyncratic volatility. Portfolios with limited diversification have higher idiosyncratic volatility, which increases portfolio risk without additional compensation (Ali et al. 2003, 358). If arbitrageurs are not able to hedge idiosyncratic risk (i.e. take an opposite position for mispriced stock with a close substitute), it is difficult for arbitrageurs to eliminate fundamental risk and they may not be able to purchase (sell) undervalued (overvalued) stocks. Hence, stocks with higher idiosyncratic risk can be mispriced as arbitrageurs cannot eliminate arbitrage opportunities.[7] Consistent with this hypothesis, mispricing seems to be persistent among stocks with higher idiosyncratic risk and lower institutional ownership. (Doukas et al. 2010, 922, 930.) As Ali et al. (2003) show that value effect is on average stronger among stocks with higher idiosyncratic volatility, higher transaction costs and lower investor sophistication, it seems that arbitrage risk can cause prices to deviate from fundamental values and thus contribute to the value effect. This seem particularly true among smaller stocks that often suffer from the above-mentioned characteristics. It has to be noted, however, that both Ali et al. (2003) and Doukas et al. (2010) use historical idiosyncratic volatility as a proxy for idiosyncratic risk, which might not be a good proxy for future risk.

2.2 Investment strategies based on fundamentals

2.2.1 Fundamental analysis in brief

Focus on traditional fundamental analysis is in evaluating the current price of stock relative to its fundamentals such as future sales growth, earnings and cash flows (Palepu & Healy 2008). Thus, fundamental analysis is essentially about valuation and identifying mispriced securities relative to intrinsic value. To be successful in practice as an investment strategy, fundamental investment strategies assume that fundamentals have predictive power regarding future stock returns and have not been priced by other market participants (Palepu & Healy 2008). Under semi-efficient markets, it would be impossible to identify systematically mispriced securities using fundamental analysis as all relevant public information would be reflected in prices. There exists, however, a variety of studies showing that fundamental investment strategies can produce abnormal returns. This indicates that stock prices do not necessarily always fully reflect all publicly available information, making fundamental analysis useful in active portfolio management.

Focus in traditional fundamental analysis is both on quantitative and qualitative information. According to Palepu and Healey (2008), fundamental analysis can be divided into four steps: (1) Business strategy analysis, (2), Accounting analysis, (3) Financial analysis and (4) Prospective analysis. Fundamental analysis often starts with business strategy

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[7] Barberis et al. (1998) suggest that there is also a behavioural reason behind arbitrage risk. Eliminating mispricing can be risky for arbitrageurs particularly in the short-term if investor sentiment varies and is unpredictable. This can cause prices to deviate from fundamentals even further (“noise trader risk”) and limits arbitrageurs’ willingness to eliminate mispricing. (Barberis et al. 1998, 309.)

analysis and includes industry analysis, competitive strategy analysis, and corporate strategy analysis. Analysing qualitative factors is important as it enables investor to better understand firm’s financial metrics, identify key profit drivers and risks and make more sound assumptions about firm’s future performance. Following business strategy analysis, investors often analyse firm’s accounting policies, estimates and flexibility in order to evaluate its appropriateness and potential distortions. Adjusting for accounting distortions is often important to get a better picture of the underlying financial development. In the next step investors use adjusted accounting numbers to analyse firm’s financial development with ratio and cash flow analysis, which can be reflected to firm’s strategy and objectives. Ratio analysis tends to focus on firm’s growth and profitability performance, whereas cash flow analysis is more about analysing operating cash flow, free cash flow, source of funds, flexibility and ability to meet financial obligations and pay dividends. The last step in fundamental analysis is prospective analysis, where focus is on forecasting firm’s future performance. This includes both financial statement forecasting and valuation, which require substantial amount of subjective judgment and information from the first three steps. (Palepu & Healy 2008.) Following valuation investors can compare public firm’s estimated intrinsic value to the current market price to determine whether its stock is over- or undervalued. This kind of fundamental analysis in portfolio selection is, however, resource-consuming, relies on individual investment results and susceptible for cognitive biases, paving the way for quantitative fundamental strategies.

The quantitative fundamental strategies are often used in portfolio selection. These strategies tend to rely more on expectable group outcome as they focus on taking advantage of various systematic accounting anomalies. The focus is on selecting stocks from a broad universe based on factors such as analysts’ earnings revisions, valuation multiples and other fundamental indicators. Hence, quantitative fundamental strategies essentially attempt to separate ex post winners from losers using signals from financial statements and other company announcements. As these strategies rely solely on quantitative data, they can be seen more robust to behavioural decision-making errors (Gray & Carlisle 2013, 31). However, these strategies may have higher transaction costs due to more frequent rebalancing of portfolios. Additionally, as mispricing is often concentrated among smaller and less liquid stocks, the feasibility of these strategies could be limited particularly among institutional investors. Quantitative fundamental strategies are argued to be more beneficial among value stocks as focus in value stocks is often more on recent fundamentals than qualitative factors. In contrast, analysis in growth stocks is often based more on long-term prospects and intangible information. (Piotroski 2000, 4.) However, as we shall later see, fundamental analysis can also be useful among growth stocks and momentum stocks as shown by Mohanram (2005) and Chen et al. (2016). As the focus in this study is on combining value and momentum with fundamentals, the rest of this chapter will focus on empirical evidence from quantitative fundamental strategies.

2.2.2 Evidence from fundamentals-based investment strategies

One of the first comprehensive studies that used fundamentals to establish investment strategy was by Ou and Penman (1989). Their investment strategy is based on the notion that future earnings are positively correlated with future stock returns, which makes identifying fundamental variables that can predict future earnings value-adding for investors if the information is not reflected in prices. Ou and Penman (1989) select first the total of 68 different accounting variables and asses the predictive power of these variables over two periods 1965–1972 and 1973–1977. Based on various statistical tests Ou and Penman (1989) select variables with the highest statistical relationship with the direction of one-year ahead earnings. They identify 16 and 18 most significant accounting variables for the two periods, which are then combined into one summary probability measure $\widehat{Pr}$ that indicates the direction of one-year ahead earnings change for each stock. The probability measure $\widehat{Pr}$ is then used to allocate stocks into 24-month buy-and-hold long and short portfolios for 1973–1977 and 1978–1983 periods. Ou and Penman (1989) allocate stocks with higher than 0.6 probability increasing their earnings in long portfolios, whereas stocks with lower than 0.4 probability increasing their earnings are included in short portfolios. These portfolios are constructed three months after the end of fiscal year, which might produce a look-ahead bias. The results show that the $\widehat{Pr}$ measure is able to predict both future earnings direction and stock returns. The long-short portfolio produces an average market-adjusted cumulative 24-month buy-and-hold return of 14.53% over the period 1973–1983, which is more driven by the short-side (Ou & Penman 1989, 314).

The robustness of Ou and Penman (1989) results have, however, been questioned. Results by Greig (1992) show that when firm size is controlled, the positive relationship between probability measure $\widehat{Pr}$ and future stock returns disappears both at portfolio- and individual firm-level. Thus, higher returns earned by fundamental strategy based on probability measure $\widehat{Pr}$ seem to be driven by the size effect rather than mispricing. (Greig 1992, 415.) Holthausen and Larcker (1992) also test Ou and Penman's (1989) strategy with a slightly different sample and time-period. Similar to the results of Ou and Penman (1989), the probability measure $\widehat{Pr}$ seems to have predictive power regarding future earnings. However, the average market-adjusted 24-month buy-and hold return for the long-short portfolio is only 2.23% over the 1978–1988 period, which is considerably less what Ou and Penman (1989) reported. This is mainly due to considerably weaker performance after 1983 as long-short strategy produces negative excess returns. (Holthausen & Larcker 1992, 403, 405). Holthausen and Larcker (1992) find, however, that the 68 accounting variables used by Ou and Penman (1989) can be useful in producing excess returns in a different setup. Instead of predicting future earnings changes, they develop a model that uses accounting variables to predict one-year ahead excess returns. This strategy produces an average 24-month buy-and hold excess return of 4.26-7.97% for market-adjusted, CAPM-adjusted and size-adjusted returns.

The early research connecting financial statement measures and equity valuation has been criticized by Nissim and Penman (2001). According to Nissim and Penman (2001, 110), the relation between stock returns and various fundamental measures has been analysed in an ad hoc manner and without a structural approach to equity valuation. Nissim and Penman (2001) take a completely different approach and use residual income equity valuation model as a starting point for identifying useful rations in financial statement analysis and valuation. They decompose the components of residual income model into key profitability and growth ratios that drive future residual income. For example, forecasting return on common equity (*ROCE*) is one of the key drivers for forecasting residual income in the residual income model. *ROCE* can be further decomposed into weighted average of the return on operating activities and the return on financing activities. Accordingly, the return on operating activities can be shown as return on operating assets (*RNOA*), and the return on financing activities can be shown as net borrowing costs or return on net financial assets (*NBC*). Hence, *ROCE* is driven by return on operations and leverage effect from net financial assets. (Nissim & Penman 2001, 115–116.) This kind of decomposition of residual income model drivers shows that there is a clear connection between financial statement variables and equity valuation. This is contrary to the above-mentioned empirical studies such as by Ou and Penman (1989), where useful financial statement ratios were identified ("fitted") from historical correlations without clear connection to equity valuation (Nissim & Penman 2001, 125).

The more structural approach to fundamental analysis introduced by Nissim and Penman (2001) is adapted by Wahlen and Wieland (2011). They study whether ex ante financial statement information is useful in predicting the change in one-year ahead earnings and if strategy based on predicted earnings changes outperforms sell-side analysts' consensus recommendations. To forecast the change in one-year ahead earnings, Wahlen and Wieland (2011) develop predicted earnings increase score (*PEIS*), which consists of six out-of-sample fundamental signals: the return on operating assets (*RNOA*), the change in gross margin less the change in sales (ΔGM), the change in the ratio of selling, general, and administrative expenses relative to sales (ΔSGA), the change in asset turnover ratio (ΔATO), the growth in net operating assets (G^{NOA}) and accruals (*ACC*). To construct an aggregate *PEIS* for each firm, they give each signal a score of +1 (top), 0 (middle) and -1 (bottom) depending on the implication for future performance.[8] Thus, higher *PEIS* indicates a greater likelihood of positive future earnings increase. Wahlen and Wieland's

[8] Although Wahlen and Wieland (2011) use somewhat similar scoring system as Piotroski (2000), there is one clear difference. In *PEIS* it is assumed that *RNOA* is negatively related to future earnings (mean-reversion), meaning that currently loss-making firms receive a higher score. Contrary to this, in *FSCORE* firms that are profitable receive a higher score as this trend is expected to continue in the future.

(2011) results show that *PEIS* is useful both in predicting future earnings and as an investment strategy in a 12-year sample period. Firstly, 63.9% of firms in the highest *PEIS* quintile increase one-year ahead earnings compared to 51.3% for firms in the lowest quintile and 59.2% for the whole sample. Secondly, investment strategy that goes long (short) for stocks in the highest (lowest) *PEIS* quintile produces annual buy-and-hold abnormal return of 9.8%. This outperforms analysts' consensus recommendations as strategy that goes long for strong buy and buy recommendations and short for sell recommendations produces a significant negative abnormal return of -9.0%. When future returns are controlled for various risk factors, long-short *PEIS* strategy produces annual abnormal return of 10.9% compared to 0.9% for long-short strategy following analysts' recommendations. This indicates that stock prices and consensus estimates by analysts do not fully corporate all relevant information in financial statements to prices, producing abnormal returns for strategies that utilize this information. (Wahlen & Wieland 2011, 111.)

Novy-Marx (2013) studies the relation between gross profit-to-assets, *B/M* ratio and stock returns between 1963 and 2010.[9] The results from Fama-Macbeth regressions suggest that both gross profit-to-assets and *B/M* ratio predict cross-sectional stock returns and that the relation is positive. Further, the predictive power of earnings-to-book equity, free cash flow-to-book equity, EBITDA-to-assets and SG&A-to-assets are subsumed after controlling for gross profit-to-assets. (Novy-Marx 2013, 3.) The predictive power of gross profit-to-assets could, however, be driven by anomalies relating to earnings quality such as accruals, research and development expenses (R&D) and advertising expenses. Sloan (1996) finds that the accrual component of earnings has lower persistence than the cash flow component of earnings. Investors do not seem to fully reflect this difference as firms with a higher (lower) cash flow component in their earnings produce positive (negative) abnormal returns. Chan, Lakonishok and Sougiannis (2001) find that many firms in growth industries such as technology and pharmaceuticals have high R&D and advertising expenditures relative to current earnings and book values. This may lead to mispricing as investors underestimate the long-term benefits of R&D and advertising. (Chan et al. 2001, 2432.) The results show that firms with high R&D and advertising spending relative to market value produce on average abnormal returns of 6.12% and 3.10% annually over a three-year post formation period, indicating that markets might be too pessimistic about these stocks. The results by Novy-Marx (2013) nevertheless show that gross profitability premium remains after controlling for accruals and R&D expenditures. When portfolios are sorted based on gross profit-to-assets, two interesting results emerge. Firstly, there is a significant gross profit premium. The average excess returns increase with profitability and high-low spread is 0.31% per month with *t*-statistic of 2.49. Secondly, the gross profitability strategy is driven by growth firms as firms with high gross

[9] Gross profit is scaled by assets as it is an unlevered measure (Novy-Marx 2013, 3).

profit-to-assets tend to have significantly lower book-to-market ratios than low profitability firms and the portfolio has a clear negative loading to high-low book-to-market portfolio factor. Further, the negative correlation of -0.57 between gross profit-to-assets strategy and value strategy produces a superb hedge portfolio over the period. (Novy-Marx 2013, 6–7.) Consistent with this, returns for value strategies improve when profitability is controlled, and returns for profitability strategies improve when value is controlled. Hence, both profitable value and growth firms outperform unprofitable ones. This strategy also works with large cap stocks, producing on average excess returns of 0.62% per month when going long (short) for value (growth) stocks with high (low) profitability. Hence, controlling profitability seems to be important both in value and growth portfolios and suggests that value premium is not driven by stocks that are financially distressed (Novy-Marx 2013, 16). Instead, there seems to be a premium towards financial quality.

2.2.3 Combining value and fundamentals – Piotroski FSCORE

Value effect and fundamental analysis was combined by Piotroski (2000) based on previous empirical research. Piotroski (2000, 2) argued that using fundamental analysis for value stocks is appropriate as value stocks are often neglected by investors and analysts, have lower informational efficiency and are often financially distressed. Even more importantly, less than 44% of value stocks earned positive market-adjusted returns during a two-year holding period. Hence, majority of value stocks underperformed the market. As a large part of value stocks are fundamentally weak ex ante and produce negative market-adjusted returns ex-post, it seemed that value portfolio's returns and return distribution could be enhanced using ex ante fundamental information.

In order to separate fundamentally strong value firms from weak ones, Piotroski (2000) created accounting-based fundamental analysis strategy known as *FSCORE*. This strategy was applied to all value stocks and was based on nine signals/variables from financial statements to measure three areas of fundamental strength: (1) Profitability, (2) Financial leverage/liquidity and (3) Operating efficiency. All nine binary signals were classified either as "good" (1) or "bad" (0) depending on financial implication for the firm's future fundamentals and stock returns. These variables are shown in table 2 and are used to calculate the aggregate score, which is the sum of the nine binary signals. The aggregate *FSCORE* measures the overall fundamental strength of the stock and can be written as:

$$\begin{aligned} FSCORE_{i,t} = {} & F\_ROA_{i,t} + F\_CFO_{i,t} + F\_\Delta ROA_{i,t} + F\_ACCRUAL_{i,t} \\ & + F\_\Delta LEVER_{i,t} + F\_\Delta LIQUID_{i,t} + EQ\_OFFER_{i,t} \\ & + F\_\Delta MARGIN_{i,t} + F\_\Delta TURN_{i,t} \end{aligned} \tag{2}$$

As there are nine binary signals, the aggregate *FSCORE* can range between zero and nine. High *FSCORE* indicates that a firm is financially strong, whereas low *FSCORE* signals weak fundamentals. Consequently, the investment strategy is based on selecting value stocks with high *FSCORE* as it is assumed that strong ex ante fundamentals are positively related to future fundamentals and stock returns. (Piotroski 2000, 7–9.) It can also be thought that financial strength contributes to margin of safety as stronger firms can better absorb shocks caused by business cycles and competition (Gray & Carlisle 2013, 114).

Table 2 *FSCORE* variable definitions

Financial performance signals	**Measurement**	**Indicator variable**[1]
Profitability		
Return on assets	ROA_t = *Net income before extraordinary items* $_t$ / *Total assets* $_{t-1}$	If $F\_ROA_t > 0$, then 1, otherwise 0
Cash flow from operations	CFO_t = *Cash flow from operations* $_t$ / *Total assets* $_{t-1}$	If $F\_CFO_t > 0$, then 1, otherwise 0
Change in return on assets	$\Delta ROA_t = ROA_t - ROA_{t-1}$	If $F\_\Delta ROA_t > 0$, then 1, otherwise 0
Accruals	$ACCRUAL_t$ = (*Net income before extraordinary items* $_t$ - *Cash flow from operations* $_t$) / *Total assets* $_{t-1}$	If $F\_ACCRUAL_t < 0$, then 1, otherwise 0
Changes in financial leverage/liquidity		
Change in leverage	$\Delta LEVER_t$ = [*Total long-term debt* $_t$ / (½*Total assets* $_t$ + ½*Total assets* $_{t-1}$)] - [*Total long-term debt* $_{t-1}$ / (½*Total assets* $_{t-1}$ + ½*Total assets* $_{t-2}$)]	If $F\_\Delta LEVER_t < 0$, then 1, otherwise 0
Change in liquidty	$\Delta LIQUID_t$ = (*Total current assets* $_t$ / *Total current liabilities* $_t$) - (*Total current assets* $_{t-1}$ / *Total current liabilities* $_{t-1}$)	If $F\_\Delta LIQUID_t > 0$, then 1, otherwise 0
Equity offer	EQ_OFFER_t = *Issuance of common equity* $_t$	If $EQ\_OFFER_t = 0$, then 1, otherwise 0
Operating efficiency		
Change in gross margin	$\Delta MARGIN_t = MARGIN_t - MARGIN_{t-1}$	If $F\_\Delta MARGIN_t > 0$, then 1, otherwise 0
Change in asset turnover	$\Delta TURN_t$ = *Total sales* $_t$ / (½*Total assets* $_t$ + ½*Total assets* $_{t-1}$) - *Total sales* $_{t-1}$ / (½*Total assets* $_{t-1}$ + ½*Total assets* $_{t-2}$)	If $F\_\Delta TURN_t > 0$, then 1, otherwise 0
Composite score		
FSCORE	$FSCORE = F\_ROA + F\_CFO + F\_\Delta ROA + F\_ACCRUAL + F\_\Delta LEVER + F\_\Delta LIQUID + EQ\_OFFER + F\_\Delta MARGIN + F\_\Delta TURN$	

[1] All financial variables are calculated from annual financial statements.

The variables used in *FSCORE* have a very intuitive interpretation in fundamental analysis. Profitability measures return on assets (*ROA*), change in return on assets (*ΔROA*) and cash flow from operations (*CFO*) provide information about firm's overall profitability, cash flow generation and earnings trend, whereas accruals (*ACCRUAL*) considers firm's cash conversion and earnings quality. It is assumed that profitability measures have predictive power regarding firm's future financial performance and thus positive relation with shareholder value creation. Financial leverage and liquidity measures focus on firm's financial risk and include change in leverage (*ΔLEVER*), change in liquidity (*ΔLIQUID*) and equity issuance (*EQ_OFFER*). These measures assume that increase (decrease) in leverage (liquidity) and issuance of common equity when stock price is low is negative for equity holders as it may signal that the firm's internal cash flow generation is insufficient to cover future operative needs, debt obligations and dividend payments.[10] The third category of financial measures relates to trend in firm's operating efficiency and includes a change in gross margin (*ΔMARGIN*) and asset turnover (*ΔTURN*). These variables signal various aspects such as firm's pricing power, cost efficiency, product mix and productivity of the asset base. Overall, the *FSCORE* variables seem to be well in line with a fundamental analysis that seeks to select value stocks with improving fundamentals instead of value stocks that continue to be distressed. However, as the *FSCORE* is an aggregate binary measure and the variables have been chosen rather intuitively, it is likely that *FSCORE* strategy eliminates some useful information. In addition, as firms' financial characteristics can vary significantly, the interpretation of the signals can be problematic. (Piotroski 2000, 7, 9–10.) Lastly, industry contextual information could be useful in benchmarking fundamental strength (Piotroski & So 2012, 2870).

The empirical results from Piotroski (2000) study show that *FSCORE* can indeed be useful to separate winners from losers among value stocks. Using a one-year holding period, the high *FSCORE* firms (score 8-9) outperform the low *FSCORE* firms (score 0-1) in 18 out of 21 years in the sample period between 1976 and 1996.[11] The mean annual market-adjusted return is 13.4% for high *FSCORE* firms compared to -9.6% for low *FSCORE* firms – a significant difference of 23.0% annually with a *t*-statistics of 5.590. The high *FSCORE* firms also outperform the whole sample of value stocks as the return difference is impressive at 7.5% annually with *t*-statistics of 3.140. Besides the higher returns, the *FSCORE* strategy also shifts the return distribution to the right. The 10th percentile, 25th percentile, 75th percentile and 90th percentile returns are clearly higher for high *FSCORE* firms compared to low *FSCORE* firms and all value stocks. The proportion of stocks earning positive market-adjusted returns also increases from 43.7% for

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[10] Issuance of common equity relates closely to the pecking order theory and information asymmetry between management and investors. According to the pecking order theory, firms prefer internal financing over debt and equity financing. Hence, equity financing is only used as a last resort. (Myers 1984, 581.)

[11] The results are also robust using a two-year holding period.

all value stocks to 50.0% for high *FSCORE* stocks. Similar results were also found by Aspris et al. (2013) in Australia between 2000 and 2010. They found that high *FSCORE* firms produced a mean market-adjusted return of 15.9%, compared with -27.2% and 8.1% for low *FSCORE* firms and all value stocks respectively. Also, the high *FSCORE* strategy shifts the return distribution to the right. However, the sample period used by Aspris et al. (2013) was relatively short and included only 369 firms. There is also contradicting evidence regarding *FSCORE*. Using a sample of US stocks from 2000 to 2013, Hanson and Dhanuka (2015) showed that various financial quality strategies have lost their ability to generate abnormal returns over one- to five-year holding periods. Only high *ROIC* strategy generates statistically significant alpha, which is not the case for *FSCORE*, gross profit-to-assets, accruals and Grantham's score. Further, one- to five-year persistence in higher financial quality does not generate significant alpha except for *ROIC*. This could reflect that the excess returns previously associated with various fundamental strategies have been mostly arbitraged away (Hanson & Dhanuka 2015, 77).

Continuing with Piotroski's (2000) original results, the *FSCORE* strategy was also found to be more robust among small and medium market capitalization stocks with low trading volumes and limited analyst coverage. Piotroski (2000) found that small and medium size stocks with high *FSCORE* earned 8.8% and 7.1% more than the average small and medium size value stock, whereas the comparable figure for large stocks was only 1.7%. The results by Aspris et al. (2013) were also similar to Piotroski's (2000) as the higher returns for the *FSCORE* strategy were driven by small and medium-sized firms, and were highest among stocks with the lowest turnover. This indicates that the higher returns earned by fundamentally strong small and medium-sized value stocks could be driven by limited information dissemination (Piotroski 2000, 3). This is logical as large stocks are more followed by analysts and traded by institutional investors, making mispricing less likely. However, as small stocks consisted almost 60% of the whole sample in Piotroski's (2000) study, the *FSCORE* strategy is likely to be unimplementable for most of institutional investors due to liquidity issues.

Finally, Piotroski's (2000) results do not support the argument that the higher return earned by the *FSCORE* strategy is due to risk-based explanations or correlation with other return patterns. Firstly, the high *FSCORE* firms are fundamentally strongest ex ante and there is a small variation in *B/M* ratios and market capitalizations. Hence, financial distress or *B/M* ratios and size are unlikely to explain the significant return difference between high and low *FSCORE* firms. (Piotroski 2000, 22.) Secondly, even after using size, *B/M* ratio, momentum, accrual, equity offering and *FSCORE* as control variables in cross-sectional regressions, the average coefficient on *FSCORE* is still 0.032 with a *t*-statistics of 5.889. Thus, a one-point increase in *FSCORE* is associated with approximately 3.2% increase in market-adjusted return even after controlling for other return patterns. Based on the above-mentioned results, it seems that *FSCORE* is a useful strategy for selecting winner value stocks as market does not recognize these signals (Piotroski 2000, 3).

According to Duong et al. (2014), a potential explanation for the success of *FSCORE* could be the confirmation bias. The confirmation bias suggests that investors misinterpret information to endorse their prior beliefs. Therefore, if investors are overly pessimistic about value stocks, they can underreact (overreact) to positive (negative) fundamental information as it is incongruent with their prior view. (Duong et al. 2014, 528.) Using data from the UK from 1991 to 2007, Duong et al. (2013) find support for the confirmation bias hypothesis among value stocks. Specifically, value stocks with high *FSCORE* earn positive market-adjusted returns, whereas value stocks with low *FSCORE* earn negative market-adjusted returns. Although the negative market-adjusted return for the low *FSCORE* portfolio is not statistically significant, the high-low return of 11.25% is clearly statistically significant with *t*-statistics of 4.276 and is more driven by the long positions in financially strong value stocks. This suggest that the bias is stronger among value stocks with positive fundamental information, supporting the conclusion that the abnormal returns are driven by the confirmation bias (Duong et al. 2014, 539).

2.2.4 Combining growth and fundamentals – Mohanram GSCORE

Although fundamental analysis is more common among value stocks due to their financial characteristics, it can also be applied to growth stocks. Whereas fundamental analysis in value stocks often focuses in capital structure, ability to meet debt service obligations and liquidity, in growth stocks analysing sustainability of growth might be more important. (Beneish et al. 2001, 165–166). The effectiveness of fundamental analysis in growth context is, however, not that unambiguous. Growth firms tend to be more followed by analysts and traded by institutional investors, have often many other disclosures than financial statements and non-financial metrics can be even more important than financials. However, these attributes can also cause growth stocks to be overvalued as investors overreact to intangible information and past performance and ignore useful information in financial statements. (Mohanram 2005, 134.) Therefore, if current fundamentals provide information about the future and are misinterpreted by the market, growth stocks with strong fundamentals could outperform growth stocks with weak fundamentals.

To see whether fundamental analysis could be useful among growth stocks, Mohanram (2005) developed the *GSCORE* to separate winners from losers among low *B/M* stocks. Whereas *FSCORE* uses financial measures suited for value stocks based on firm's historical financial development, *GSCORE* uses measures in an industry context which have been tailored for growth firms. In *GSCORE* there are eight signals/variables from financial statements that measure three areas: (1) Earnings and cash flow profitability, (2) Naïve extrapolation and (3) Accounting conservatism. As in the *FSCORE*, the *GSCORE* signals are binary and are aggregated into a single measure to separate strong growth firms from weak ones. Although *GSCORE* also includes traditional signals focusing on profitability, cash flows and accruals (*G1*, *G2* and *G3*), there are several important distinctions.[12] Firstly, *GSCORE* includes signals for naïve extrapolation (*G4* and *G5*) and accounting conservatism (*G6*, *G7* and *G8*) that are not part of *FSCORE*. There is evidence that investors tend to naively extrapolate growth firms' past sales and earnings growth into the future and that firms with more stable fundamentals tend to on average perform better in the future. Hence, distinguishing firms with stable historical sales and earnings growth from firms which are overvalued as investors extrapolate growth rates too far into the future could improve portfolio returns. In addition, conservative accounting relating to R&D expenditures, capital expenditures and advertising expenditures is likely to lower earnings in the short-term and thus book value, but could potentially lead to higher than expected future sales and earnings growth in the future. (Mohanram 2005, 139–140.) Secondly, *GSCORE* compares all variables except accruals to firm's industry median values, whereas *FSCORE* focuses on firm's own historical development. Thus, the *GSCORE* assumes implicitly that firms with above the industry median values are likely to perform better in the future. This kind of industry contextual information is commonly used in practice and could enhance fundamental analysis as firms in the same industry often share similar operating, financial and risk characteristics.

The empirical results show that *GSCORE* is useful for separating winners from losers among growth stocks. Growth firms with high *GSCORE* (score 6-8) earn on average size-adjusted return of 3.1% annually, whereas low *GSCORE* (score 0-1) firms earn a significant negative average return of -17.5%. The high *GSCORE* firms also outperform the whole sample as the average annual size-adjusted return is -8.7% for all growth firms. The positive size-adjusted returns are particularly strong for growth firms with *GSCORE* of 7 or 8 as these firms earn an average annual size-adjusted return of 6.8% and 11.4%. However, these firms consist only 4.2% of the total sample compared to 9.8% and 12.9% for firms with *GSCORE* of 6 (mean return of 1.3%) and 0 or 1 (mean returns of -19.1% and -17.0%). Thus, the significant average annual return of 20.6% (*t*-statistics of 10.41) for high-low *GSCORE* strategy is mainly due to the extremely weak performance of low *GSCORE* firms. This could limit effectiveness of the strategy if there are restrictions on short-selling as the strategy relies more on shorting/eliminating weak growth stocks (Mohanram 2005, 148).[13] Similar to the *FSCORE* strategy, the *GSCORE* strategy also shifts

[12] Accruals is the only signal that does not correlate positively with future returns. As growth firms often have negative accruals due to increasing working capital requirements and depreciation, it could be that accruals component is less important for growth stocks than for value stocks (Mohanram 2005, 144).

[13] Mohanram (2005) also addresses issues relating to shorting stocks such as liquidity and availability of put options, and finds evidence that positive returns could be achieved.

the return distribution. High *GSCORE* earn higher returns than low *GSCORE* firms or all growth firms in each percentile group, and the proportion of stocks earning positive returns increases from 34.6% for all growth stocks to 45.8% for high *GSCORE* stocks.

The *GSCORE* strategy is also robust for growth stocks across time, controlling for other return patterns and using *FSCORE* strategy for growth stocks. High *GSCORE* firms outperform low *GSCORE* firms in 21 out of 23 years (of which 16 were statistically significant) and in almost each year the return difference is more than 10% (Mohanram 2005, 156). When using size, *B/M* ratio, momentum, accruals, equity offering and *GSCORE* as control variables, the average coefficient for *GSCORE* is 0.034 with *t*-statistics of 5.53. What is even more interesting is the usefulness of contextual fundamental analysis. The *GSCORE* does not work well with value stocks, and *FSCORE* does not work as well with growth stocks as with value stocks. In both cases, the returns for high-low strategies are much lower and there is a limited number of firms in extreme portfolios, which reduces effectiveness of the strategy (Mohanram 2005, 165–166.) According to Mohanram (2005), there could be two explanations why *FSCORE* does not work well with growth stocks. Firstly, as growth firms' fundamentals are on average unstable compared to value firms, it might be that extrapolation of these fundamentals does not work well among growth stocks. Secondly, as information dissemination is more effective among growth stocks, mispricing relating to fundamentals might be rather small. (Mohanram 2005, 166.) It could also be that *FSCORE* signals are not suitable for growth stocks as these signals focus on finding value stocks that are likely to recover from financial distress. In the end, Mohanram (2005, 167) argues that the success of fundamental analysis among value stocks is due to mispricing as investors ignore relevant fundamental information, whereas misinterpretation seems to be the key reason for growth stocks. Although Mohanram's (2005) results emphasize the importance of tailored signals for value and growth stocks, contradicting results have also been found as Duong et al. (2014, 537) found that both *FSCORE* and *GSCORE* strategies worked in value and growth context.

2.3 The momentum effect

2.3.1 Evidence from momentum premium

The efficient market hypothesis argues that past stock prices cannot predict future returns. However, there exists strong and persistent evidence that past 3 to 12-month stock returns can be used to predict future stock returns and this effect is generally known as medium-term/intermediate-term momentum. This evidence contradicts even the weakest form of the efficient market hypothesis, which makes momentum a puzzling anomaly.

Jegadeesh and Titman (1993) were one of the first researchers to show evidence that buying past winners and selling past losers could create significant positive returns in the US between 1965 and 1989. They examine relative strength portfolios formed based on 3 to 12-month historical returns for 3 to 12-month holding periods and find that returns for all except one, winners minus losers portfolios are positive and statistically significant. The highest average monthly return of 1.31% is achieved when stocks are selected based on the past 12 months' performance and are hold for 3 months. The results also show that momentum returns do not last for longer than 12 months. Using 6-month lagged returns, the average monthly returns are positive for each first 12 months following portfolio formation, but are negative for each month in the second year and half of the year in the third year. This is consistent with the long-term return reversal suggested by De Bondt and Thaler (1985) where past long-term winners (losers) underperform (outperform) past losers (winners). Jegadeesh and Titman (1993) argue that this is not driven by higher systematic risk but by biased expectations. It is possible that investors underreact to short-term positive prospects, driving abnormal returns in the first 12 months. Following the abnormal returns in the short-term, the returns mean-revert in the later period as investors have overreacted to long-term prospects. (Jegadeesh & Titman 1993, 90.)

Since the findings by Jegadeesh and Titman (1993) the term momentum was officially conceptualized and it has been found to be a persistent anomaly also in international markets. Rouwenhorst (1998) studied momentum in 12 European countries between 1980 and 1995. Similarly to Jegadeesh and Titman (1993), Rouwenhorst (1998) finds a strong medium-term momentum with similar continuity pattern. All portfolios with long in past winners and short in past losers produce positive returns and are statistically significant irrespective of the look-back period used for ranking and holding period (both between 3 to 12 months). The highest average monthly return of 1.35% is again achieved with a portfolio using 12-month historical returns and 3-month holding period. Although average momentum returns are positive for all holding periods, these returns tend to decrease when moving from 3-month holding period to 12-month holding period (Rouwenhorst 1998, 269). For example, the average monthly return is only 0.64% when using a 3-month look-back period and a 12-month holding period. The monthly momentum returns also turn to negative at the end of the first year and continue to be negative in the second year, indicating that momentum premium cannot be captured using over a 12-month buy-and-hold strategy. Interestingly, the momentum effect also seems to be stronger for smallest firms as smaller momentum firms (deciles 1-2) earn on average 1.45–1.65% per month compared to 0.73–1.02% per month for largest momentum firms (deciles 8-10).

Momentum effect has also been studied with a more extensive international country sample. Griffin, Xiuqing and Spencer (2003) study momentum effect in 39 countries besides the US across Americas, Europe, Asia and Africa. They use a 6-month look-back and a holding period and report an overall significant momentum across the international markets. Excluding Africa (country sample size only two), the momentum effect is strongest in Americas (excluding the US) and Europe, where the average monthly momentum returns are 0.78% and 0.77%. Interestingly, momentum profits are not statistically significant in emerging markets and in Asia even if Japan is excluded (Griffin et al. 2003, 2522). The weak momentum effect in Asia is not, however, an exception as it has been documented by many other researchers. For example, Chui, Titman and Wei (2010) report negative average monthly momentum returns in Japan, Korea and Taiwan between 1984 and 2003. The positive momentum returns are also statistically insignificant in China, Indonesia, Malaysia, Pakistan, the Philippines, Singapore and Thailand. More recently, Fama and French (2012) and Asness, Moskowitz and Pedersen (2013) report a positive momentum premium in each international region studied over a long sample period (strongest in Europe), but the premium is small and statistically insignificant in Japan. Hence, there can be significant regional differences in momentum returns. Griffin, Xiuqing and Spencer (2003) also show that momentum profits tend to reverse after the end of first year, which is in line with findings by Jegadeesh and Titman (1993) and Rouwenhorst (1998). The momentum effect seems to be strongest during the first six months after portfolio formation and is positive in each region (on average 0.66% per month globally), but turns to negative in each single region and month in the second year. Overall, based on the above described empirical evidence, it seems that momentum premium is significant over intermediate term particularly in developed markets (excluding Japan), exhibits a strong short-term continuation as positive momentum returns continue on average around 12-months from the portfolio formation, and produces higher returns with a shorter rebalance frequency.

2.3.2 Drivers for intermediate-term momentum returns

Explanations for momentum anomaly are even more controversial and miscellaneous than for value. There are both risk-based and behavioural explanations for momentum anomaly. Risk-based explanations such as the three-factor model do not, however, seem to explain the large and continuing short-term returns associated with momentum. The three-factor model does not appear to capture the momentum returns as intercepts are clearly different from zero for both short-term losers and winners and the model predicts revisions of returns for past short-term winners and losers (Fama & French 1996, 68). According to Chui, Titman and Wei (2010, 361), the documented annual momentum premium of around 12% both in the US and Europe seems to be too large to be explained with higher systematic risk. Although researchers have proposed other risk-based models based on firm-specific attributes, it appears that behavioural explanations for momentum anomaly have become increasingly more popular.

One of the most common behavioural explanations for momentum anomaly is underreaction hypothesis. According to the hypotheses, stock prices underreact to various fundamental information such as earnings. This causes information to be incorporated gradually into prices, resulting in positive momentum returns in the short-term. (Barberis et al. 1998, 307–308.) Chan, Jegadeesh and Lakonishok (1996) show that both past returns (price momentum) and earnings surprises (earnings momentum) predict future returns over the next 6 and 12 months.[14] Stocks with high (low) past six-month returns and positive (negative) earnings surprises continue to earn positive returns and analysts are slow to revise their earnings expectations. Hence, investors tend to underreact to new information, leading to momentum returns. (Chan et al. 1996, 1693.) When price and earnings momentum are studied jointly, return spreads are positive and widest between jointly ranked high and low category portfolios. Both price and earnings momentum also have separate explanatory power when controlling for each other, indicating that they exploit different information that market is only gradually taking into account. Positive returns associated with price momentum are, however, higher and longer-lived than for earnings momentum. This might reflect large and gradual revisions by market participants instead of focus on short-term earnings, resulting in persistent drift in returns. (Chan et al. 1996, 1695, 1697, 1970.) Chan et al. (1996) also test risk-based explanations using the three-factor model and downside risk as a proxy for systematic risk. Risk-based models do not seem to be a plausible explanation as regression intercepts are clearly statistically different from zero and positive momentum stocks outperform negative momentum stocks in months when the overall index underperforms.

Similar results were also found by Hong, Lim and Stein (2000). They studied momentum from a firm-specific information diffusion view with a hypothesis that stocks with lower information dissemination should exhibit stronger momentum returns. To test this hypothesis, they used firm market capitalization and analyst coverage as a proxy for information dissemination. This approach is rather similar to that of Piotroski (2000) who argued that lower information dissemination among small firms contributes to value premium. The results by Hong et al. (2000) support the hypothesis. Firstly, momentum strategy is on average more profitable among smaller market capitalization stocks. Although momentum strategy is not profitable among microcap stocks, there is a rather monotonic negative relation between size and momentum returns when moving past the smallest stocks. This relation is particularly strong among the largest stocks where momentum returns are not statistically different from zero. Secondly, stocks with low analyst coverage have higher momentum returns. The difference is significant as momentum returns are 1.13% for stocks with low analyst coverage compared to 0.72% for stocks with high analyst coverage. The third key finding is that the relation between momentum returns

[14] Chan et al. (1996) use various earning surprise measures including abnormal returns around earnings, standardized unexpected earnings (*SUE*) and analyst revisions.

and analyst coverage is driven by loser (low) momentum stocks with a low analyst coverage. Thus, negative information dissemination appears to be weaker among loser stocks, which drives momentum returns between stocks with low and high analyst coverage. (Hong et al. 2000, 279.) All in all, the results by Hong et al. (2000) seem to support the underreaction hypothesis as momentum strategies work better with firms that have small market cap and low analyst coverage.

The underreaction to information could also relate to disposition effect as suggested by Frazzini (2006). According to the disposition effect, investors tend to sell stocks that have gone up and keep stocks that have gone down. This tendency can contribute to momentum profits as investors underreact to information, which increases (decreases) future returns for stocks that have gone up (down). (Frazzini 2006, 2018–2019.) To test this hypothesis, Frazzini (2006) uses data from mutual fund holdings and constructs long-short portfolios based on a proxy for unrealized capital gains (losses). Stocks with positive (negative) capital gain overhang underreact to positive (negative) news, predicting positive (negative) future stock returns for stocks with capital gains (losses) (Frazzini 2006, 2028). The results show that disposition effect seems to predict momentum returns as stocks with positive (negative) earnings announcements and with high capital gains (losses) overhang produce positive (negative) future returns. The long-short strategy that goes long for stocks with positive earnings news and positive capital gain overhang and short for stocks with negative earnings news and negative capital gain overhang produces abnormal returns over 1- to 12-month holding periods. Thus, information seems to travel slowly across capital gain/loss portfolios, resulting in underreaction and momentum profits (Frazzini 2006, 2030). These results are further supported by the three-factor regressions as intercepts are statistically significant for long-short portfolios, meaning that systematic risk factors do not explain the large overhang spread (Frazzini 2006, 2035).

Hur, Pritamani and Sharma (2010) study disposition effect and momentum returns from a different standpoint. As individual investors are more likely to suffer from disposition effect, Hur et al. (2010, 1156) argue that disposition effect should better predict momentum profits among stocks with greater individual investor ownership and share of trading volumes. When portfolios are first sorted based on past returns and capital gains overhang, results confirm earlier results by Frazzini (2006). In each past return category, the average monthly returns of high minus low capital gains overhang portfolios are positive regardless of the individual investors ownership, supporting the disposition effect as a driver for momentum effect (Hur et al. 2010, 1162). When portfolios are further sorted according to individual investors ownership, momentum portfolios with higher individual investor ownership produce statistically higher returns for 1, 3 and 6-month ranking and holding periods. Hence, momentum returns driven by the disposition effect are larger when there is a higher individual investor ownership (Hur et al. 2010, 1165). This is also somewhat in line with the evidence in the US by Hong et al. (2000) and globally by Fama and French (2012) that momentum returns are stronger among small cap stocks as small stocks are more likely to be owned by private investors.[15]

Momentum profits can also relate to seasonality. Sias (2007) studies seasonality caused by tax-loss selling and window dressing hypotheses. According to the tax-loss selling hypothesis, investors prefer to sell losers and avoid selling winners in December to optimize tax benefits. In the case of window dressing hypothesis, institutional investors want to sell stocks that have underperformed, which are replaced by buying stocks that have performed well. This kind of window-dressing is done prior the quarter-ends (particularly before the year-end) to improve portfolios' appearance to investors. Both hypotheses should thus contribute to higher momentum returns at the quarter-ending months. In addition, these effects should be stronger among institutional investors and during the latter part of the sample period as institutional investors' share of trading and ownership has increased. (Sias 2007, 48.) The results give strong support for both hypotheses. In the later period from 1984 to 2004 average momentum profits for quarter-ending months are 3.10% compared to 0.59% for non-quarter-ending months even when January is excluded.[16] In contrast, momentum returns are virtually the same for non-quarter-ending months excluding January and for quarter-ending months in the earlier period from 1963 to 1984. The momentum returns are also clearly strongest in December at 5.52%, giving support to both tax-loss selling and window dressing hypotheses (Sias 2007, 50). Compared to the evidence by Sias (2007), Grinblatt and Moskowitz (2004) found strong momentum returns in December only in high tax regimes. Therefore, the tax-loss selling hypothesis was a more prominent driver for the strong momentum returns in December than window-dressing (Grinblatt & Moskowitz 2004, 543). However, as results by Sias (2007) show higher momentum returns also in other quarter-ending months, it seems difficult to conclude that window-dressing does not play a role in momentum anomaly. The final tests by Sias (2007) also show that institutional investors are likely to contribute significantly to momentum profits. Firstly, momentum returns are 2.53% per month during all months for stocks with high institutional ownership and 0.91% for stocks with low institutional ownership. Secondly, momentum profits are more than double for stocks with high institutional ownership in quarter-ending months (5.82% per month) compared to stocks with low institutional ownership (2.73% per month). The significant return spread is primarily driven by the last two sub-periods 1990–1997 and 1997–2003, supporting the hypothesis that institutional investors role in driving momentum returns has become more important (Sias 2007, 52).

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[15] It could also be that the positive relation between momentum returns and individual investor ownership is due to higher individualism among these private investors as suggested by Chui et al. (2010).

[16] It is assumed that tax-motivated trading reverts at the beginning of the year, which causes negative momentum returns in January. The results by Sias (2007) support this assumption as momentum returns are over 10% negative in January between 1984 and 2004.

2.3.3 Enhancing intermediate-term momentum strategies

As with value effect, the question that arises is how could we further improve traditional momentum returns? According to Gray and Vogel (2016, 93), one way is to focus on the time-series characteristics of momentum returns. The argument is that investors should avoid momentum stocks with lottery characteristics. That is, momentum profits could be enhanced by selecting momentum stocks with smoother returns in the ranking period as these stocks are less likely to be mispriced compared to momentum stocks with jumpy price paths. (Gray & Vogel 2016, 99.) Thus, the key argument here is that by looking at the time-series characteristics of momentum stocks, we can improve momentum portfolios returns by selecting undervalued momentum stocks and by eliminating overvalued momentum stocks that have performed well due to investors' expectation errors.

The idea of eliminating momentum stocks with lottery characteristics is followed by Da, Gurun and Warachka (2014). Investors' limited cognitive resources causes investors to underreact to frequent and gradual information. Instead, investors appear to pay more attention to large-scale events that are infrequent by nature. (Da et al. 2014, 2171–2172.) Da et al. (2014, 2172) develop a frog-in-the-pan hypothesis that predicts investors' underreaction to continuous and small information compared to discrete and large information. To test this hypothesis, Da et al. (2014, 2177) construct information discreteness (*ID*) measure, or $ID = sgn(PRET) \times [\%neg - \%pos]$, that tries to capture whether momentum returns are driven by continuous or discrete information. In the *ID* measure, higher past 12-month momentum returns (*PRET*) and percentage of positive daily returns (*%pos*) compared to negative returns (*%neg*) indicate that momentum is driven by small and continuous information. Hence, the lower the value of *ID* measure, the stronger the momentum signal as it is resulting from small and frequent return signals (Da et al. 2014, 2172). To test the hypothesis, Da et al. (2014) use a long sample period in the US from 1927 to 2007 and double-sort portfolios first by traditional momentum measure i.e. *PRET* and then by *ID*. The results are consistent with the hypothesis as the long-short returns in the 6-month holding period increase monotonically when moving from high *ID* portfolio to low *ID* portfolios. Both raw return and the three-factor model adjusted return spreads are considerably large and statistically significant as high *ID* portfolios earn -2.07% and -2.01% compared to 5.94% and 8.77% for low *ID* portfolios. Moreover, momentum returns persist significantly longer in low *ID* portfolios. Continuous momentum portfolios produce statistically significant three-factor alpha for 8 months after portfolio formation, whereas the comparable figure for discrete portfolios is only 3 months. (Da et al. 2014, 2183.) It thus seems that investors underreact systematically to continuous positive information and thus momentum returns can be enhanced by separating strong momentum stocks with continuous information from weak ones with discrete information.

Fundamental analysis is still rarely used together with momentum anomaly. Momentum anomaly is based on past returns, whereas firm-specific fundamentals have not been used that much in separating winners from losers among momentum stocks (Chen et al. 2016, 224). Using fundamentals to enhance portfolio returns seems to be more popular in value strategy due to the financial characteristics of value stocks. However, if momentum stocks are also mispriced due to investors' expectation errors, could it be that fundamental analysis is also useful in momentum investing framework? Specifically, what if part of stocks with momentum signals are undervalued as investors are not giving enough credibility for improving fundamentals? Continuing with the same logic, part of momentum stocks could be overvalued as investors have bid prices past intrinsic value. In this case, separating winners from losers using fundamental analysis could also enhance momentum portfolios returns in a similar manner as in the value framework. Although this is not directly stated by Chen et al. (2016), they combine both fundamental analysis and momentum strategy to see if momentum returns can be improved. They form long-short strategy using both past 12-month cumulative returns and fundamental strength based on *FSCORE* and *GSCORE*. The results give strong support for combining stocks with strong momentum signal and fundamental strength. Going long for stocks with highest past returns (*QM5*) and highest *FSCORE* (*QF5*) and short for stocks with lowest past returns (*QM1*) and lowest *FSCORE* (*QF1*) produces abnormal returns that are statistically significant irrespective of holding period length. The average monthly returns vary from 1.05% to 1.56% and are highest (lowest) for 3-month (12-month) holding period. More importantly, the combined momentum and *FSCORE* strategy outperforms the traditional momentum strategy in each holding period by 0.42% to 0.53% per month. These results are also similar and statistically significant using *GSCOR*E, but fundamental momentum strategy that uses *FSCORE* produces more significant returns.[17]

It is also worthy to point out that combining momentum and value can be a powerful way to enhance portfolio's risk and return characteristics. Asness, Moskowitz and Pedersen (2013) find a significant negative correlation of around -0.60 between momentum and value strategies. This is in line with the earlier evidence by Asness (1997) that the value effect is strongest among low momentum stocks and that the momentum effect is strongest among growth stocks. This seems natural as value stocks often have poor historical fundamentals, resulting in low historical returns and thus higher *B/M* ratios. On the other hand, growth stocks are often companies that have increased revenues and earnings rapidly, translating into higher historical returns and thus *B/M* ratios. The high excess returns earned by momentum and value strategies and their inverse relation indicate that combining these strategies is likely enhance the risk-return characteristics of the portfolio. Following this logic, Asness et al. (2013) show that a simple equal 50/50 combination of

[17] *FSCORE* and *GSCORE* also produce abnormal returns in the traditional value-growth context, which supports the earlier results by Piotroski (2000), Mohanram (2005) and Piotroski and So (2012).

pure-play value and momentum portfolios produces superior risk adjusted returns measured by the Sharpe ratio across international markets. Thus, combining pure-play value and momentum strategies can produce significant diversification benefits.

2.3.4 Implementability under trading costs

Momentum is more a short-term strategy compared to value. Whereas value portfolios are often rebalanced annually, momentum portfolios tend to produce higher returns with a shorter rebalance frequency. As most academic studies focus on gross returns, it naturally raises the doubt of whether momentum strategy can be profitable net of transaction costs. (Gray & Vogel 2013, 58–59.) As implementing momentum strategy can be costly, a more realistic version of the strategy should consider whether marginal benefits exceed the marginal costs. If arbitrage costs exceed momentum profits, it can delay the price adjustment towards intrinsic value and thus increase the persistence of momentum anomaly. (Lesmond et al. 2004, 350.)

The profitability of momentum strategies under transaction costs has been questioned by Lesmond et al. (2004). Long-short momentum strategies are trading intensive as they require frequent opening and closing of positions and incur various trading costs including bid-ask spread, taxes, short-sale costs and holding period risk. Further, long-short momentum strategies are often tilted towards unprofitable, smaller and illiquid stocks, meaning that short-sale costs can be high and using a simple trade-weighted measure as a proxy for trading costs is likely to be misleading. (Lesmond et al. 2004, 350–351.) Lesmond et al. (2004) take these issues into account and test momentum strategies profitability after trading costs. The results show that the average momentum profits range from 4.74% to 8.90% over a 6-month holding period before trading costs. When trading costs and actual turnover are taken into account, the momentum profits decline substantially; the momentum profits are only between -2.47% and 2.20% and are statistically insignificant. Lesmond et al. (2004, 369) argue that momentum strategies are dependent on stocks with high trading costs and estimate that the one-way trading costs are between 1.9-2.8%, which prevents the profitable implementation of momentum strategies net of transaction costs. Trading costs of momentum strategies also relate to the size of the position taken. Korajczyk and Sadka (2004) test profitability of momentum strategies using both proportional trading costs such as commissions and spreads, as well as non-proportional trading costs caused by the price impact of taken momentum trades. They estimate that abnormal returns for momentum strategies vanish after initial investment of around USD 4.5-5.0 billion, which is the implied break-even size for a momentum fund.

The results by Lesmond et al. (2004) and Korajczyk and Sadka (2004) have recently been challenged by Frazzini, Israel and Moskowitz (2015). Frazzini et al. (2015) use over a trillion dollars of real trading data from institutional investors across 21 markets from 1998 to 2013, increasing the credibility of their results. Frazzini et al. (2015) find that momentum strategies are robust after transaction costs and that they can be implemented profitably at a significantly larger scale both in the US and internationally.[18] They estimate that the average annual realized costs for long-short momentum strategies are 3.03% and 2.24% in the US and internationally respectively, well-below the previously estimated trading costs. The momentum strategy also outperforms both value and size strategies net of transaction costs in the US and Europe. Although trading costs for momentum strategy are significantly larger due to higher turnover and market price impact costs, the momentum premium is sufficiently large to make the strategy a winner. Frazzini et al. (2015, 30) argue that their estimates are better proxies for true trading costs for institutional investors as they use real trading and cost data from institutional investors, whereas in previous studies the estimated trading costs are based on average investors. Further, due to lower annual trading costs, the estimated break-even sizes for momentum portfolios are larger than by Korajczyk and Sadka (2004). Frazzini et al. (2015, 31) find that the momentum portfolio break-even size is USD 56.2 billion in the US based on the annual momentum premium of 8.20% which is more than 10 times the break-even size suggested by Korajczyk and Sadka (2004). It is, however, very difficult to believe that momentum strategy could actually be scaled up to USD 56.2 billion without a significant impact on the profitability and implementability of the strategy.

[18] Frazzini et al. (2015) also find similar results for value and size effect.

3 DATA AND METHODOLOGY

3.1 Data description

The data used in the empirical part of this thesis is from Thomson Reuters Datastream and Kenneth R. French Data Library. The empirical part is conducted using data from stocks listed in the S&P Composite 1500 index, which combines three different indices: The S&P 500, S&P MidCap 400 and S&P SmallCap 600. The S&P 500, S&P 400 and S&P 600 indices measure the large-cap, mid-cap and small-cap segments of the US equity market respectively, and cover together approximately 91% of the US market capitalization as at the end of November 2016 (S&P Composite 1500 Month-End Factsheet 2016). Therefore, the data should give a good proxy of the profitability of fundamental value and momentum strategies in the US. To calculate market-adjusted returns for each stock and portfolios, the S&P 1500 composite index is considered as a proxy for the market portfolio. Further, to measure the risk-adjusted performance in the portfolio analysis, the Sharpe ratios, the CAPM, the Fama-French three-factor and the Carhart four-factor alphas are calculated when testing the robustness of the strategies.

The sample period is from the beginning of July 1997 to the end of June 2015, which should be sufficient to study the investment strategies and includes various market events such as the tech bubble and the financial crisis. The key reason why we have chosen this time period is that we want to test combined investment strategies with a more recent data than Piotroski (2000) and Duong et al. (2014) following the widespread implementation of the latest electronic and automated trading systems and improved information availability. The data from Thomson Reuters Datastream contains monthly total returns and annual financial statement information for all stocks that constitute S&P Composite 1500 index at the beginning of each investment period in July in year t. For each stock to be included in the sample, we required the following data: (1) Book-to-market ratio at the end of December, (2) raw total returns for the past 12 months, (3) market value at the end of June, (4) Industry Classification Benchmark (ICB) by FTSE, and (5) all fiscal year-end financials required for calculating the *FS_SCORE*. All stocks with incomplete data are excluded from portfolio formation in the year when data is not available. If a stock delists within one-year of portfolio formation, it is assumed that the delisting return is the last return provided by Datastream. Thus, as Datastream uses a constant total return value equal to the last valid data point after the stock delists, we assume that the delisting return of the stock is zero after the month the stock ceases trading. This is likely to cause a delisting return bias of some kind, which can be particularly problematic if the stock is delisted for performance-related reasons. We also exclude all firms with negative book-to-market ratio in December and firms classified as financials or utilities according to the

ICB industry classification. Excluding financials and utilities is a common practice as firms in these industries often have vastly different financial statements, weakening the fundamental comparison of these firms relative to other industries.[19] Further, each year we exclude all stocks below the 5th percentile in market value at the end of June to minimize potential issues arising from the most illiquid stocks. However, as empirical evidence shows that value, momentum and fundamental investment strategies tend to produce higher returns among smaller stocks, we still want to include a comprehensive sample of small-sized stocks.

The total sample of all stocks with required data consist of 18,747 firm-year observations across all investment years between 1997 and 2014. The total sample is used to sort out value and momentum stocks and construct fundamental value and momentum portfolios for each holding period. As the total sample size is relatively large each year, it should partly mitigate the bias relating to delisting returns. Figure 1 below reports the annual firm-year observations varying between 997 and 1,083 stocks across the 18 investment years.

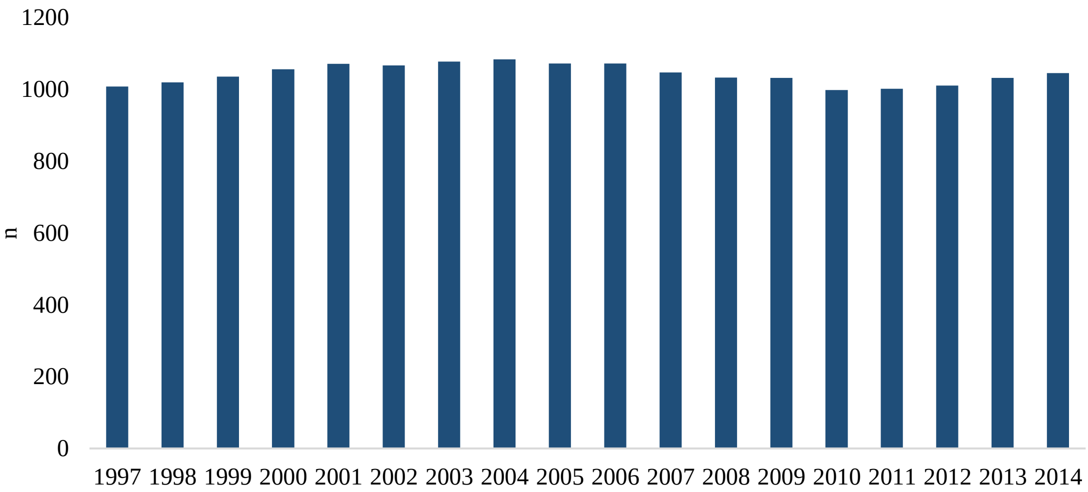

Figure 1 Total firm-year observations across the investment years

[19] For example, firms operating in the financial sector often have highly leveraged capital structures due to their business model (Fama & French 1992, 429). Thus, higher than average leverage across financial firms does not necessarily reflect financial distress. In addition, the financial ratios that are used to analyse financial firms are often vastly different.

3.2 Methodology

3.2.1 Value and momentum measures

As the literature review shows, there are various ways to compute both value and momentum for stocks. In this thesis, the most commonly used measures will be used. Although other measures and enhancements could be applied, we want to form value and momentum portfolios in a simple and efficient manner to avoid data mining bias. Further, as value and momentum portfolios will be double-sorted using fundamental information, we are most interested in studying whether fundamental information can be used to enhance returns for value and momentum portfolios.

Starting from the value measure, the firm-specific book-to-market ratio (*B/M*) will be used to form value portfolios. The book-to-market ratio will be calculated each year as the inverse of the market-to-book ratio provided by Datastream, which equals the firm's book value of common equity (*BE*) divided by market value of equity (*ME*) both at the end of December in year $t-1$. As Datastream uses the book value and market value at the end of the last calendar quarter for all US stocks, the *B/M* ratio does not necessarily reflect the financial year-end *B/M* ratio for all stocks due to varying fiscal-year ends. To avoid the look-ahead bias, value portfolios are formed each year at the beginning of July in year t. This approach should ensure that all data required to calculate the *B/M* ratios is publicly available before calculating returns for stocks.[20]

Continuing with momentum (*MOM-12*) measure, it will be calculated as the past 12-month cumulative raw total return prior the portfolio formation at the beginning of July in year t, skipping the most recent month. Specifically, the momentum will be calculated as the cumulative total return (*TR*) of the stock during the 11-month period from month $t-11$ to month $t-1$. We exclude the most recent month $t-1$ in calculating intermediate-term momentum to avoid the effect from short-term reversal in stock returns, which is commonly calculated as the one-month stock return (Bali et al. 2016, 208). The value and momentum measures of stock i in year t can now be written as

$$B/M_{i,t} = \frac{BE_{t-1}}{ME_{t-1}} \tag{3}$$

$$MOM\text{-}12_{i,t} = 100\left[\prod_{m \epsilon \{t-11:t-1\}} \left(1 + TR_{i,t}\right) - 1\right] \tag{4}$$

[20] Hou et al. (2011, 2533) also use the market-to-book ratio (WC09304) from Worldscope to calculate the book-to-market ratio for US stocks and match the year-end financial statement data for year $t-1$ to returns from July in year t to June of year $t+1$.

3.2.2 Enhanced Piotroski FSCORE – FS_SCORE

As momentum investing is not directly growth investing (although momentum stocks are likely to be fundamentally closer to growth stocks) and there is evidence that combining *FSCORE* with momentum can produce economically and statistically significant abnormal returns (see Chen et al. 2016), we are intrigued to test whether fundamentally strong momentum stocks outperform fundamentally weak momentum stocks. Further, we will also test the same among value stocks, where fundamentals are more commonly used to separate winners from losers.

To separate winners from losers, we will use the *FS_SCORE* created by Gray and Carlisle (2013) to calculate the financial strength of each value and momentum stock. The *FS_SCORE* is very similar to the original *FSCORE* by Piotroski (2000) as it seeks to separate winners from losers among value stocks, but there are some important enhancements. In the *FS_SCORE*, three of the original variables in the *FSCORE* have been modified and classified into three slightly different categories: (1) Current profitability, (2) Stability and (3) Recent operational improvements. There a total of 10 binary variables in the composite *FS_SCORE* compared to nine in the *FSCORE* and these are shown in table 3. As we use financial statement data from Datastream, we have to try to replicate the *FS_SCORE* variables in the best way possible. Although majority of the financials signals are relatively straightforward to replicate using Datastream, there are few exceptions. All financial statement items that have been downloaded from the Datastream to calculate *FS_SCORE* are shown in Appendix 1.

In the current profitability category, there are three variables that are used to measure firm's current profitability and cash flow generation. Variables *ROA* and *ACCRUAL* are the same as in *FSCORE*, but the variable cash flow from operations scaled by the beginning of the year total assets (*CFO*) has been changed. Instead of using *CFO*, Gray and Carlisle (2013) use free cash flow scaled by total assets (*FCFTA*). This can be seen as a relevant improvement as *FCFTA* takes into account capital expenditures that are necessary to maintain and expand future cash flows. For example, a firm may have a strong cash conversion and thus operating cash flow, but operates in an industry which requires high capital expenditures, increasing the need for continuous investments to maintain cash flows. Also, if the firm has a weak free cash flow profile, this is likely to increase the need for external debt and equity financing, which are negative fundamental signals. *FCFTA* has also a more robust connection to the intrinsic valuation of a firm as the enterprise (equity) value of a firm equals the present value of future free cash flows to the firm (equity). We calculate *FCFTA* in a similar manner as Gray and Carlisle (2013) and Novy-Marx (2013) taking net income before extraordinary items and preferred dividends plus depreciation and amortization (including depletion) minus changes in working capital minus capital expenditures, scaled by the beginning of the year total assets. Like *CFO*, *FCFTA* is defined as one if *FCFTA* is positive and otherwise zero.

Table 3 *FS_SCORE* variable definitions

Financial performance signals	**Measurement**[1]	**Indicator variable**[2]
Current profitability		
Return on assets	ROA_t = Net income before extraordinary items $_t$ / Total assets $_{t-1}$	If $FS\_ROA_t > 0$, then 1, otherwise 0
Free cash flow	$FCFTA_t$ = (Net income before extra items/preferred dividends $_t$ + Depreciation and amortization $_t$ - Change in working capital $_t$ - Capital expenditures $_t$) / Total assets $_{t-1}$	If $FS\_FCFTA_t > 0$, then 1, otherwise 0
Accruals	$ACCRUAL_t$ = (Net income before extraordinary items $_t$ - Cash flow from operations $_t$) / Total assets $_{t-1}$	If $FS\_ACCRUAL_t < 0$, then 1, otherwise 0
Stability		
Change in leverage	$\Delta LEVER_t$ = [Total long-term debt $_t$ / (½Total assets $_t$ + ½Total assets $_{t-1}$)] - [Total long-term debt $_{t-1}$ / (½Total assets $_{t-1}$ + ½Total assets $_{t-2}$)]	If $FS\_\Delta LEVER_t < 0$, then 1, otherwise 0
Change in liquidty	$\Delta LIQUID_t$ = (Total current assets $_t$ / Total current liabilities $_t$) - (Total current assets $_{t-1}$ / Total current liabilities $_{t-1}$)	If $FS\_\Delta LIQUID_t > 0$, then 1, otherwise 0
Net equity issuance	$NEQISS_t$ = Equity repurchases $_t$ - Equity issuance $_t$	If $NEQISS_t > 0$, then 1, otherwise 0
Recent operational improvements		
Change in return on assets	$\Delta ROA_t = ROA_t - ROA_{t-1}$	If $FS\_\Delta ROA_t > 0$, then 1, otherwise 0
Change in free cash flow	$\Delta FCTA_t = FCFTA_t - FCFTA_{t-1}$	If $FS\_\Delta FCFTA_t > 0$, then 1, otherwise 0
Change in gross margin	$\Delta MARGIN_t = MARGIN_t - MARGIN_{t-1}$	If $FS\_\Delta MARGIN_t > 0$, then 1, otherwise 0
Change in asset turnover	$\Delta TURN_t$ = Total sales $_t$ / (½Total assets $_t$ + ½Total assets $_{t-1}$) - Total sales $_{t-1}$ / (½Total assets $_{t-1}$ + ½Total assets $_{t-2}$)	If $FS\_\Delta TURN_t > 0$, then 1, otherwise 0
Composite score		
FS_SCORE	$FS\_SCORE = FS\_ROA + FS\_FCFTA + FS\_ACCRUAL + FS\_\Delta LEVER + FS\_\Delta LIQUID + NEQISS + FS\_\Delta ROA + FS\_\Delta FCFTA + FS\_\Delta MARGIN + FS\_\Delta TURN$	

[1] All financial signals are calculated as in Piotroski's (2000) study except FS_FCFTA_t, $NEQISS_t$ and $FS\_\Delta FCFTA_t$.
[2] All financial variables are calculated from annual financial statements.

The stability category is otherwise identical to leverage, liquidity, and source of funds category in *FSCORE*, but the equity issuance variable (*EQ_ISSUE*) has been replaced with net equity issuance variable (*NEQISS*), which is calculated as equity repurchases minus equity issuance. Gray and Carlisle (2013, 121) argue that the *EQ_ISSUE* variable used by Piotroski (2000) can be misleading as firms often issue shares for numerous reasons that do not relate to financial distress including management and employee incentive programmes. Even though a firm issued equity, it could also make share buybacks at the same time that would potentially reverse the negative impact from equity issue. It follows that *EQ_ISSUE* variable in *FSCORE* would incorrectly penalize a firm. (Gray & Carlisle 2013, 121.) We believe that this is a relevant issue in the US, where share buybacks are a very common way to distribute funds and signal information to shareholders.[21] We calculate *NEQISS* as the difference between common/preferred equity redeemed, retired and converted, and net proceeds from sale/issue of common/preferred equity. Thus, if equity redeemed, retired and converted exceeds net proceeds from sale/issue of equity, *NEQISS* is defined as one and otherwise zero.

The last category in the *FS_SCORE*, recent operational improvements, is rather similar to operational efficiency category in the *FSCORE*. However, the focus is slightly more on analysing the trend in fundamentals as it includes change in return on assets (Δ*ROA*) and change in free cash flow (Δ*FCFTA*) in addition to change in gross margin (Δ*MARGIN*) and change in asset turnover (Δ*TURN*). Δ*ROA* is the same variable as in the *FSCORE*, but it has been transferred from profitability category to recent operational improvements category in the *FS_SCORE*. Δ*FCFTA* measures change in free cash flow and is calculated as the current fiscal year's *FCFTA* less prior fiscal year's *FCFTA*. Thus, if Δ*FCFTA* is positive, it is defined as one and otherwise zero.

Finally, the aggregate *FS_SCORE* for each stock i is calculated in a similar manner to *FSCORE* and the formula can be written as follows:

$$\begin{aligned} FS\_SCORE_{i,t} = {} & FS\_ROA_{i,t} + FS\_FCFTA_{i,t} + FS\_ACCRUAL_{i,t} \\ & + FS\_\Delta LEVER_{i,t} + FS\_\Delta LIQUID_{i,t} + NEQISS_{i,t} \\ & + FS\_\Delta ROA_{i,t} + FS\_\Delta FCFTA_{i,t} + FS\_\Delta MARGIN_{i,t} \\ & + FS\_\Delta TURN_{i,t} \end{aligned} \tag{5}$$

As there are ten binary signals, the aggregate *FS_SCORE* ranges between zero and ten compared to from zero to nine in *FSCORE*. Hence, the aggregate *FS_SCORE* measures fundamental strength similar fashion to *FSCORE*, but with some important modifications to avoid buying stocks that are likely to continue to underperform ("value trap").

[21] According to Grullon and Michaely (2002, 1649), expenditures on share repurchase programmes relative to total earnings have increased from less than 5% in 1980 to almost 42% in 2000 in the US. Expenditures on share repurchases have grown significantly faster than dividends since 1980s and were higher than dividend payments in 1999–2000 (Grullon & Michaely 2002, 1649).

3.2.3 Portfolio formation and hypotheses

The main purpose of this thesis is to study whether one-year ahead buy-and-hold returns for value and momentum strategies can be enhanced using fundamentals based on *FS_SCORE*. Each year at the end of June between 1997 and 2014 we sort out value and momentum stocks listed in the S&P Composite 1500 index with all required data to form fundamental value and momentum portfolios. There are total of 18 one-year buy-and-hold periods in our sample period. The investment process and hypotheses go as follows.

Firstly, in each holding period the book-to-market ratio and past 12-month momentum are computed for each stock and then ranked. All stocks above the 70th percentile based on the prior calendar year-end book-to-market ratio and the past 12-month momentum are classified as value and momentum stocks. Hence, the final sample retains only the stocks in the over 70th percentile *B/M* and *MOM-12* rank. From the total sample of 18,747 firm-year observations, we obtain 5,639 and 5,627 firm-year observations classified as value and momentum stocks. Secondly, *FS_SCORE* is calculated for each value and momentum stock using the fiscal year-end data. Gray and Carlisle (2013) only compare long-only strategies for stocks with an *FS_SCORE* greater than or equal to seven against stocks with an *FSCORE* greater than or equal to six. In comparison, Piotroski (2000) classifies stocks with *FSCORE* greater than or equal to eight as fundamentally strong and stocks with *FSCORE* equal to or less than one as fundamentally weak. Piotroski (2000) then compares high *FSCORE* stocks against both low *FSCORE* stocks and all value stocks. As we want to test whether *FS_SCORE* can be used to enhance value and momentum portfolios, we will follow a similar method as Piotroski (2000). Hence, each year we classify stocks with an aggregate *FS_SCORE* greater than or equal to six as high *FS_SCORE* stocks and stocks with an aggregate *FS_SCORE* equal to or less than four as low *FS_SCORE* stocks. This scoring system ensures that there are enough observations both in high and low *FS_SCORE* portfolios.

At the final stage, the performance of fundamental value and momentum strategies are examined. Each year at the beginning of July in year t we form equally-weighted fundamental value and momentum portfolios. We hold these portfolios for the following 12 months and rebalance them annually at the end of each June in year $t + 1$. Thus, the initial equal-weight for each stock changes during the 12-month buy-and-hold period as we do not rebalance monthly to maintain equal weights. The reason why we use this weighting approach is that our sample contains a significant proportion of smaller stocks and thus we want to avoid a heavy tilt towards large market capitalization stocks. Further, although it might be possible to achieve higher returns with more frequent rebalancing (particularly for momentum strategy) and with different weighting schemes, this would in all probability increase practical trading costs significantly. It is important to note that Piotroski (2000) also uses the 12-month buy-and hold period, but calculates the return for each stock starting from the beginning of the fifth month after each firm's individual fiscal year-end. Thus, unlike Piotroski (2000), we compute the buy-and-hold monthly returns from July of year t to June of year $t + 1$ for each stock irrespective of the fiscal year-end. As Duong et al. (2014, 532) point out, this can be problematic as there is a long gap between the fiscal year-ends in year $t - 1$ and portfolio formation date at the beginning of July in year t. This is particularly true for stocks with a fiscal-year end before December in year $t - 1$. However, as we want to test fundamentals-based strategies using both mean returns calculated from the pooled firm-year observations like Piotroski (2000) and as a more practical portfolio strategy like Duong et al. (2014), we use the same portfolio formation date for all stocks each year. The complete investment process is summarized in figure 2 below.

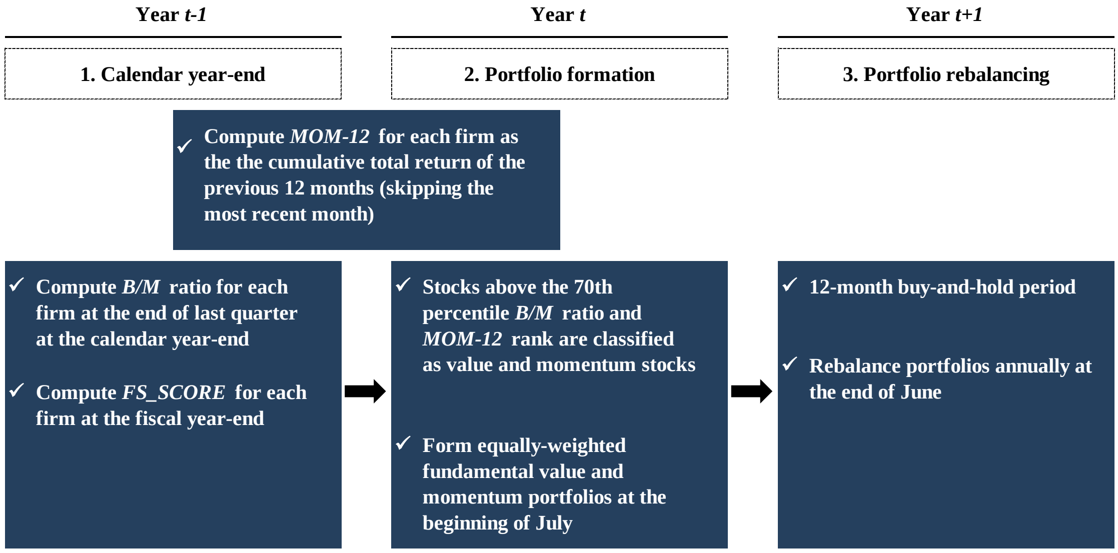

Figure 2 Portfolio formation and investment process

Like Piotroski (2000) and Chen et al. (2016), we expect portfolios with value and momentum stocks that have strong fundamentals to outperform against (1) portfolios with value and momentum stocks that have weak fundamentals and (2) all value and momentum stocks. Specifically, we have the following four hypotheses:

H1: Value stocks with high *FS_SCORE* outperform value stocks with low *FS_SCORE*.

H2: Value stocks with high *FS_SCORE* outperform all value stocks.

H3: Momentum stocks with high *FS_SCORE* outperform momentum stocks with low *FS_SCORE*.

H4: Momentum stocks with high *FS_SCORE* outperform all momentum stocks.

To test these hypotheses, we use two parametric tests. Firstly, like Piotroski (2000), we use the two-sample *t*-test to investigate whether high *FS_SCORE* minus low *FS_SCORE* (high-low) and high *FS_SCORE* minus all value/momentum stocks (high-all) mean raw and market-adjusted one-year buy-and-hold returns calculated from the pooled firm-year observations are significantly different from zero. Secondly, like Duong et al. (2014), we apply the one-sample *t*-test in the portfolio analysis to see whether monthly portfolios' returns are statistically different from zero. It is also important to mention that both Piotroski (2000, 11) and Duong et al. (2014, 534) note that traditional parametric tests are problematic when using long-run buy-and-hold returns and complement parametric tests with the bootstrapping method. We do not, however, implement bootstrapping method in this thesis, but we recognize that our parametric tests for long-run buy-and-hold returns are likely to suffer from statistical biases.

3.3 Portfolio performance measurement

Following portfolio formation, the next step is to evaluate portfolios performance. We use gross total returns to calculate portfolios' performance and thus we do not take trading costs into account. One of the simplest ways to measure abnormal returns for portfolios is to compute market-adjusted returns using a benchmark portfolio. Like Piotroski (2000), we use a value-weighted market index as a benchmark portfolio. To compute market-adjusted returns, we use firm-specific and S&P 1500 monthly total return indices to compute one-year market-adjusted buy-and-hold returns. The S&P Composite 1500 index is a float-adjusted and market capitalization weighted index that is rebalanced quarterly (S&P Composite 1500 Month-End Factsheet 2016). Thus, the one-year market-adjusted buy-and-hold return $MARET$ for firm i can be written as:

$$MARET_{i,t} = RAWRET_{i,t} - MKTRET_{Mkt,t} \qquad (6)$$

where $RAWRET_{i,t}$ is the raw total return for firm i and $MKTRET_{Mkt,t}$ is the raw total market return for S&P 1500.

Using one-year market-adjusted buy-and-hold returns to measure abnormal performance can, however, be problematic. Although Barber and Lyon (1997, 342) argue that calculating long-run abnormal returns as simply the buy-and-hold return on sample firm less the buy-and-hold return on a benchmark portfolio/index is more robust than using cumulative abnormal returns, this method also has its problems. Specifically, it suffers from new listing, rebalancing and positive long-run return skewness biases. Furthermore, it does not take firm-specific risk characteristics into account. This results in test statistics where the null hypothesis for mean abnormal returns is rejected more often than the theoretical rejection rate would suggest i.e. negative bias. (Barber & Lyon 1997, 342.) To correct these misspecifications, Barber and Lyon (1997, 342) argue that abnormal returns on a sample firm should be calculated using the control-firm approach based on similar size and *B/M* ratio cut-offs. Although we only calculate market-adjusted abnormal returns for individual sample firms, we also apply more sophisticated risk-adjusted performance measurement methods when calculating portfolio performance for fundamental value and momentum strategies.

The first more intuitive risk-adjusted performance measure that we use is the traditional Sharpe ratio (*SR*), which can be written as:

$$SR_p = \frac{R_p - R_f}{\sigma_p}, \tag{7}$$

where $R_p - R_f$ is the mean equity risk premium for the portfolio p and σ_p is the standard deviation i.e. total risk of the portfolio. Hence, the Sharpe ratio (also known as the reward-to-variability ratio) measures the risk-adjusted compensation – the higher the slope the better the risk-adjusted performance. To calculate the ex-post Sharpe ratio for portfolios, we use realised return and standard deviation and one-month Treasury bill rate downloaded from Kenneth R. French website as a proxy for risk-free rate. One could, however, criticize the Sharpe ratio as it uses a measure for the total risk instead of the systematic risk, it suffers if the stock returns are not normally distributed and it does not allow for a clear comparison of the economic significance of portfolios performance. Further, the Sharpe ratio is an unstable and biased measure for portfolio performance during economic downturns, when the average excess returns ($R_p - R_f$) are clearly negative (Grable & Chatterjee 2008, 13).

To obtain a more practical view of the risk-adjusted performance, we also measure whether portfolios generate risk-adjusted abnormal returns with the Capital Asset Pricing Model (CAPM), the Fama and French three-factor model (FF3) and the Carhart four-factor model (Carhart). The CAPM argues that the cross-sectional variation in excess stock returns is explained by the market risk (beta). Hence, the CAPM is a single risk factor model and can be written as the following time-series regression:

$$r_{p,t} - r_f = \alpha_p + \beta_{MKT,p} MKT_t + \varepsilon_{p,t}, \tag{8}$$

where $r_{p,t} - r_f$ is the excess return of the portfolio in year t, $\beta_{MKT,p}$ is the portfolio's market beta, MKT_p is the excess return of the market portfolio and $\varepsilon_{p,t}$ is the residual.

There has, however, been a lot of criticism towards the CAPM and various studies have documented that the market risk does not explain the cross-sectional variation in stock returns. This motivates us to use also the FF3 and the Carhart models, which seek to explain returns with three and four risk factors: Market factor (*MKT*), size factor (*SMB*), value factor (*HML*) and momentum factor (*WML*). Hence, besides the *MKT* factor, the *SMB*, the *HML* and the *WML* factors measure the additional risk exposure to investing in smaller, high *B/M* and high momentum stocks. The key reason why we also use the Carhart model besides the most commonly used three-factor model is due to the evidence that the three-factor model explains weakly the cross-sectional variation in momentum portfolios (Carhart 1997, 61).

To measure whether the portfolio generates an excess return over these risk factors, we can now write the three-factor and the Carhart model as the following time-series regressions:

$$r_{p,t} - r_f = \alpha_p + \beta_{MKT,p} MKT_t + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \varepsilon_{p,t}, \quad (9)$$

$$r_{p,t} - r_f = \alpha_p + \beta_{MKT,p} MKT_t + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \beta_{WML,p} WML_t + \varepsilon_{p,t}, \quad (10)$$

where $r_{p,t} - r_f$ is the excess return of the portfolio in year t and MKT_t, SMB_t, HML_t and WML_t are the returns for the market, size, value and momentum risk factor mimicking portfolios.[22] The betas $\beta_{MKT,p}$, $\beta_{SMB,p}$, $\beta_{HML,p}$ and $\beta_{WML,p}$ represent the sensitivity of the portfolio to the market, size, value and momentum risk factors. Thus, the key purpose is to regress the excess returns of the fundamental portfolios on the excess returns of the risk factor mimicking portfolios to measure whether fundamental portfolios generate risk-adjusted abnormal returns i.e. alpha α_i. If the estimated α_i is statistically different from zero, it means that the excess returns of the portfolios are not explained by the portfolios sensitivity to the above-mentioned risk factors. A statistically significant and positive alpha would thus indicate abnormal returns over the systematic risk factors. However, it is worthy to remember that the CAPM, the FF3 and the Carhart model are just proxies for the total systematic risk and it is possible that there are other risk factors not captured by the models. To measure the CAPM, the FF3 and the Carhart alphas, we use the monthly factors for US stocks provided at the Kenneth R. French's website. We also control the potential autocorrelation and heteroscedasticity problems by using Newey-West (1987) correction for standard errors when calculating t-values.

[22] *SMB* is the difference between the returns for small and large market capitalization stocks, *HML* is the difference between the returns for high book-to-market and low book-to-market stocks and *WML* is the difference between the returns for past winners and losers.

4 EMPIRICAL RESULTS

4.1 Descriptive statistics

We provide three kinds of descriptive statistics. Firstly, we calculate descriptive statistics for the S&P 500, S&P MidCap 400, S&P SmallCap 600 and S&P Composite 1500 indices using daily raw total returns. As our sample includes high *B/M* and *MOM-12* stocks from the above-mentioned indices, we believe that daily index-level data provides a good overview of the US market during the sample period. We have used daily raw returns when calculating index-level descriptive statistics due to higher statistical significance, but all other return calculations are based on monthly raw returns. Secondly, we provide a summary of the financial characteristics of all high *B/M* and *MOM-12* stocks. Thirdly, the Spearman correlation analysis is used to study the relation between the one-year buy-and-hold raw and market-adjusted returns and the fundamental signals.

Starting from the index-level data in table 4, the annualized cumulative return has been positive across all indices from the beginning of July 1997 to the end of June 2015. The S&P 400 has produced the highest annual cumulative return and Sharpe ratio of 10.7% and 0.498 respectively. The S&P 500 has been the worst performer by a wide margin, which can be seen as the lowest cumulative return. The higher returns for the S&P 400 and S&P 600 indices could indicate the existence of small cap premium, but it is good to note that the S&P 600 has underperformed against the S&P 400. When analysing the degree of symmetry in returns, we can see that index returns have been negatively skewed. This means that the return distributions for the indices have had frequent small gains and few extreme losses. Hence, the return distributions have a longer tail on the left side. Further, the return distributions for the indices are clearly more peaked i.e. leptokurtic than normal distribution when looking at kurtosis. For all indices, the kurtosis is clearly over three, meaning that the return distributions for the indices have fatter tails than in normal distribution. Thus, the return distributions do not seem to be normally distributed, which is also confirmed by Jarque-Bera test as the null hypothesis of a normal distribution is rejected at a 1% significance level for all indices.[23] Overall, our results for the return distributions seem to be in line with previous research as negative skewness and excess kurtosis have been reported to be common characteristic for stock returns.

Table 5 provides the financial characteristics of high *B/M* and *MOM-12* stocks. The mean (median) end of June market capitalization of high *B/M* stocks is 3,509 (931) million dollars, which is considerably less than 9,638 (2,253) million dollars for high *MOM-12* stocks. The mean market capitalization is significantly larger than the median both for

[23] Results are also similar when using daily continuously compounded returns (not reported in table 4).

high *B/M* and *MOM-12* stocks, indicating that the S&P 500 stocks represent a large portion of the total market capitalization. This characteristic is similar to the results reported by Piotroski (2000) and Duong et al. (2014), which motivates us to use equally-weighted approach when constructing portfolios. Otherwise portfolio weights would be heavily tilted towards large market capitalization stocks. However, as S&P 400 and S&P 600 stocks are likely to contain the majority of the sample portfolios, there could be practical liquidity and trading cost constraints when implementing the strategies.

Table 4 Descriptive statistics for the S&P 500, S&P MidCap 400, S&P SmallCap 600 and S&P Composite 1500 indices

This table reports descriptive statistics for S&P 500, S&P 400, S&P 600 and S&P 1500 indices from the beginning of July 1997 to the end of June 2015. We have used daily raw total returns. Thus, there are total of 4,696 daily observations for each index. Cumulative return, standard deviation and Sharpe ratio have been annualized assuming 252 trading days. When calculating the Sharpe ratio, we have used annualized cumulative return instead of mean return, and we have also excluded the risk-free rate when calculating the excess return. Additionally, we report skewness, kurtosis and Jarque-Bera p-value for each index.

Period	**Cumulative return (%)**	**Stdev (%)**	**Skewness**	**Kurtosis**	**Jarque-Bera p-**	**Sharpe ratio**	**n**
S&P 500	0.065	0.197	-0.032	11.120	0.000	0.331	4 696
S&P 400	0.107	0.215	-0.204	9.290	0.000	0.498	4 696
S&P 600	0.094	0.226	-0.144	7.658	0.000	0.417	4 696
S&P 1500	**0.069**	**0.198**	**-0.064**	**10.872**	**0.000**	**0.350**	**4 696**

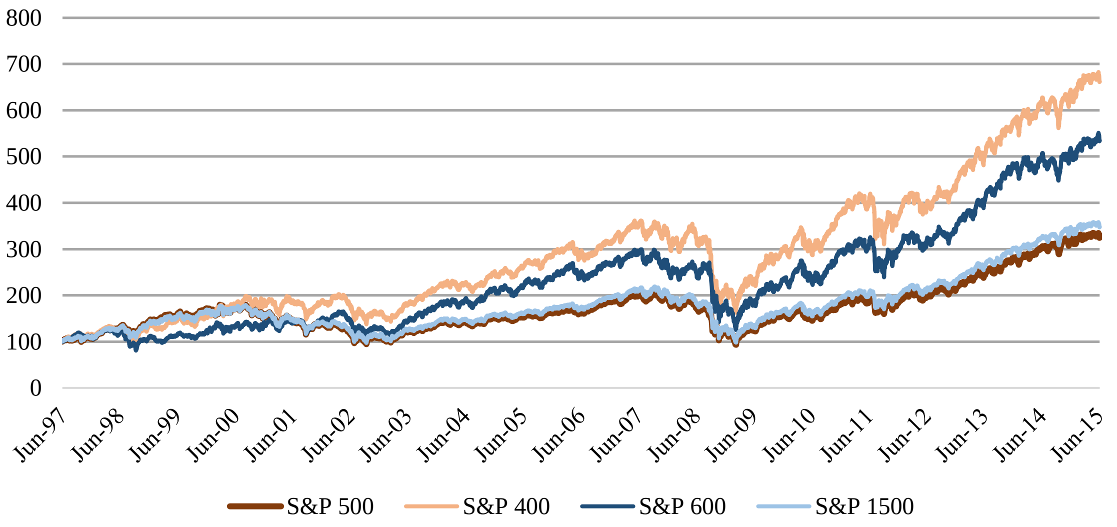

Figure 3 Performance of the S&P 500, S&P MidCap 400, S&P SmallCap 600 and S&P Composite 1500 indices

The average *B/M* ratio and *MOM-12* are 0.822 and 0.091 for value stocks, whereas corresponding figures are 0.425 and 0.569 for momentum stocks. Thus, value stocks tend to be on average smaller, trade on lower valuation relative to book value, and have poor historical stock returns compared to momentum stocks. When looking at the fundamentals, we can see why. Value stocks have on average distinctly lower current profitability and weaker year-on-year trend in fundamentals compared to momentum stocks. This is true for each profitability and operational improvement signal. For example, value stocks average *ROA*, *FCFTA*, Δ*ROA*, Δ*FCTA* and Δ*GM* are 0.029, 0.004, -0.013, 0.007 and -0.004 respectively, whereas the corresponding figures for momentum stocks are 0.075, 0.022, 0.007, 0.012 and 0.002. It is also interesting to note that *ΔLEVER* and *ΔLIQUID* are very close for value and momentum stocks. The fact that *ΔLIQUID* is negative for momentum stocks could potentially be explained by the supposedly higher growth, which increases need for working capital. Overall, the results for value stocks are fairly similar to Fama and French (1995), Chen and Zhang (1998) and Piotroski (2000) as value stocks' ex ante fundamental strength appears to be relatively weak. Hence, many high *B/M* stocks could be financially distressed and thus bear higher risk, whereas high *MOM*-12 stocks show on average better fundamental signals.

Table 5 Financial characteristics of high *B/M* and *MOM-12* stocks

This table reports the financial characteristics of all high *B/M* and high *MOM-12* firms across the sample period between 1997 and 2015. There are total of 5,639 and 5,627 firm-year observations respectively. Using all sample firms, we have calculated mean, median and standard deviation for each *FS_SCORE* signal, market value, *B/M* ratio and *MOM-12* . In addition, we report the proportion of companies with positive signal value.

Variable	**Mean**	**Median**	**Standard deviation**	**Proportion with positive signal**
Panel A: High B/M firms				
MVE[1]	3 509	931	11 298	n.a
B/M	0.822	0.735	0.354	n.a
MOM-12[2]	0.091	0.058	0.414	n.a
FS_SCORE	5.651	6.000	1.805	n.a
ROA	0.029	0.038	0.141	0.804
FCFTA	0.004	0.015	0.163	0.591
ACCRUAL	-0.059	-0.052	0.127	0.849
ΔLEVER	0.000	-0.003	0.092	0.608
ΔLIQUID	-0.038	0.003	1.069	0.503
ΔROA	-0.013	-0.004	0.153	0.440
ΔFCFTA	0.007	0.002	0.206	0.514
ΔMARGIN	-0.004	-0.002	0.082	0.447
ΔTURN	-0.036	-0.012	0.275	0.453

Variable	Mean	Median	Standard deviation	Proportion with positive signal
Panel B: High MOM-12 firms				
MVE[1]	9 638	2 253	29 713	n.a
B/M	0.425	0.366	0.297	n.a
MOM-12[2]	0.569	0.476	0.452	n.a
FS_SCORE	6.180	6.000	1.789	n.a
ROA	0.075	0.070	0.109	0.884
FCFTA	0.022	0.030	0.160	0.650
ACCRUAL	-0.066	-0.059	0.095	0.863
ΔLEVER	-0.003	-0.003	0.101	0.660
ΔLIQUID	-0.039	0.001	1.008	0.501
ΔROA	0.007	0.005	0.105	0.573
ΔFCFTA	0.012	0.007	0.229	0.530
ΔMARGIN	0.002	0.003	0.201	0.557
ΔTURN	-0.013	-0.001	0.212	0.497

[1] Market value of equity at the end of June in year *t*.

[2] Previous 12-month cumulative total return (skipping the most recent month) computed at the end of June in year *t*.

When testing the hypotheses, we classify stocks with a composite score greater than or equal to six as high *FS_SCORE* stocks and stocks with a score less than or equal to four as low *FS_SCORE* stocks. The weaker fundamentals for high *B/M* stocks can be seen in table 6 as lower (higher) share of high *B/M* stocks belongs to high (low) *FS_SCORE* group compared to high *MOM-12* stocks. In general, most observations are clustered between score 3 and 7 portfolios as there fewer observations in the extreme portfolios. Additionally, similar to Piotroski (2000) and Aspris et al. (2013), there is a significant difference between the amount of observations in the high and low *FS_SCORE* portfolios. There are total of 3,026 (53.7%) and 3,696 (65.7%) observations classified as high *FS_SCORE* firms in value and momentum portfolios, compared to 1,527 (27.1%) and 1,028 (18.3%) observations classified as low *FS_SCORE* firms. However, the amount of observations in the extreme portfolios seems to be large enough to test the ability of fundamental analysis in order to separate winners from losers.

Table 6 Distribution of *FS_SCORE* values across high *B/M* and *MOM-12* stocks

This table reports the distribution of the aggregate *FS_SCORE* values of all high *B/M* and high *MOM-12* firms across the sample period between 1997 and 2015. There are total of 5,639 and 5,627 firm-year observations respectively.

FS_SCORE	N	FS_SCORE group	N	(%)
Panel A: High B/M stocks				
0	2			
1	39			
2	188	Low *FS_SCORE*	1 527	27.1
3	456			
4	842			
5	1 086			
6	1 162			
7	952			
8	610	High *FS_SCORE*	3 026	53.7
9	253			
10	49			
Total	5 639			
Panel B: High MOM-12 stocks				
0	2			
1	25			
2	112	Low *FS_SCORE*	1 028	18.3
3	272			
4	617			
5	903			
6	1 145			
7	1 131			
8	917	High *FS_SCORE*	3 696	65.7
9	424			
10	79			
Total	5 627			

The Spearman correlations and level of significances between one-year raw and market-adjusted buy-and-hold returns, the ten fundamental signals and the composite *FS_SCORE* are presented in table 7. Like Piotroski (2000), we focus on analysing the relation between the fundamentals and market-adjusted returns (*MARET*). The results are not consistent with the expectations as the composite *FS_SCORE* does not have a statistically significant correlation with one-year ahead *MARET*. For high *B/M* stocks, the correlation between *FS_SCORE* and *MARET* is only 0.020 and clearly statistically insignificant with confidence level of 0.05. For high *MOM-12* stocks the corresponding results are similar as the correlation is only 0.023 and also statistically insignificant. In comparison, Piotroski (2000) reported a statistically significant correlation of 0.121 between *FSCORE* and one-year ahead *MARET* for high *B/M* stocks. Chen et al. (2016) also reported a positive correlation between *FSCORE*, past 12-month buy-and hold returns and future returns, but future returns were measured using 1- and 3-month periods. One could argue that this reflects the weakness of *FS_SCORE* relative to *FSCORE*, but we believe this to be unlikely. Only two of the original variables, *OCF* and *EQ_ISSUE*, have been changed, and Δ*FCFTA* is the only additional variable in *FS_SCORE*. As *FCFTA* and *NEQISS* are very close substitutes to *OCF* and *EQ_ISSUE*, we find it difficult to believe that *FS_SCORE* would not capture the same return characteristics as the original *FSCORE*. When looking at the individual fundamental variables, the results are also intriguing. For high *B/M* stocks, only Δ*TURN* variable has a statistically significant positive correlation with one-year ahead *MARET*. For high *MOM-12* stocks, *FCFTA*, Δ*LIQUID* and *NEQISS* variables have a statistically significant and positive relation with *MARET*, giving slightly more support for using fundamentals among momentum stocks.

Table 7 Spearman correlation analysis between the one-year buy-and-hold returns, the individual fundamental signals and the composite *FS_SCORE*

Panel A shows Spearman correlation analysis between raw (*RAWRET*) and market-adjusted (*MARET*) 12-month buy-and-hold returns, the ten fundamental *FS_SCORE* signals and the composite *FS_SCORE* for high *B/M* firms. The level of significances (2-tailed) are presented below the correlations. Individual fundamental signals equal one (zero) if the signal was good (bad) about the future performance. *RAWRET* is calculated for each stock as the 12-month buy-and-hold return commencing at the beginning of July in each calendar year *t*. *MARET* is calculated for each stock as the 12-month buy-and-hold return commencing at the beginning of July in each calendar year *t* less the corresponding return of S&P 1500 index over the respective holding period. All binary fundamental signals are calculated as defined in Appendix 1. The sample includes 5,639 firm-year observations in holding periods between 1997 and 2015.

Variable	**ROA**	**FCFTA**	**ACCRUAL**	**ΔLEVER**	**ΔLIQUID**	**NEQISS**	**ΔROA**	**ΔFCFTA**	**ΔMARGIN**	**ΔTURN**	**FS_SCORE**
Panel A: High B/M firms											
RAWRET	-0.036	-0.008	0.033	0.005	0.007	-0.010	0.010	-0.008	0.000	0.019	0.002
	0.007	0.560	0.013	0.716	0.599	0.464	0.473	0.526	0.978	0.152	0.877
MARET	-0.005	0.007	0.021	-0.002	0.001	0.025	0.010	-0.001	-0.008	0.030	0.020
	0.695	0.603	0.111	0.898	0.944	0.065	0.437	0.958	0.561	0.024	0.134
ROA	1.000	0.230	-0.131	0.070	0.047	0.102	0.243	0.085	0.130	0.022	0.436
		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.097	0.000
FCFTA	—	1.000	0.038	0.161	-0.332	0.170	0.079	0.415	0.017	0.074	0.488
			0.005	0.000	0.000	0.000	0.000	0.000	0.214	0.000	0.000
ACCRUAL	—	—	1.000	0.060	-0.059	0.050	-0.102	0.003	-0.041	0.015	0.159
				0.000	0.000	0.000	0.000	0.840	0.002	0.252	0.000
ΔLEVER	—	—	—	1.000	0.070	-0.047	0.057	0.118	0.044	0.074	0.425
					0.000	0.000	0.000	0.000	0.001	0.000	0.000
ΔLIQUID	—	—	—	—	1.000	-0.036	0.035	-0.326	0.030	-0.041	0.093
						0.007	0.008	0.000	0.024	0.002	0.000
NEQISS	—	—	—	—	—	1.000	-0.068	0.028	-0.035	-0.022	0.291
							0.000	0.035	0.008	0.098	0.000
ΔROA	—	—	—	—	—	—	1.000	0.109	0.362	0.299	0.554
								0.000	0.000	0.000	0.000
ΔFCFTA	—	—	—	—	—	—	—	1.000	0.055	0.020	0.406
									0.000	0.129	0.000
ΔMARGIN	—	—	—	—	—	—	—	—	1.000	0.103	0.453
										0.000	0.000
ΔTURN	—	—	—	—	—	—	—	—	—	1.000	0.423
											0.000
FS_SCORE	—	—	—	—	—	—	—	—	—	—	1.000

Panel B shows Spearman correlation analysis between raw (*RAWRET*) and market-adjusted (*MARET*) 12-month buy-and-hold returns, the ten fundamental *FS_SCORE* signals and the composite *FS_SCORE* for high *MOM-12* firms. The sample includes 5,627 firm-year observations in holding periods between 1997 and 2015. All other information is as presented in Panel A.

Variable	ROA	FCFTA	ACCRUAL	ΔLEVER	ΔLIQUID	NEQISS	ΔROA	ΔFCFTA	ΔMARGIN	ΔTURN	FS_SCORE
Panel B: High MOM-12 firms											
RAWRET	-0.009	0.036	0.021	0.001	0.038	0.030	-0.011	-0.022	-0.013	-0.018	0.015
	0.487	0.006	0.113	0.942	0.004	0.025	0.425	0.103	0.331	0.173	0.276
MARET	0.017	0.047	0.010	0.000	0.040	0.052	-0.012	-0.017	-0.021	-0.017	0.023
	0.190	0.000	0.453	0.986	0.003	0.000	0.374	0.192	0.108	0.211	0.087
ROA	1.000	0.206	-0.078	0.085	0.076	0.132	0.247	0.049	0.145	0.029	0.394
		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.028	0.000
FCFTA	—	1.000	0.055	0.100	-0.296	0.266	0.056	0.374	0.018	0.073	0.467
			0.000	0.000	0.000	0.000	0.000	0.000	0.167	0.000	0.000
ACCRUAL	—	—	1.000	0.066	-0.052	0.041	-0.079	0.005	-0.004	0.011	0.192
				0.000	0.000	0.002	0.000	0.698	0.788	0.415	0.000
ΔLEVER	—	—	—	1.000	0.079	-0.062	0.065	0.101	0.077	0.060	0.398
					0.000	0.000	0.000	0.000	0.000	0.000	0.000
ΔLIQUID	—	—	—	—	1.000	-0.024	0.058	-0.352	0.046	-0.055	0.120
						0.078	0.000	0.000	0.000	0.000	0.000
NEQISS	—	—	—	—	—	1.000	-0.027	0.055	-0.025	0.023	0.359
							0.042	0.000	0.065	0.080	0.000
ΔROA	—	—	—	—	—	—	1.000	0.081	0.351	0.317	0.561
								0.000	0.000	0.000	0.000
ΔFCFTA	—	—	—	—	—	—	—	1.000	0.057	0.036	0.376
									0.000	0.007	0.000
ΔMARGIN	—	—	—	—	—	—	—	—	1.000	0.086	0.468
										0.000	0.000
ΔTURN	—	—	—	—	—	—	—	—	—	1.000	0.443
											0.000
FS_SCORE	—	—	—	—	—	—	—	—	—	—	1.000

Overall, the results from Spearman correlation analysis are problematic when considering our hypotheses. The statistically insignificant correlation between *FS_SCORE* and future returns could potentially reflect biases in our data, sample period specific issues or too long a gap between the fiscal year-ends in year $t-1$ and portfolio formation date at the beginning of July in year t. However, it is also possible that abnormal returns have been arbitraged away as our sample period is 1997–2015 compared to 1976–1996 by Piotroski (2000), or that our results reflect an average mean-reversion in ex post fundamentals. Thus, we continue with our original fundamental value and momentum strategies and hypotheses as we believe that this will still provide valuable information.

4.2 Performance of fundamental strategies

4.2.1 Returns for all high book-to-market and momentum stocks

As our empirical tests for fundamental value and momentum strategies rely on the existence of positive market-adjusted returns for value and momentum stocks, we need to first confirm this. Table 8 presents the one-year buy-and-hold returns for long-only value and momentum portfolios that have been calculated from the pooled firm-year observations between July 1999 and June 2015. To test the statistical significance of returns, we use the one-sample *t*-test for market-adjusted returns, where the null hypothesis is defined as zero and the confidence level is set at 0.05. Additionally, table 8 shows the proportion of high *B/M* and *MOM-12* stocks with positive raw and market-adjusted buy-and-hold returns over the one-year buy-and-hold period.

The mean one-year raw buy-and-hold return has been 13.3% for all high *B/M* stocks. Consistent with Piotroski (2000), the mean one-year market-adjusted buy-and-hold return is also clearly positive and economically significant at 5.0% with *p*-value less than 0.000. Therefore, value stocks have outperformed the market during the sample period. It is also important to note that 59.9% (48.8%) of all high *B/M* stocks earn positive raw (market-adjusted) one-year buy-and-hold returns. The return distribution for value stocks is thus skewed to the left as reported by Piotroski (2000), although not as much as only 43.7% of value stocks earned positive one-year ahead market-adjusted returns in his study. The fact that over 50% of all high *B/M* stocks earn negative one-year ahead market-adjusted returns indicates that the returns earned by value strategy could be improved by separating winners from losers using fundamental analysis.

The high *MOM-12* stocks have produced a mean one-year raw buy-and-hold return of 11.6%. The mean market-adjusted return of 3.3% is also statistically and economically significant with *p*-value of 0.000. Although high *MOM-12* stocks have also outperformed the market, the mean market-adjusted return is clearly lower than for high *B/M* stocks. This is likely to be partially due to the 12-month holding and rebalancing frequency, lowering momentum returns as momentum strategies have been shown to perform better with higher rebalancing frequency (i.e. turnover) and shorter holding periods. However, as we want to combine annual fundamentals with momentum and to make the strategy more comparable to the fundamental value strategy, we believe that it is convenient to form portfolios annually. Interestingly, the proportion of high *MOM-12* stocks with positive one-year ahead returns is also very close to the high *B/M* stocks. Out of all high *MOM-12* stocks, 59.2% (48.0%) earn positive raw (market-adjusted) returns. Thus, the conclusion is rather similar as with value stocks as the return distribution is skewed to the left. Overall, the evidence suggest that value and momentum stocks have produced positive market-adjusted returns, but the returns could potentially be further improved using fundamentals to separate winners from losers.

Table 8 One-year buy-and-hold returns for all high *B/M* and high *MOM-12* stocks

This table reports 12-month raw and market-adjusted buy-and-hold returns for all high *B/M* and *MOM-12* stocks. There is a total of 5,639 and 5,627 firm-year observations for high *B/M* and *MOM-12* stocks between 1997 and 2015. Raw return is calculated for each stock as the 12-month buy-and-hold return commencing at the beginning of July in each calendar year *t*. Market-adjusted return is calculated for each stock as the 12-month buy-and-hold return commencing at the beginning of July in each calendar year *t* less the corresponding return of S&P 1500 index over the respective holding period. We also report a one-sample *t*-statistics and *p*-values for 12-month market-adjusted buy-and-hold returns using a 0.05 confidence level, where the null hypothesis (*H0*) for mean return is defined as zero.

Returns	Mean	10th percentile	25th percentile	Median	75th percentile	90th percentile	Proportion positive
Panel A: High B/M stocks							
Raw	0.133	-0.373	-0.155	0.087	0.354	0.666	0.599
Market-adjusted	0.050	-0.425	-0.224	-0.010	0.259	0.563	0.488
t-statistics	*8.396*	—	—	—	—	—	—
p-value (α = 0.05)	*0.000*	—	—	—	—	—	—
Panel B: High MOM-12 stocks							
Raw	0.116	-0.375	-0.165	0.073	0.324	0.614	0.592
Market-adjusted	0.033	-0.410	-0.221	-0.017	0.217	0.494	0.480
t-statistics	*5.781*	—	—	—	—	—	—
p-value (α = 0.05)	*0.000*	—	—	—	—	—	—

4.2.2 Returns for fundamental value and momentum strategies

Tables 9 and 10 present raw and market-adjusted one-year buy-and-hold returns for fundamental value and momentum strategies. Similar with Piotroski (2000), we calculate the returns as equally-weighted average from the pooled firm-year observations for each composite *FS_SCORE* portfolio. To be consistent, our analysis focuses on the one-year market-adjusted returns, which are reported at panel B in tables 9 and 10.

We start by looking at the results for fundamental value strategy in table 9. Whereas Piotroski (2000) finds a stable and positive relationship between *FSCORE* and one-year market-adjusted returns in high *B/M* portfolio, we find no support for fundamental value strategy as low *FS_SCORE* stocks outperform high *FS_SCORE* stocks; the mean one-year market-adjusted return is 6.2% for low *FS_SCORE* stocks compared to 4.7% for high *FS_SCORE* stocks. The mean high-low return difference of -1.5% is not, however, statistically significant at the 0.05 significance level using the parametric two-sample *t*-test. High *FS_SCORE* stocks also underperform against the complete portfolio of high *B/M* firms; the mean high-all return difference is -0.3%, but also clearly statistically insignificant. These return differences are mainly driven by stocks with *FS_SCORE* between 1 and 3 as these stocks produce mean market-adjusted return of 14.7%, 6.7% and 6.9% respectively. Also, stocks with *FS_SCORE* of 10 produce only a mean market-adjusted return of 3.0%.

The fact that low *FS_SCORE* stocks outperform high *FS_SCORE* stocks is likely to reflect both return bias and mean-reversion in fundamentals. Firstly, as we assume a delisting return of zero, the performance-related delisting returns are likely to be biased upwards. Secondly, if investors have extrapolated weak fundamentals too far into the future, the mean-reversion in fundamentals for previously distressed firms is likely to produce exceptional returns. Hence, it is also possible that value investors overreact to bad financial information as suggested by Lakonishok, Shleifer and Vishny (1994), which causes more significant under-pricing of value stocks with low *FS_SCORE*. Also, it could reflect the confirmation bias if value investors underreact to good fundamental information for low *FS_SCORE* stocks as it contradicts with their previous view. Although Duong et al. (2014) find support for the confirmation bias hypothesis among value stocks using *FSCORE*, our suggestions are incongruent with their results. According to Duong et al. (2014, 543–544), the fundamental value strategy produces abnormal returns by going long for high *FSCORE* stocks as value investors underreact to good fundamental information, but our results seem to reflect the opposite. Overall, we can reject our first two hypotheses that (H1) value stocks with high *FS_SCORE* outperform value stocks with low *FS_SCORE* and (H2) value stocks with high *FS_SCORE* outperform all value stocks. The rejection of the first two hypotheses is in line with the recent evidence by Hanson and Dhanuka (2015), who found that various fundamental strategies including *FSCORE* did not generate abnormal returns in the US between 2000 and 2013.

When looking at the relation between *FS_SCORE* and return distribution of high *B/M* stocks, some interesting results emerge. The fundamental value strategy seems to shift the return distribution to the right only when looking at the lower percentiles as the 10th percentile, 25th percentile and median returns of the high *FS_SCORE* portfolio are higher than the corresponding returns of both the low *FS_SCORE* and the complete high *B/M* portfolio. However, similar with Piotroski (2000), our results show that the proportion of winners in the high *FS_SCORE* portfolio (49.3%) is higher than in the low *FS_SCORE* portfolio (48.8%) or the complete high *B/M* portfolio (48.8%), although the shift is very modest compared to Piotroski's (2000) results. When looking at the 75th and 90th percentile returns, the low *FS_SCORE* stocks produce excessive returns compared to the high *FS_SCORE* stocks and the complete high *B/M* portfolio. As our sample period includes two financial market crises, namely the tech bubble and the financial crisis during 1999–2001 and 2007–2009, it could be that this is explained by the superior returns of distressed turnaround value stocks. Thus, overall, the fundamental value strategy does not seem to shift the return distribution in a way that is economically meaningful.

Table 9 One-year buy-and-hold returns to fundamental value strategy

This table reports the 12-month buy-and-hold returns of the pooled firm-year observations for fundamental value strategy, which combines high *B/M* strategy with fundamental strength measured as *FS_SCORE*. *FS_SCORE* is equal to the sum of ten individual binary variables, or

$$FS\_SCORE_{i,t} = FS\_ROA_{i,t} + FS\_FCFTA_{i,t} + FS\_ACCRUAL_{i,t} + FS\_\Delta LEVER_{i,t} + FS\_\Delta LIQUID_{i,t} + NEQISS_{i,t} + FS\_\Delta ROA_{i,t} + FS\_\Delta FCFTA_{i,t} + FS\_\Delta MARGIN_{i,t} + FS\_\Delta TURN_{i,t}$$

where each binary variable equals one (zero) if the signal about future performance is good (bad). Stocks with an aggregate *FS_SCORE* between 6 and 10 (0 and 4) are classified as high (low) *FS_SCORE* stocks. There is a total of 5,639 firm-year observations between 1997 and 2015.

Panel A: Raw returns[1]

	Mean	10th percentile	25th percentile	Median	75th percentile	90th percentile	Proportion positive returns	n
All firms	0.133	-0.373	-0.155	0.087	0.354	0.666	0.599	5 639
FS_SCORE								
0	0.011	-0.256	-0.256	0.011	—	—	0.500	2
1	0.239	-0.470	-0.268	-0.001	0.495	1.480	0.487	39
2	0.182	-0.458	-0.179	0.056	0.524	0.863	0.564	188
3	0.161	-0.468	-0.179	0.100	0.422	0.795	0.586	456
4	0.148	-0.402	-0.161	0.105	0.385	0.712	0.605	842
5	0.123	-0.397	-0.160	0.071	0.343	0.678	0.585	1 086
6	0.118	-0.369	-0.180	0.061	0.330	0.644	0.572	1 162
7	0.128	-0.335	-0.123	0.103	0.352	0.592	0.634	952
8	0.121	-0.327	-0.129	0.084	0.324	0.615	0.621	610
9	0.146	-0.291	-0.124	0.107	0.353	0.672	0.632	253
10	0.129	-0.286	-0.107	0.112	0.340	0.617	0.653	49
Low score	0.158	-0.430	-0.170	0.098	0.407	0.766	0.591	1 527
High score	0.124	-0.349	-0.143	0.087	0.337	0.621	0.608	3 026
High-All	-0.009	0.024	0.012	-0.001	-0.017	-0.045	0.009	—
t-statistics[3]	-0.925	—	—	—	—	—	—	—
p-value (α = 0.05)	0.355	—	—	—	—	—	—	—
High-Low	-0.034	0.081	0.027	-0.012	-0.070	-0.146	0.017	—
t-statistics	-2.177	—	—	—	—	—	—	—
p-value (α = 0.05)	0.030	—	—	—	—	—	—	—

Panel B: Market-adjusted returns[2]	Mean	10th percentile	25th percentile	Median	75th percentile	90th percentile	Proportion positive returns	n
All firms	0.050	-0.425	-0.224	-0.010	0.259	0.563	0.488	5 639
FS_SCORE								
0	-0.141	-0.348	-0.348	-0.141	—	—	0.500	2
1	0.147	-0.699	-0.218	-0.042	0.381	1.277	0.410	39
2	0.067	-0.531	-0.324	-0.034	0.383	0.702	0.473	188
3	0.069	-0.516	-0.279	-0.022	0.321	0.654	0.482	456
4	0.054	-0.446	-0.228	-0.003	0.283	0.583	0.498	842
5	0.041	-0.424	-0.245	-0.021	0.246	0.605	0.473	1 086
6	0.043	-0.420	-0.235	-0.029	0.246	0.538	0.461	1 162
7	0.049	-0.364	-0.192	0.015	0.240	0.504	0.514	952
8	0.044	-0.395	-0.198	0.006	0.242	0.494	0.503	610
9	0.065	-0.394	-0.194	0.021	0.264	0.564	0.534	253
10	0.030	-0.306	-0.162	-0.012	0.198	0.436	0.490	49
Low score	0.062	-0.483	-0.256	-0.015	0.305	0.638	0.488	1 527
High score	0.047	-0.400	-0.205	-0.006	0.243	0.516	0.493	3 026
High-All	-0.003	0.025	0.020	0.004	-0.016	-0.048	0.005	—
t-statistics	-0.315	—	—	—	—	—	—	—
p-value (α = 0.05)	0.752	—	—	—	—	—	—	—
High-Low	-0.015	0.083	0.052	0.009	-0.062	-0.122	0.005	—
t-statistics	-1.020	—	—	—	—	—	—	—
p-value (α = 0.05)	0.308	—	—	—	—	—	—	—

[1] Raw return is calculated for each stock as the 12-month buy-and-hold return commencing at the beginning of July in each calendar year *t* .

[2] Market-adjusted return is calculated for each stock as the 12-month buy-and-hold return commencing at the beginning of July in each calendar year *t* less the corresponding return of S&P 1500 index over the respective holding period.

[3] Parametric *t* -statistics for returns are from the two-sample test for means (assuming unequal variances) under the null hypothesis (*H0*) that the difference between the means is zero.

The results are not supportive for applying fundamental analysis to the complete *MOM-12* portfolio either. Looking at table 10, although momentum stocks with high *FS_SCORE* outperform momentum stocks with low *FS_SCORE*, the mean market-adjusted return difference of 1.3% is not statistically significant at the 0.05 significance level. Further, the high *FS_SCORE* stocks outperform all momentum stocks only by 0.3% and the mean return difference is also clearly statistically insignificant. Interestingly, there seems to be a negative monotonic relationship between the one-year ahead returns and fundamental strength among high *FS_SCORE* stocks as the returns decrease monotonically when moving from score 6 to 10. This indicates that the relationship between fundamental strength and future returns when applied to the complete momentum portfolio is not economically sound. Thus, we also reject the latter two hypotheses that (H3) momentum stocks with high *FS_SCORE* outperform momentum stocks with low

FS_SCORE and (H4) momentum stocks with high *FS_SCORE* outperform all momentum stocks. When looking at the return distribution, the results are also very similar to value stocks. The fundamental momentum investment approach does seem to help to shift the return distribution to the right at the lower percentiles, but fails to do this above the median. However, the proportion of winners in the high *FS_SCORE* portfolio (48.6%) is slightly higher than in the low *FS_SCORE* portfolio (45.9%).

The explanation for the weak performance the fundamental momentum strategy is unlikely to be the 12-month holding period, we believe. For example, Chen at al. (2016) found that the high-low *FSCORE* strategy produced a mean monthly excess return of 0.35% over the 12-month holding period when applied to US stocks with the highest past 12-month cumulative returns[24]. Instead, we believe that a more likely explanation could be the time gap between financial year-end and performance measurement. As firms in the US have to file Form 10-K report between 60 and 90 days after the fiscal-year end (depending on the public float), it is possible that ignoring the returns between the financial year-end and actual financial statement release date causes problems. Additionally, as market participants continually discount new information to prices (e.g. based on quarterly 10-Q reports), it is possible that fundamental information based on previous year's financial statements is outdated. Consequently, it may be that momentum strategy could be enhanced using the latest quarterly financials and earnings momentum.

Generally speaking, it is evident that *FS_SCORE* does not help to discriminate winners from losers among high *B/M* or *MOM-12* stocks as we reject all our hypotheses. We find no clear positive relation between *FS_SCORE* and one-year market-adjusted returns in either the complete value or momentum portfolio, and the return spreads are either negative and/or statistically insignificant. Further, the *FS_SCORE* strategy does not shift the entire return distribution of value and momentum stocks to the right as it does not capture the exceptional 75th and 90th percentile returns for low *FS_SCORE* stocks. Hence, *FS_SCORE* seems to differentiate only between winners and losers in the lowest return percentiles. We believe that this could demonstrate that *FS_SCORE* does not capture either mean-reverting fundamentals or other meaningful intangible information among stocks with weak ex ante fundamentals. Based on these results, it also seems difficult to conclude that the market does not discount all ex ante fundamental information or that the market systematically underreacts to good financial information among stocks that are fundamentally strong ex ante as argued by Piotroski (2000), Duong et al. (2014) and Chen et al. (2016). Otherwise we would presumably expect to see a positive and more linear relationship between *FS_SCORE* and one-year ahead returns.

[24] We wish to highlight, however, that our results are not fully comparable to Chen et al. (2016) as their sample included all non-financial firms listed on the NYSE, AMEX and NASDAQ between 1973 to 2013, and stocks were sorted at the end of each month based on the past 12-month momentum and *FSCORE*.

Table 10 One-year buy-and-hold returns to fundamental momentum strategy

This table reports the 12-month buy-and-hold returns of the pooled firm-year observations for fundamental momentum strategy, which combines high *MOM-12* strategy with fundamental strength measured as *FS_SCORE*. *FS_SCORE* is equal to the sum of ten individual binary variables, or

$$FS\_SCORE_{i,t} = FS\_ROA_{i,t} + FS\_FCFTA_{i,t} + FS\_ACCRUAL_{i,t} + FS\_\Delta LEVER_{i,t} + FS\_\Delta LIQUID_{i,t} + NEQISS_{i,t} + FS\_\Delta ROA_{i,t} + FS\_\Delta FCFTA_{i,t} + FS\_\Delta MARGIN_{i,t} + FS\_\Delta TURN_{i,t}$$

where each binary variable equals one (zero) if the signal about future performance is good (bad). Stocks with an aggregate *FS_SCORE* between 6 and 10 (0 and 4) are classified as high (low) *FS_SCORE* stocks. There is a total of 5,627 firm-year observations between 1997 and 2015.

Panel A: Raw returns[1]

	Mean	10th percentile	25th percentile	Median	75th percentile	90th percentile	Proportion positive returns	n
All firms	0.116	-0.375	-0.165	0.073	0.324	0.614	0.592	5 627
FS_SCORE								
0	0.301	0.278	0.278	0.301	—	—	1.000	2
1	0.073	-0.773	-0.355	0.143	0.424	0.936	0.560	25
2	0.134	-0.480	-0.166	0.048	0.425	0.653	0.554	112
3	0.102	-0.471	-0.240	0.015	0.360	0.742	0.522	272
4	0.123	-0.416	-0.200	0.068	0.338	0.732	0.562	617
5	0.107	-0.437	-0.204	0.057	0.327	0.669	0.585	903
6	0.133	-0.365	-0.162	0.079	0.343	0.634	0.590	1 145
7	0.126	-0.314	-0.130	0.090	0.315	0.583	0.620	1 131
8	0.105	-0.351	-0.142	0.075	0.300	0.569	0.603	917
9	0.094	-0.384	-0.167	0.081	0.311	0.516	0.618	424
10	0.077	-0.289	-0.091	0.064	0.258	0.414	0.570	79
Low score	0.118	-0.448	-0.208	0.053	0.349	0.735	0.552	1 028
High score	0.118	-0.349	-0.145	0.081	0.316	0.585	0.605	3 696
High-All	0.002	0.026	0.020	0.007	-0.008	-0.029	0.013	—
t-statistics[3]	0.210	—	—	—	—	—	—	—
p-value (α = 0.05)	0.834	—	—	—	—	—	—	—
High-Low	0.000	0.099	0.063	0.028	-0.033	-0.149	0.054	—
t-statistics	0.028	—	—	—	—	—	—	—
p-value (α = 0.05)	0.978	—	—	—	—	—	—	—

Panel B: Market-adjusted returns[2]

	Mean	10th percentile	25th percentile	Median	75th percentile	90th percentile	Proportion positive returns	n
All firms	0.033	-0.410	-0.221	-0.017	0.217	0.494	0.480	5 627
FS_SCORE								
0	0.158	0.066	0.066	0.158	—	—	1.000	2
1	-0.017	-0.693	-0.439	-0.020	0.230	1.001	0.440	25
2	0.015	-0.526	-0.326	0.008	0.258	0.540	0.509	112
3	0.017	-0.484	-0.282	-0.060	0.222	0.579	0.463	272
4	0.028	-0.452	-0.261	-0.043	0.225	0.556	0.447	617
5	0.033	-0.435	-0.238	-0.019	0.225	0.529	0.480	903
6	0.053	-0.401	-0.209	-0.011	0.245	0.543	0.490	1 145
7	0.038	-0.366	-0.198	-0.006	0.214	0.445	0.492	1 131
8	0.023	-0.383	-0.194	-0.015	0.190	0.450	0.479	917
9	0.015	-0.384	-0.203	-0.009	0.189	0.411	0.476	424
10	0.003	-0.317	-0.157	-0.028	0.167	0.328	0.481	79
Low score	0.023	-0.475	-0.276	-0.041	0.230	0.555	0.459	1 028
High score	0.036	-0.385	-0.202	-0.011	0.211	0.469	0.486	3 696
High-All	0.003	0.025	0.019	0.006	-0.006	-0.024	0.006	—
t-statistics	0.303	—	—	—	—	—	—	—
p-value (α = 0.05)	0.762	—	—	—	—	—	—	—
High-Low	0.013	0.090	0.075	0.030	-0.019	-0.086	0.027	—
t-statistics	0.767	—	—	—	—	—	—	—
p-value (α = 0.05)	0.444	—	—	—	—	—	—	—

[1] Raw return is calculated for each stock as the 12-month buy-and-hold return commencing at the beginning of July in each calendar year *t* .

[2] Market-adjusted return is calculated for each stock as the 12-month buy-and-hold return commencing at the beginning of July in each calendar year *t* less the corresponding return of S&P 1500 index over the respective holding period.

[3] Parametric *t* -statistics for returns are from the two-sample test for means (assuming unequal variances) under the null hypothesis (*H0*) that the difference between the means is zero.

4.2.3 Returns conditional on firm size

Like Piotroski (2000), we also make a size partition analysis as the majority of stocks in our sample are smaller stocks listed in the S&P 400 and S&P 600 indices. Although fundamental value and momentum strategies did not yield abnormal returns when applied to the whole sample, it is possible that there are considerable differences in returns across size categories. In order to analyse return differences across size categories, all high *B/M* and *MOM-12* stocks are divided annually into size terciles based on the market value at the end of June in year t. Using the 33.3 and 66.7 percentile size cut-offs yields a total of

1,874–1,886 and 1,869–1,881 sample firms for small, medium and large size high *B/M* and *MOM-12* portfolios. The results are presented in table 11 and 12.

Table 11 shows that fundamental analysis is not more beneficial among small and medium size value firms than among large value firms. In fact, it is more close to the opposite. The difference in mean market-adjusted returns for the high-low and high-all portfolios is negative for small and medium-sized firms and increases monotonically when moving from portfolio of small stocks to large stocks. Applying *FS_SCORE* for large stocks earns a mean market-adjusted return of 1.5% and 0.3% for the high-low and high-all portfolios respectively. All return differences are, however, statistically insignificant. Consequently, there does not seem to be a statistically significant difference in returns across size categories. These results are surprising as various studies such as Fama and French (2012) have reported a small cap value premium and Piotroski (2000) found that the benefits of the *FSCORE* strategy concentrated among smaller stocks. Overall, we conclude that *FS_SCORE* strategy is not more beneficial among smaller value stocks.

Table 11 One-year buy-and-hold returns to fundamental value strategy by size partition

This table reports the 12-month market-adjusted buy-and-hold returns of the pooled firm-year observations for fundamental value strategy partioned by size. Each year high *B/M* firms are divided into size terciles based on the market value of equity at the end of June. Thus, the 33.3 and 66.7 percentile cutoffs are used to classify high *B/M* firms into small, medium and large firms each year. There is a total of 1,879, 1,886 and 1,874 firm-year observations in small, medium and large portfolios between 1997 and 2015. All other definitions and test statistics are as described in table 9.

	Small firms			**Medium firms**			**Large firms**		
	Mean	**Median**	**n**	**Mean**	**Median**	**n**	**Mean**	**Median**	**n**
All firms	0.051	-0.028	1 879	0.047	-0.014	1 886	0.052	0.014	1 874
FS_SCORE									
0	—	—	1	0.066	0.066	1	—	—	0
1	0.095	-0.142	10	0.091	-0.042	13	0.225	0.113	16
2	0.166	0.088	81	0.030	-0.049	60	-0.056	-0.072	47
3	0.103	-0.052	155	0.026	-0.047	158	0.079	0.052	143
4	0.062	-0.015	309	0.074	0.029	284	0.023	-0.032	249
5	0.023	-0.059	354	0.041	-0.011	400	0.060	0.009	332
6	0.037	-0.046	393	0.088	-0.024	364	0.009	-0.025	405
7	0.052	-0.001	293	0.012	-0.003	339	0.086	0.046	320
8	0.037	-0.007	190	0.016	-0.029	191	0.072	0.049	229
9	0.030	-0.034	77	0.068	0.006	64	0.087	0.029	112
10	-0.021	-0.062	16	0.046	0.049	12	0.061	-0.012	21
Low score	0.088	-0.016	556	0.055	-0.017	516	0.039	-0.007	455
High score	0.040	-0.025	969	0.045	-0.015	970	0.054	0.023	1 087
High-All	-0.011	0.003	—	-0.002	-0.001	—	0.003	0.009	—
t-statistics	-0.613	—	—	-0.087	—	—	0.189	—	—
p-value (α = 0.05)	0.540	—	—	0.930	—	—	0.850	—	—
High-Low	-0.048	-0.009	—	-0.009	0.002	—	0.015	0.030	—
t-statistics	-1.672	—	—	-0.355	—	—	0.662	—	—
p-value (α = 0.05)	0.095	—	—	0.723	—	—	0.508	—	—

Table 12 shows slightly different results for high momentum stocks partitioned by size. Although small and medium size high *FS_SCORE* stocks earn higher returns than low *FS_SCORE* stocks and all momentum stocks, the return differences are clearly statistically insignificant for all portfolios. The high-low strategy works best among medium-sized stocks, producing a mean market-adjusted return of 4.5% with *t*-statistics of 1.625. Among large stocks both high-low and high-all strategies produce negative returns (although statistically non-meaningful). Consequently, these results confirm that fundamental analysis is not associated with higher returns among high momentum stocks in any particular size category, which is in line with the results from value portfolios.

Table 12 One-year buy-and-hold returns to fundamental momentum strategy by size partition

This table reports the 12-month market-adjusted buy-and-hold returns of the pooled firm-year observations for fundamental momentum strategy partioned by size. Each year high *MOM-12* firms are divided into size terciles based on the market value of equity at the end of June. Thus, the 33.3 and 66.7 percentile cutoffs are used to classify high *MOM-12* firms into small, medium and large firms each year. There is a total of 1,877, 1,881 and 1,869 firm-year observations in small, medium and large portfolios between 1997 and 2015. All other definitions and test statistics are as described in table 10.

	Small firms			**Medium firms**			**Large firms**		
	Mean	**Median**	**n**	**Mean**	**Median**	**n**	**Mean**	**Median**	**n**
All firms	0.028	-0.043	1 877	0.033	-0.019	1881	0.037	0.001	1 869
FS_SCORE									
0	0.066	0.066	1	0.250	0.250	1	—	—	0
1	-0.035	-0.026	14	-0.115	0.009	4	0.074	-0.218	7
2	0.015	-0.033	55	0.018	0.060	33	0.014	-0.016	24
3	-0.009	-0.109	114	0.010	-0.077	88	0.069	0.050	70
4	0.048	-0.059	236	-0.014	-0.080	215	0.053	0.018	166
5	-0.016	-0.064	326	0.049	-0.019	300	0.074	0.029	277
6	0.061	-0.022	392	0.053	-0.011	378	0.045	-0.005	375
7	0.034	-0.026	355	0.048	0.001	394	0.030	-0.003	382
8	0.047	-0.009	245	0.009	-0.032	313	0.019	0.001	359
9	0.005	-0.009	122	0.065	0.023	125	-0.014	-0.036	177
10	-0.028	-0.064	17	-0.018	-0.041	30	0.041	0.065	32
Low score	0.026	-0.065	420	-0.005	-0.059	341	0.054	0.024	267
High score	0.042	-0.024	1 131	0.040	-0.010	1240	0.026	-0.007	1 325
High-All	0.014	0.019	—	0.007	0.009	—	-0.011	-0.008	—
t-statistics	0.803	—	—	0.433	—	—	-0.838	—	—
p-value (α = 0.05)	0.422	—	—	0.665	—	—	0.402	—	—
High-Low	0.016	0.041	—	0.045	0.049	—	-0.028	-0.030	—
t-statistics	0.581	—	—	1.625	—	—	-0.910	—	—
p-value (α = 0.05)	0.561	—	—	0.105	—	—	0.364	—	—

We believe there are various economically sound reasons which could explain our results that fundamental analysis is not more beneficial among smaller stocks. Firstly, information dissemination has presumably improved significantly over our sample period compared to early studies. As a significant portion of equity screening, analysis and trading is nowadays automated and information availability has increased dramatically over the past 20 years, simple fundamental strategies based on ex ante measures utilized five to seven months after the financial year-end could have lost their discriminative power. Secondly, unlike in the Piotroski's (2000) study, our sample excludes all stocks below the 5th percentile in market value at the end of June each year. This could potentially have an adverse impact on fundamental value and momentum returns, but on the other hand we believe that the returns for the smallest stocks would be difficult to achieve due to various constraints such as illiquidity and arbitrage risk.

4.3 Robustness checks

4.3.1 Risk-adjusted returns for portfolios

Table 13 reports returns on the *FS_SCORE* strategies across value and momentum portfolios together with the corresponding results from the one-sample *t*-tests and the time-series tests. In the time-series regressions we have regressed the monthly excess returns of fundamental value and momentum portfolios from 1997 to 2015 on the CAPM, the Fama-French three-factor model and the Carhart four-factor model risk-factors downloaded from the Kenneth R. French website. Hence, if these risk-adjusted return models explain the portfolios' excess returns, the monthly regression intercepts should be close to zero and statistically insignificant using parametric *t*-tests.

In the value portfolios it can be observed that the returns for hedge portfolios are clearly negative and statistically significant using the 0.05 significance level when returns are market-adjusted. The annualized market-adjusted returns for high-low and high-all portfolios are -10.2% and -8.9% with *t*-statistics of -2.193 and -2.268 respectively. The annualized market-adjusted return of 4.3% for long-only high *FS_SCORE* strategy is also statistically insignificant, whereas the corresponding return of 6.3% for long-only low *FS_SCORE* strategy is statistically significant with *t*-statistics of 2.040. Thus, these results confirm that low *FS_SCORE* stocks outperform high *FS_SCORE* stocks in the value context by a wide margin that is economically and statistically meaningful. This is also more in line with risk-based explanations for value premium as value stocks with low *FS_SCORE* are likely to be distressed and thus fundamentally riskier.

When looking at the regression intercepts, it seems that the CAPM, the FF3 and the Carhart regressions explain relatively well the portfolio returns for fundamental value strategies. The regression intercepts are small and clearly statistically insignificant for high *FS_SCORE*, low *FS_SCORE*, high-low and all value stocks portfolios, leading us to reject statistically significant excess returns. However, the monthly intercept is around -0.2% for high-all portfolio using all return models and clearly more than two standard errors from zero (*t*-statistics = -3.588, -3.410 and -3.646), which rejects the CAPM, the FF3 and the Carhart model easily. Generally, the evidence from the parametric tests and the time-series regressions verifies our earlier results that led us to reject hypotheses H1 and H2. Thus, we find no support for applying fundamental analysis in the value context, which is incongruent with the results of Piotroski (2000), Piotroski and So (2012) and Duong et al. (2014).

For momentum portfolios the parametric tests reject the significance of market-adjusted returns across the board. Although high *FS_SCORE* portfolio produces an annualized market-adjusted return of 3.9% (*t*-statistics = 1.928) compared to 1.8% (*t*-statistics = 0.597) and 3.3% (*t*-statistics = 1.567) for low *FS_SCORE* portfolio and all momentum stocks portfolio respectively, all returns are less than two standard errors from zero. Further, the annualized market-adjusted returns for high-low and high-all portfolios are negative and economically meaningful at -6.1% (*t*-statistics = -1.291) and -7.6% (*t*-statistics = -1.936), although statistically insignificant. Therefore, the parametric tests support the evidence that financially stronger momentum stocks do not outperform financially weaker momentum stocks and the complete portfolio of all momentum stocks when the returns are market-adjusted.

The time-series regressions for momentum portfolios also support the conclusion that separating winners from losers using *FS_SCORE* does not produce abnormal returns. The monthly intercept for long-only high *FS_SCORE* portfolio is 0.3% and barely statistically meaningful with *t*-statistics of 1.989 using the CAPM regression. When size and value risk-factors are included in the regression, the monthly intercept drops to 0.2% and becomes statistically insignificant (*t*-statistics = 1.926). Further, when momentum is included in the regression as the fourth risk-factor, the monthly intercept drops to 0.1% and becomes clearly statistically insignificant with *t*-statistics of 1.238. The monthly intercept for high-low hedge portfolio is also economically non-meaningful at around 0.1% and clearly less than two standard errors from zero using all return models (*t*-statistics = 0.350, 0.410 and 0.361). Lastly, similar to the high-all value portfolio, the monthly intercept for high-all momentum portfolio is negative at around -0.1% and at least two standard errors from zero using all return models. Consequently, as with value portfolios, the parametric tests and regression analysis is fully in line with the earlier findings from the pooled portfolio tests in the previous section that rejected hypotheses H3 and H4.

In summary, our robustness tests strengthen the conclusion that high *FS_SCORE* strategy has not been useful in separating winners from losers in either value or momentum context from 1997 to 2015. We believe that this is most likely due to the significant time gap between financial year-ends and portfolio formation dates and/or due to the fact that fundamental strategies are no longer as useful as they used to be. In addition, it could be that our assumption for delisting returns of zero causes a positive return bias among low *FS_SCORE* stocks that are more likely to delist for performance related reasons. If a stock delists due to performance related reasons, it is highly likely that the return could be negative for shareholders. Therefore, it is possible that our results overstate the performance of low *FS_SCORE* stocks.

Table 13 Portfolio returns to *FS_SCORE* strategies across value and momentum context

This table reports the annualised raw returns, market-adjusted returns and Sharpe ratios for high *FS_SCORE*, low *F_SCORE* and hedge portfolios across value and momentum samples. We also report the Capital Asset Pricing Model (CAPM), the Fama-French Three-Factor model (FF3) and the Carthart Four-Factor model (Carhart) alphas for the excess returns of different investment strategies. Each year at the beginning of July in year *t* we form equally-weighted portfolios and we hold these portfolios for the following 12-months (annual rebalancing). Hence, the initial equal-weight for each stock changes in the portfolios during the 12-month buy-and-hold period as we do not rebalance monthly to maintain equal weights. The *t*-statistics for raw returns and market-adjusted returns are from the two-sided *t*-test under the null hypothesis that the portfolio returns are zero. When calculating the CAPM, the FF3 and the Carthart adjusted alphas, the *t*-statistics have been calculated using the Newey-West standard errors to take into account potential autocorrelation issues. All other definitions are as previously described.

	Value portfolios					**Momentum portfolios**				
	FS_High	FS_Low	All high B/M	High-Low	High-All	FS_High	FS_Low	All high MOM-12	High-Low	High-All
Raw	0.125	0.145	0.132	-0.020	-0.007	0.121	0.100	0.115	0.021	0.006
t-statistics	*2.666*	*2.679*	*2.730*	*-1.057*	*-1.031*	*2.828*	*1.905*	*2.566*	*0.931*	*1.050*
p-value	*0.008*	*0.008*	*0.007*	*0.292*	*0.304*	*0.005*	*0.058*	*0.011*	*0.353*	*0.295*
Market-adjusted	0.043	0.063	0.050	-0.102	-0.089	0.039	0.018	0.033	-0.061	-0.076
t-statistics	*1.666*	*2.040*	*1.930*	*-2.193*	*-2.268*	*1.928*	*0.597*	*1.567*	*-1.291*	*-1.936*
p-value	*0.097*	*0.043*	*0.055*	*0.029*	*0.024*	*0.055*	*0.551*	*0.119*	*0.198*	*0.054*
Sharpe ratio	0.518	0.536	0.537	-0.518	-0.978	0.546	0.351	0.490	-0.013	-0.644
CAPM alpha	0.003	0.004	0.004	-0.003	-0.002	0.003	0.001	0.002	0.001	-0.001
t-statistics	*1.190*	*1.496*	*1.342*	*-1.815*	*-3.588*	*1.989*	*0.204*	*1.432*	*0.350*	*-2.000*
FF3 alpha	0.001	0.001	0.001	-0.002	-0.002	0.002	-0.001	0.001	0.001	-0.001
t-statistics	*0.482*	*0.711*	*0.688*	*-1.677*	*-3.410*	*1.926*	*-0.246*	*1.217*	*0.410*	*-2.093*
Carhart alpha	0.001	-0.003	0.002	-0.003	-0.002	0.001	-0.001	0.001	0.001	-0.001
t-statistics	*1.000*	*-1.743*	*1.351*	*-1.743*	*-3.646*	*1.238*	*-0.466*	*0.639*	*0.361*	*-2.057*

4.3.2 Performance over time

Tables 14 and 15 present the annual one-year market-adjusted buy-and-hold returns for fundamental value and momentum strategies over the sample period from 1997 to 2015. Additionally, figures 4 and 5 show the performance of fundamental value and momentum strategies as well as the market (S&P 1500 index) over the sample period.

Starting with value stocks, the portfolio of low *FS_SCORE* stocks has outperformed the portfolio of high *FS_SCORE* stocks on average by 1.7% over the sample period. Although the high *FS_SCORE* strategy has outperformed the market on average by 4.2%, the market-adjusted return has been positive only 10 out of 18 years. Further, the high-low return difference has been positive only 7 out of 18 years, meaning that low *FS_SCORE* stocks have outperformed continually. This was particularly the case between 2003 and 2010, when low *FS_SCORE* stocks outperformed the high *FS_SCORE* stocks for eight consecutive years. Surprisingly, the low *FS_SCORE* portfolio outperformed during the financial crisis between 2007 and 2009. The highest annual market-adjusted return for high *FS_SCORE* portfolio has been 50.7% in 2000, compared to 45.6% for low *FS_SCORE* portfolio in the same year. On the other hand, the lowest return for both high *FS_SCORE* and low *FS_SCORE* portfolio was in 1998 when portfolios returned -23.8% and -17.7% respectively. It can also be seen that the annual return sign has been similar for both portfolios (the only exception being year 2006).

Table 14 One-year market-adjusted returns to fundamental value portfolios by investment year

This table shows the one-year market-adjusted returns by investment year to high *FS_SCORE* , low *FS_SCORE* , all high *B/M* and hedge portfolios. All other definitions are as previously described.

Investment year	**High FS_SCORE Market-adjusted Returns**	**Low FS_SCORE Market-adjusted Returns**	**All high B/M Market-adjusted returns**	**High-Low Return Difference**	**High-All Return Difference**
1997	-0.063	-0.150	-0.093	0.088	0.030
1998	-0.238	-0.177	-0.206	-0.060	-0.031
1999	-0.098	-0.098	-0.111	0.000	0.013
2000	0.507	0.456	0.492	0.052	0.015
2001	0.330	0.162	0.282	0.168	0.048
2002	-0.069	-0.082	-0.088	0.013	0.019
2003	0.168	0.215	0.206	-0.047	-0.037
2004	0.095	0.137	0.100	-0.042	-0.005
2005	0.083	0.139	0.084	-0.055	0.000
2006	-0.009	0.058	0.016	-0.068	-0.025
2007	-0.044	-0.035	-0.043	-0.009	-0.001
2008	0.022	0.069	0.053	-0.047	-0.031
2009	0.056	0.232	0.136	-0.176	-0.080
2010	0.037	0.124	0.086	-0.087	-0.049
2011	-0.116	-0.135	-0.112	0.019	-0.004
2012	0.123	0.120	0.093	0.003	0.029
2013	0.054	0.117	0.076	-0.064	-0.022
2014	-0.087	-0.089	-0.093	0.002	0.006
Mean	**0.042**	**0.059**	**0.049**	**-0.017**	**-0.007**
# Positive	**10**	**11**	**11**	**7**	**7**

Figure 4 shows the performance of fundamental value strategies as well as the market. It can be seen that both high and low *FS_SCORE* portfolios performed relatively similarly until the 2007–2008 financial crisis. Both strategies have overperformed the market during the sample period, but since the financial crisis low *FS_SCORE* portfolio has outperformed high *FS_SCORE* portfolio by a wide margin. This strengthens our view that *FS_SCORE* does not capture all relevant information among fundamentally weaker value stocks.

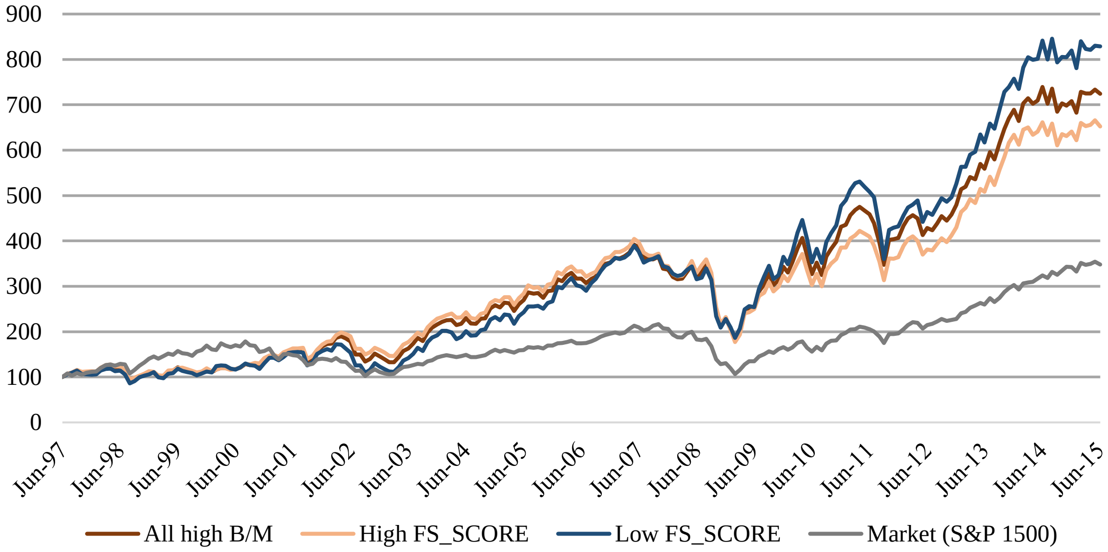

Figure 4 Performance of fundamental value strategies

Continuing with momentum stocks, the high *FS_SCORE* strategy has been much more successful among momentum stocks than among value stocks. The high *FS_SCORE* portfolio outperformed the low *FS_SCORE* portfolio on average by 2.0% and in 11 out of 18 years. The highest and the lowest market-adjusted returns for high *FS_SCORE* portfolio were 26.3% and -12.4% in 2001 and 1998, whereas the corresponding returns for low *FS_SCORE* portfolio were 38.3% and -28.9% in 1999 and 1997 respectively. Interestingly, there seems to be more variation in returns between the high and low *FS_SCORE* portfolios among momentum stocks than value stocks. For momentum stocks, the return sign was the opposite 5 out of 18 years for high and low *FS_SCORE* portfolios. However, as there is a small number of annual observations in the low *FS_SCORE* portfolios relative to the high *FS_SCORE* portfolios particularly among momentum stocks, it could be just a coincidence.

Table 15 One-year market-adjusted returns to fundamental momentum portfolios by investment year

This table shows the one-year market-adjusted returns by investment year to high *FS_SCORE*, low *FS_SCORE*, all high *MOM-12* and hedge portfolios. All other definitions are as previously described.

Investment year	High FS_SCORE Market-adjusted Returns	Low FS_SCORE Market-adjusted Returns	All high MOM-12 Market-adjusted returns	High-Low Return Difference	High-All Return Difference
1997	-0.044	-0.289	-0.111	0.245	0.067
1998	-0.124	-0.053	-0.109	-0.070	-0.015
1999	0.172	0.383	0.248	-0.211	-0.077
2000	0.054	-0.007	0.013	0.061	0.041
2001	0.263	0.177	0.235	0.086	0.028
2002	-0.018	-0.080	-0.031	0.062	0.013
2003	0.144	0.127	0.142	0.017	0.002
2004	0.039	-0.027	0.019	0.066	0.020
2005	0.092	0.001	0.069	0.091	0.023
2006	-0.038	0.045	-0.027	-0.083	-0.011
2007	0.016	0.037	0.016	-0.021	0.000
2008	0.015	-0.171	-0.026	0.186	0.040
2009	0.035	0.098	0.045	-0.063	-0.010
2010	0.129	0.123	0.142	0.006	-0.012
2011	-0.101	-0.127	-0.101	0.026	0.000
2012	0.013	0.074	0.028	-0.061	-0.015
2013	0.027	0.062	0.038	-0.035	-0.011
2014	0.012	-0.050	-0.014	0.062	0.026
Mean	**0.038**	**0.018**	**0.032**	**0.020**	**0.006**
# Positive	**13**	**10**	**11**	**11**	**10**

Figure 5 shows the performance of fundamental momentum strategies and the market. Interestingly, it can be seen that high *FS_SCORE* portfolio has outperformed low *FS_SCORE* portfolio almost during the entire sample period. This is particularly true after the financial crisis, as momentum portfolio with high *FS_SCORE* stocks has risen by 108% compared to 63% for momentum portfolio with low *FS_SCORE* stocks. This verifies our earlier results that fundamentals work better in momentum than value context. Although this is somewhat surprising, it could be that *FS_SCORE* captures some of the factors that drive momentum anomaly. It is possible that investors underreact to frequent and gradual information among momentum stocks such as improving sales and earnings, which would support results by Da et al. (2014).

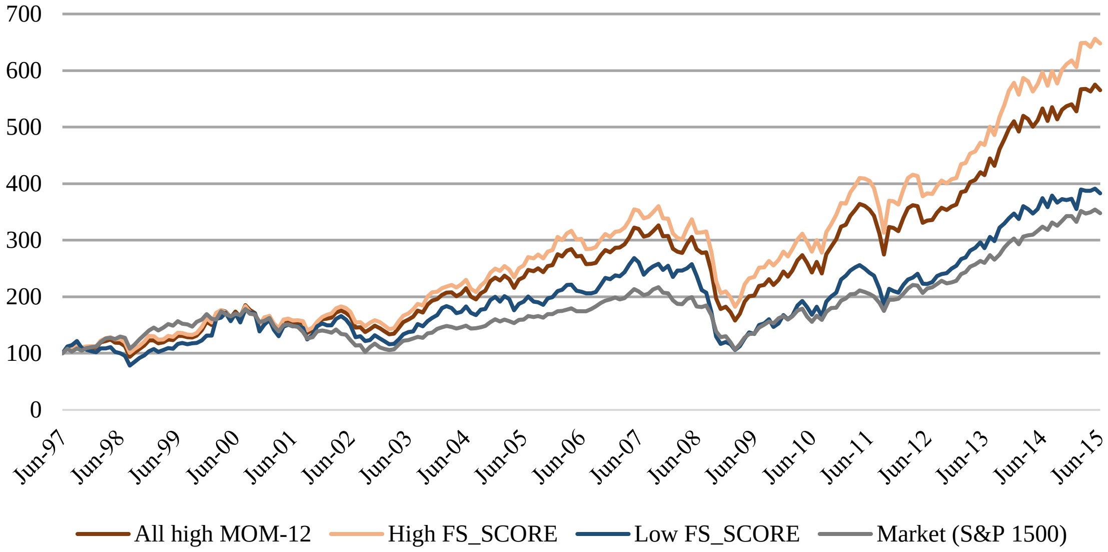

Figure 5 Performance of fundamental momentum strategies

5 CONCLUSIONS

The key purpose of this thesis was to examine whether a simple accounting-based fundamental analysis could be used to enhance value and momentum strategies. Both value and momentum effects have been studied extensively from asset pricing point of view, whereas the evidence on combining style and fundamentals is still fairly limited. Previous studies have shown, however, that both value and momentum returns can be improved by controlling for fundamental strength and/or quality. Piotroski (2000), Piotroski and So (2012) and Chen et al. (2016) found that fundamentally stronger value and momentum stocks outperformed weaker ones, whereas Novy-Marx (2013) showed that there is a gross profit premium among value stocks. These results imply some kind of premium towards fundamentally stronger value and momentum stocks, which provided an interesting framework to study fundamental value and momentum strategies. In order to separate winners from losers using fundamental analysis, we applied the *FS_SCORE* developed by Gray and Carlisle (2013). The *FS_SCORE* is based on the original *FSCORE* by Piotroski (2000), but Gray and Carlisle (2013) have made some relatively minor but well-argued improvements.

Our main findings were somewhat unexpected based on the previous research. Although less than 50% of all value and momentum stocks produced positive one-year ahead market-adjusted returns, we found no support for fundamental analysis in either value or momentum portfolios between 1997 and 2015. Within the portfolio of high *B/M* stocks, the high *FS_SCORE* stocks produced a mean one-year market-adjusted return of 4.7%, compared to mean return of 6.2% for the low *FS_SCORE* stocks. The surprising return spread was, however, statistically insignificant using parametric *t*-test. In the case of high *MOM-12* stocks, the strategy that bought expected winners and shorted expected losers generated a one-year market-adjusted return of 1.3%, but the return difference was also clearly statistically insignificant. Further, the size partition analysis showed that fundamental analysis was not economically or statistically more beneficial among small-sized stocks. Consequently, the return earned by the investors selecting the complete portfolio of high *B/M* or high *MOM-12* stocks could not be increased in a meaningful way by selecting fundamentally stronger stocks.

The main findings were also strengthened using portfolio approach and the CAPM, the Fama-French three-factor model and the Carhart four-factor model time-series regressions. Time-series tests showed that the monthly regression intercepts were primarily close to zero and less than two standard errors from zero. Thus, fundamental value and momentum strategies did not produce abnormal risk-adjusted returns after controlling for well-known systematic risk factors. The results were also relatively robust across the sample period as the high *FS_SCORE* portfolio outperformed the low *FS_SCORE* portfolio only 7 out of 18 years in the value context, compared to 11 out of 18 years among momentum stocks.

Overall, it is evident that the *FS_SCORE* strategy does not help to discriminate winners from losers among value or momentum stocks as we rejected all our hypotheses. These results are incongruent with the earlier results by Piotroski (2000), Piotroski and So (2012) and Chen et al. (2016) as well as by Mohanram (2005) to some extent. We believe this demonstrates that ex ante fundamental measures such as *FS_SCORE* do not always capture mean-reverting fundamentals and other meaningful information among stocks that are fundamentally weak ex ante. We also believe that the significant time gap between financial year-ends and portfolio formation dates is likely to be problematic as the information dissemination has presumably greatly improved over the past 20 years. It could thus be more meaningful to study fundamental value and momentum strategies using quarterly financial information. Further, it is also possible that fundamental strategies have partly lost their ability to generate abnormal returns over long-term holding periods. This argument is in line with the recent evidence from US by Hanson and Dhanuka (2015), who found that various fundamental strategies including *FSCORE* did not produce statistically significant abnormal returns between 2000 and 2013. However, it is good to remember that our results could overstate the performance of low *FS_SCORE* stocks due to the assumption of zero delisting returns or due to other biases relating to the treatment of delistings in the Thomson Reuters Datastream database.

Based on our results it is difficult to argue that the financial markets are inefficient or that the information dissemination is weak among value and momentum stocks. Otherwise the financial markets would not discount all publicly available historical information into prices, which could potentially produce abnormal returns among value and momentum stocks that are fundamentally strong ex ante. Continuing with the same logic, if the market participants systematically underreacted to good financial information over long time periods among stocks that are fundamentally strong ex ante, we would presumably expect to see a strong positive and linear relationship between *FS_SCORE* and one-year ahead returns. This also motivates us to focus on short-term fundamental strategies besides long-term strategies and we believe that new research on this topic could produce important information both for practitioners and academics in the world of finance.

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APPENDIX 1 FS_SCORE VARIABLE DEFINITIONS

Financial performance signals	Measurement[1]	Indicator variable[2]	Datastream fields[3]
Current profitability			
Return on assets	ROA_t = *Net income before extra items/preferred dividends* $_t$ / *Total assets* $_{t-1}$	If $FS\_ROA_t > 0$, then 1, otherwise 0	WC01551 and WC02999
Free cash flow	$FCFTA_t$ = (*Net income before extra items/preferred dividends* $_t$ + *Depreciation, depletion and amortization* $_t$ - *Change in working capital* $_t$ - *Capital expenditures* $_t$) / *Total assets* $_{t-1}$	If $FS\_FCFTA_t > 0$, then 1, otherwise 0	WC01551, WC01151, WC04900, WC04601 and WC02999
Accruals	$ACCRUAL_t$ = (*Net income before extra items/preferred dividends* $_t$ - *Net cash flow from operating activities* $_t$) / *Total assets* $_{t-1}$	If $FS\_ACCRUAL_t < 0$, then 1, otherwise 0	WC01551, WC04860 and WC02999
Stability			
Change in leverage[4]	$\Delta LEVER_t$ = [*Total debt* $_t$ / (½*Total assets* $_t$ + ½*Total assets* $_{t-1}$)] - [*Total debt* $_{t-1}$ / (½*Total assets* $_{t-1}$ + ½*Total assets* $_{t-2}$)]	If $FS\_\Delta LEVER_t < 0$, then 1, otherwise 0	WC03255 and WC02999
Change in liquidty	$\Delta LIQUID_t$ = (*Total current assets* $_t$ / *Total current liabilities* $_t$) - (*Total current assets* $_{t-1}$ / *Total current liabilities* $_{t-1}$)	If $FS\_\Delta LIQUID_t > 0$, then 1, otherwise 0	WC02201 and WC03101
Net equity issuance	$NEQISS_t$ = *Common/preferred redeemed, retired, converted etc.* $_t$ - *Net proceeds from sale/issue of common & preferred equity* $_t$	If $NEQISS_t > 0$, then 1, otherwise 0	WC04751 and WC04251
Recent operational improvements			
Change in return on assets	$\Delta ROA_t = ROA_t - ROA_{t-1}$	If $FS\_\Delta ROA_t > 0$, then 1, otherwise 0	WC01551 and WC02999
Change in free cash flow	$\Delta FCFTA_t = FCFTA_t - FCFTA_{t-1}$	If $FS\_\Delta FCFTA_t > 0$, then 1, otherwise 0	WC01551, WC01151, WC04900, WC04601 and WC02999
Change in gross margin	$\Delta MARGIN_t = MARGIN_t - MARGIN_{t-1}$	If $FS\_\Delta MARGIN_t > 0$, then 1, otherwise 0	WC08306
Change in asset turnover	$\Delta TURN_t$ = *Total sales* $_t$ / (½*Total assets* $_t$ + ½*Total assets* $_{t-1}$) - *Total sales* $_{t-1}$ / (½*Total assets* $_{t-1}$ + ½*Total assets* $_{t-2}$)	If $FS\_\Delta TURN_t > 0$, then 1, otherwise 0	WC07240 and WC02999
Composite score			
FS_SCORE	$FS\_SCORE = FS\_ROA + FS\_FCFTA + FS\_ACCRUAL + FS\_\Delta LEVER + FS\_\Delta LIQUID + NEQISS + FS\_\Delta ROA + FS\_\Delta FCFTA + FS\_\Delta MARGIN + FS\_\Delta TURN$		

[1] All financial signals are calculated as in Piotroski's (2000) study except FS_FCFTA_t, $NEQISS_t$ and $FS\_\Delta FCFTA_t$.

[2] All financial variables are calculated from annual financial statements.

[3] These Datastream fields are used to calculate the financial signals.

[4] Includes all interest-bearing debt and capitalized lease obligations. Piotroski (2000) also uses total long-term debt (including long-term debt classified as current) to calculte change in leverage.