Erasmus University Rotterdam

Erasmus School of Economics

Master Thesis Audit, Accounting & Control

Discover Recovery: A Fundamental Analysis of Special Item-Low Accrual Firms

Key Words: Fundamental Analysis, F-Score, Low-Accrual Firms, Special items

Name: Tibo Bouter

Studentnr.: 296710

Supervisor: David Veenman

Abstract

This thesis examines whether a fundamental analysis is able to distinguish special item-low accrual firms that delist from those that turn themselves around. Negative special items are often recognized in low accrual firms. Typically, these firms perform poorly, are in financial distress and delist more for performance related reasons. Although negative special items highly relate to poor underlying economics, the causes and consequences can differ substantially and are therefore highly uncertain. However, prior research finds that investors often react too pessimistically towards the recognition of special items in low accrual firms. Evidence suggests that special item-low accrual firms earn higher abnormal returns than other low accrual firms. Hence, this thesis employs a fundamental analysis to support investor' decision making in low accrual firms when special items are recognized. This fundamental analysis is performed by means of the F-Score of Piotroski (2000) and examines a sample of US listed firms in the period 1988-2009. I find that the F-Score is useful to assess the probability of delisting for special item-low accrual firms. On the other hand, it appears that investors already incorporate the fundamental information of the F-Score in their assessment. Market mispricing does remain significant for recognized negative special items. Thus, although the F-Score is valuable for investors to assess future firm performance, the F-Score does not explain market inefficiency in special item-low accrual firms.

Table of contents

1. Introduction

Investors consider a wide array of information to develop expectations on returns from current and potential investments. These expected returns depend heavily on the ability of the investees to generate future net cash flows (Richardson et al., 2010). However, these future cash flows are highly uncertain and require the use of financial information that is relevant and reliable. To this end, financial reporting has the primary objective to provide financial information that is useful for decisions of investors, lenders and other creditors. To achieve this goal, accruals are used to time and match the effects of economic events and circumstances on a firm's resources to the periods in which they occur. Herewith, accrual accounting composes an earnings measure that better reflects a firm's periodic performance than solely cash flows (SFAC No.8, OB2/17/18). Accounting research confirms this notion, because earnings appear more persistent than cash flows due to the revenue recognition and matching principles (Dechow, 1994). In this manner, financial reporting enables investors to better assess a firm's ability to generate future net cash flows and make well-informed investment decisions (SFAC No.8, OB3).

Furthermore, not only earnings are informative, but also the reported accruals themselves, because they are fundamentally related to a firm's underlying economics. High (i.e. large positive) accruals indicate that a firm increases its assets base to achieve sales or earnings growth. Low (i.e. large negative) accruals show a firm that is downsizing its assets and exiting lines of business (Dechow and Ge, 2006). Although these accruals provide useful information for investor's decisions, Sloan (1996) finds that investors fail to correctly assess the information provided by the separate components of earnings. Accruals tend to reverse in future periods and therefore are less persistent than cash flows. However, the results suggest that investors act as if they naïvely fixate on earnings.

On the other hand, accruals have a downside that negatively affects their usefulness for investor' decision making. As a result of intentional and unintentional errors in measuring accruals they are less reliable than cash flows. Dechow and Dichev (2002) state that this implies that larger accruals will result in lower earnings quality and less persistent earnings. Furthermore, Dechow and Ge (2006) argue that not only the magnitude, but also the sign of accruals influences the persistence of earnings. Large positive accruals improve earnings persistence relative to cash flows, but in firms with large negative accruals earnings are more transitory. They find that this is mainly due to the recording of negative special items in low accrual firms. Special items are 'unusual' or 'infrequent' events, such as restructuring charges and asset revaluations. These items are more likely to be found in firms that experience difficulties in their performance which generally applies to low accrual firms. The trouble with special items is that their underlying cause and implications can differ considerably. As a result, earnings are less persistent and less useful to predict future firm performance. Therefore, firms with low accruals and negative special items (special item-low accrual firms) are likely to operate in a more uncertain and volatile business environment.

In contrast, Dechow and Ge (2006) find that investors treat special items as if they have more consequences for future earnings than actually occurs. Investors typically have low expectations of the future performance of low accrual firms. These firms have a higher possibility of bankruptcy and delist more for performance related reasons. Delisting is defined as a removal from a stock exchange due to poor performance and/or bankruptcy (Beaver et al., 2007). Special items seem to confirm these prospects of low accrual firms, because investors react as if special items are 'bad news'. However, Dechow and Ge (2006) find that investors are too pessimistic, because on average special item-low accrual firms earn higher positive stock returns than other low accrual firms. These findings suggest that investors fail to distinguish the firms that improve their future performance from the ones that are less successful after the recognition of special items.

Hence, a method that is able to discover the firms that recover after the recognition of special items in low accrual firms can be of great value to investors. Prior research finds that special items do not improve the forecast model for future firm profitability which is consistent with the transitory nature of these items (Fairfield et al, 2009). Furthermore, managers tend to disclose further information on reported special items which could be useful for investors. Nonetheless, investors typically value this information as unreliable, because especially in firms that perform badly, this information is likely in favor of managers' own incentives (Doyle et al., 2003). However, a more reliable source of information is the reported financial statements of these firms. A financial statement analysis is a tool that uses current and past firm fundamentals to assess a firm's underlying value and to identify when stock prices differ from this value (Abarbanell and Bushee, 1998).[1] Although special items are surrounded with uncertainties, an analysis of firm fundamentals can be a powerful tool to circumvent these difficulties.

Moreover, the absence of other relevant and more reliable information in investor's assessment could explain the mispricing of special item-low accrual firms. This is because it

[1] Throughout this thesis, the terms *financial statement analysis*, *firm fundamental analysis* and *fundamental analysis* are interchangeable, because they refer all to the same concept.

appears that these investors behave in accordance with the 'confirmatory bias'. This theory of behavioral finance states that people (i.e. investors) tend to react more strongly to information confirming current beliefs and herewith disregard other news (Duong et al., 2010; Rabin and Schrag, 1999). This theory could imply that due to the typical low prospects of low accrual firms investors react too pessimistic toward the recognition of special items and concurrently disregard other fundamental information. Then, a fundamental analysis adds value to investor' decision making.

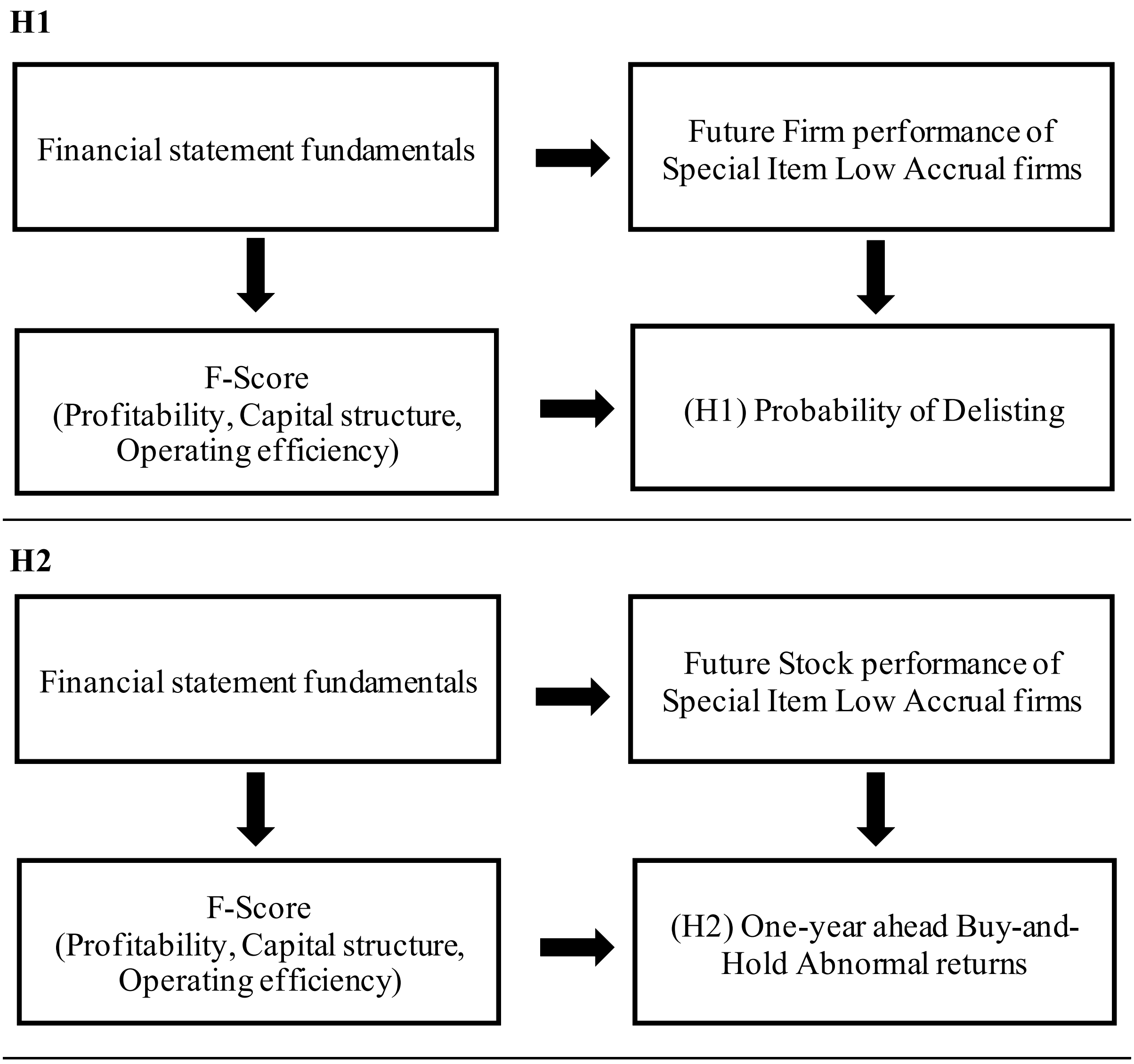
Therefore, this thesis examines whether a fundamental analysis is able to separate special item-low accrual firms that delist from the ones that turn themselves around and herewith can improve investors' assessment. This research on fundamental analysis is performed by means of the *F-Score* of Piotroski (2000). The F-Score is an aggregate score of nine fundamental signals that measures firms' profitability, capital structure and operational efficiency. A high (low) F-Score indicates that a firm has many (a few) good performance indicators and herewith a strong financial position. Moreover, I choose this method, because special item-low accrual firms show many similarities with Piotroski's sample of high book-to-market (BM) firms. Both firms are usually in financial distress; are performing poorly and the market often has low expectations of their future growth (Bird and Casavecchia, 2007; Dechow and Ge, 2006; Desai et al., 2004). While previous research finds that the F-Score is broadly applicable, this reduces the likelihood that the fundamental signals are misspecified for this study (Duong et al., 2010). Herewith, I develop two sub questions for the main research question.

First, I am interested in whether the fundamental signals of the F-Score relate to future firm performance in special item-low accrual firms. Previous research has found that low accrual firms have typically more firms that delist for performance related reasons which is a problem for investors (Dechow and Ge, 2006). Therefore, in this thesis the proxy for future firm performance is the probability of delisting. Then, the first hypothesis states that special item-low accrual firms with high F-Scores are less likely to delist than low F-Score firms.

Second, if the F-Score is useful to assess future firm performance, the second sub question arises whether investors fail to use this fundamental information in their assessment of special item-low accrual firms. The mispricing of special item-low accrual firms results in findings of significant excess returns. This can be due to the lack of use of the firm fundamental information contained in the F-Score. So, the second question can be addressed by examining whether a higher F-Score earns higher future stock returns. The proxy for these returns is the one-year ahead buy-and-hold abnormal returns (1yr BHAR). Then, the second hypothesis argues that firms with a high F-Score have higher abnormal returns than firms with a low F-Score.

Figure 1 illustrates the experimental tests of this thesis with the predictive validity framework of Libby et al. (2002). This shows that the research addresses both the relation of the F-Score with future firm and stock performance. I perform these tests on a sample of US-listed firms that report low accruals and negative special items in the period 1988-2009.

Figure 1 'Libby Boxes', Predictive validity framework (Figure 1, Libby et al., 2002)



Furthermore, the thesis builds upon and extends the recent literature on financial statement analysis. This stream of research has focused financial statement analysis on more context specific and refined subsets of firms. These are firms where the rewards of an analysis are expected to be the highest due to the likelihood of investor mispricing (Richardson et al., 2010). Prior findings suggest that a financial statement analysis could benefit investors, because these show that investors misprice low accrual firms when they record special items.

The results of this study suggest that the F-Score is able to predict future firm performance in special item-low accrual firms. However, it does not explain the mispricing of special item-low accrual firms, because investors already use the fundamental information of the F-Score in their decision making.

First, the results confirm that the F-Score is useful in identifying firms that are more likely to delist in special item-low accrual firms. Firms with a high F-Score are less likely to delist than firms with low F-Scores. The probability of delisting decreases from 20,39% to 10,60% in accordance with an increase of the F-Score. Thus, the association between F-Score and future delisting appears to be both statistically and economically significant.

Furthermore, the F-Score cannot explain the future stock performance of special item-low accrual firms. However, an additional test shows that investors appear to use the information of the F-Score in the assessment of special item-low accrual firms. Nonetheless, in other low accrual firms, the F-Score does relate to future abnormal returns. Moreover, although the F-Score is useful to assess future firm performance, market mispricing remains significant due to the inefficiencies related to special items. Thus, other omitted variables may explain market mispricing better than the F-Score in special item-low accrual firms.

Besides, an additional analysis shows that firm size influences the relation of the F-Score with future firm and stock performance. The probability of delisting is the lowest for large special item-low accrual firms. Furthermore, the largest firms also have the lowest future stock returns. This is consistent with the fact that large firms have high analyst following. This reduces information uncertainty and herewith the possibility of investor mispricing (Dechow and Ge, 2006; Piotroski, 2000).

The thesis is organized as follows. The next section provides the theoretical background on fundamental analysis and the characteristics of special item-low accrual firms. Section 3 develops the two hypotheses related to the main research question. Next, the fourth section discusses the research design and the empirical tests performed in this thesis, while Section 5 presents the results and findings of the financial statement analysis. Finally, Section 6 provides the main conclusions of this thesis.

2. Theoretical background

2.1. Fundamental analysis and firm valuation

The relevant academic literature on capital market research begins in the late 1960's with the influential paper of Ball and Brown (1968). Since then accounting research has been mainly performed in this broad research area. This study relates to the subarea within capital market research that is fundamental analysis and valuation (Kothari, 2001). Kothari (2001) states that the principal motivation of research on fundamental analysis is to support investment decisions, while Richardson et al. (2010) define this main purpose as forecasting. Both definitions apply to the purpose of research on valuation as well. That is why they often are grouped together. Not only is evidence on fundamental analysis found in the accounting literature on capital markets, it is also addressed by literature on behavioral finance. This finance research renders more in dept theory on investor' behavior that could explain the evidence on successful trading strategies based on fundamental analysis. Therefore, I include these findings further on in this literature review. Next, the concept and motive of fundamental analysis is further addressed.

2.1.1. Fundamental analysis

Current and potential investors evaluate a firm and its prospects on the basis of equity security analysis. This process involves establishing objectives, forming expectations of stock returns and risks, and combining the stocks in portfolios to utilize investor's objectives. Investors are often interested in having a comparative advantage in identifying market mispricing of stocks. Although there is more related to security analysis than only mispricing, it is mostly a key objective. A primary approach is to use a business or "fundamental" analysis which consists of a strategy analysis, accounting analysis, financial analysis and prospective analysis. Herewith, an investor attempts to evaluate the current market price relative to projections of the firm's future earnings and cash flow generating potential. This is one method for investors to predict future return behavior. Another method frequently employed by investors is technical analysis which does not observe firm fundamentals, but instead predicts share price movements on graphs, trends and/or market indicators (Palepu et al, 2010). Besides, when markets are efficient and so stocks are correctly priced, fundamental analysis can still be useful in contrast to technical analysis. This is because it aids the understanding of the determinants of firm' value which is useful for the valuation of non-publicly traded stocks (Kothari, 2001).

Accounting research focuses on traditional fundamental analysis which does not involve a huge amount of subjective judgment, but is based on more quantitative measures of firm's financial statements. This is basically the financial analysis in the overall business analysis. The analysis is based on the notion that firm value is indicated by the firm fundamentals and that market prices are mispriced when they differ from this value (Ou and Penman, 1989). Therefore, fundamental analysis can be defined as an analysis of current and past financial statement data to assess underlying firm value to determine when market prices differ (Abarbanell and Bushee, 1998).

Prior research has enhanced the basics of this fundamental analysis in two manners. First, it is important for the success of such an analysis to discover the key fundamentals in a firm's financial statements which are determinants of firm value. So, literature that documents evidence on value relevant fundamentals support investor' decision making. Second, although it can be useful in an efficient market, the main rewards on fundamental analysis are obtained when it helps to develop trading strategies that exploit market inefficiencies. Therefore, the theory on market efficiency or rather inefficiency is valuable to analysis of financial statements as well. Underneath, I discuss the prior findings on these important factors that have enhanced the theory on fundamental analysis.

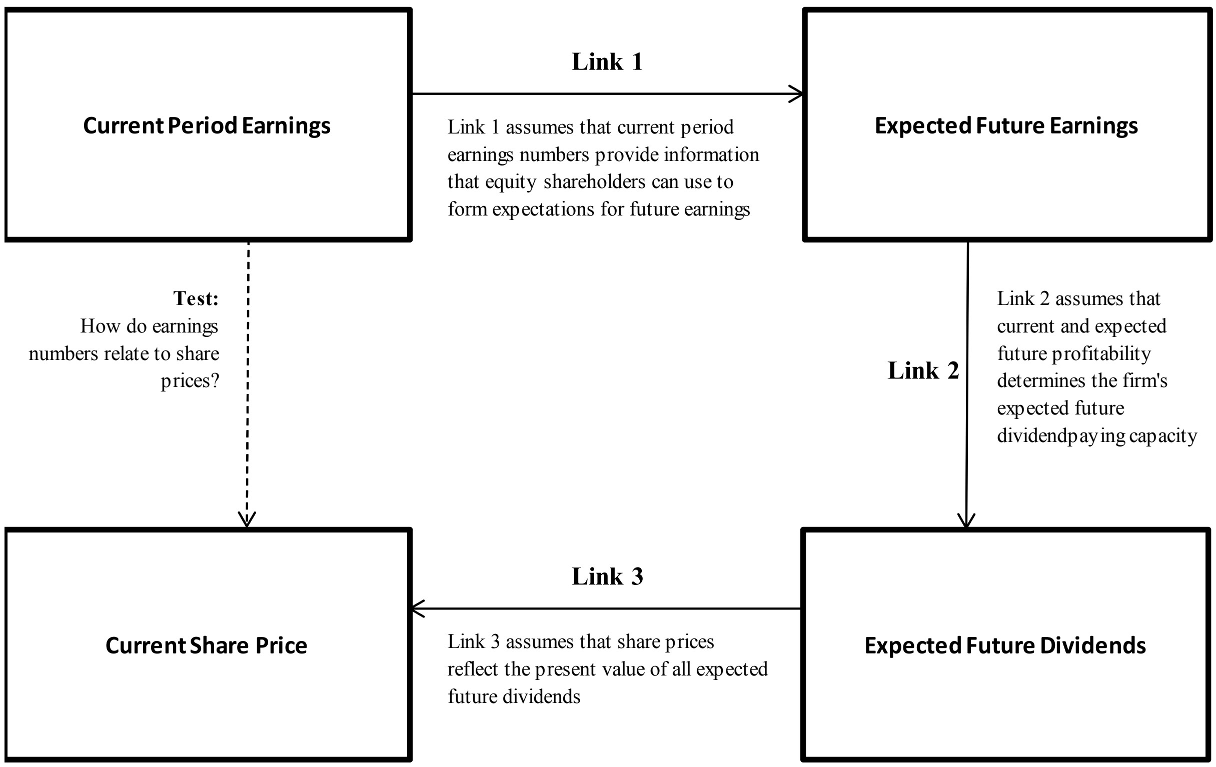
2.1.2. Value relevance and firm valuation

Several subareas in capital market research have been valuable for research on fundamental analysis in discovering key firm fundamentals.

First, fundamental analysis is enhanced by early capital market research on the value relevance of accounting attributes. An accounting attribute is inferred value-relevant when it is contemporaneously associated with stock prices. Ball and Brown (1968) were the first to indicate the value relevance of accounting earnings and some of its components. They find that a part of the information content of earnings components is incorporated in prevailing market prices, but its timeliness is rather low and the market seems to use other more prompt media. The study of Ball and Brown (1968) is followed by many other event and association studies in this area. Event studies test the information flow to the market when an accounting event (e.g., an earnings announcement) occurs and association studies test the relation of an accounting figure (e.g., earnings) and stock returns over a long, contemporaneous time period (e.g., one year). Herewith, accounting research examines whether and how quickly accounting measures capture changes in information that is reflected in stock returns (Kothari, 2001). E.g., Dechow (1994) examines whether the accrual component improves the association of earnings with stock returns. The paper shows the value-relevance of accruals, because cash flows are less able to reflect firm performance than earnings as a result of timing and matching problems. These early value-relevance studies have shown that earnings (and its components) and stock returns are related.

Furthermore, the study of Beaver (1998) shows how these earnings relate to returns by a theoretical framework that consists of three theoretical links. These links are: (1) current earnings provide information to predict future earnings, which (2) provide information to develop expectations about future dividends, which (3) provide information to determine share value, which then represents the present value of expected future dividends. Figure 2 illustrates these three links. The framework is based on three main assumptions. First, earnings (i.e. firm fundamentals) are informative to investors to assess current and future profitability. Second, these profitability figures provide investors with information on current and expected future dividends. Last, the framework assumes that share prices equal the present value of expected dividends (Nichols and Wahlen, 2004).

Figure 2 The Three Links Relating Earnings to Stock Returns, (Figure 1, Nicholas and Wahlen, 2004)



These links and assumptions are in conformity with theory on fundamental analysis, because it assumes that information of current fundamentals can determine earnings growth and eventually can lead to a firm's 'intrinsic' value. However, the perspective of the value relevance of accounting attributes is traditionally not the underlying notion of fundamental analysis. Value relevance assumes that market prices are sufficient for establishing firm values and serve as a benchmark to which the accounting information can be evaluated. So, it is not assumed that accounting attributes are relevant to determine the market price. In short, value relevance states that prices lead earnings. On the other hand, fundamental analysis does not use the stock price as the value benchmark, but instead compares the 'intrinsic value' discovered from firm fundamentals with the stock price to detect mispriced stocks (Ou and Penman, 1989).

Another stream of accounting research that examines earnings-returns relations is the earnings response coefficient literature. The earnings response coefficient (ERC) determines investors' responsiveness towards an earnings change and so proxies for the informativeness of earnings (Dechow et al., 2010). However, as the theoretical study of Holthausen and Verrechia (1988) states, although the ERC is useful in examining the price response to new information, a large number of other determinants are of influence to this relation. Kothari (2001) states that four main economic determinants are found in the literature. These are earnings persistence, risk, growth and interest rates. These factors are important in research on fundamental analysis, because they aid in identifying relevant and reliable firm fundamentals to include in an analysis and may explain the mispricing of stocks by investors.

Lastly, research on accounting-based valuation models is related to financial statement analysis, because these studies use accounting figures (instead of discounted dividends) to determine firm value. A commonly used accounting-based model is the residual income model, also called the Edwards-Bell-Ohlson (EBO) model. It is derived from the dividends-based valuation model that determines a stock's fundamental value as the present value of expected future dividends. This model is consistent with the three-links framework of Beaver (1998) discussed above. A firm's equity value (V) consists of present equity book value and a measure of the present value of 'residual income'. Residual income is defined as earnings less the costs of equity capital assuming the concept of clean surplus accounting. This holds when all changes in equity book value are accounted for in earnings except transactions to capital providers, such as dividends and capital contributions. The difficult task in this model is to estimate a firm's future residual income. Research finds that current year's return on equity (ROE) and analyst' forecasts are reasonable estimates to use to predict future residual income.

Furthermore, Frankel and Lee (1998) and Lee et al. (1999) find that value-to-price (V/P) ratios using estimates of analysts' forecasts are better predictors of US market returns than other measures, such as earnings-to-price (E/P) and dividend-to-price (D/P) ratios. Thus, the persistence of current period residual income is an important determinant of firm value (Frankel and Lee, 1998; Nichols and Wahlen, 2004).

Moreover, the theory of the accounting-based valuation model is aligned with traditional fundamental analysis. Lee et al. (1999) state that when intrinsic values are difficult to measure or transaction costs are high, the adjustment of price to value takes time. So, price does not always reflect firm value. In this case, the relation between price and value can be seen as a continuous process of convergence rather than a static equality. The difference of fundamental analysis with the residual income model is that the intrinsic value is not determined by discounting residual income (or other accounting measures), but instead using an analysis of current and past firm fundamentals to determine firm value and herewith stock prices that deviate from this intrinsic value.

2.1.3. Market efficiency and inefficiency

Secondly, an important theory in capital market research (e.g. value relevance studies) is the efficient market hypothesis. In its semi-strong form the market incorporates all information that is available to the market in a firm's stock price. Ball and Brown (1968) argue that capital market efficiency justifies tests on the value relevance of accounting information by examining stock return behavior. However, if market prices reflect all public information , the rewards of financial statement analysis will be diminished. So, in contrast to value relevance studies, market *inefficiency* is an important underlying notion for the usefulness of fundamental analysis. Prior accounting and finance research have found much evidence on inefficiencies in the stock market. Moreover, many research papers have developed trading strategies based on financial signals (that is typical for fundamental analysis) to exploit these market inefficiencies. They widely demonstrate the existence of predictable abnormal returns due to various market anomalies (Bird and Casavecchia, 2007).

Furthermore, two main explanations for these abnormal returns have emerged from prior research, the risk and mispricing explanation. The "risk versus mispricing" discussion has been central in the early literature on investors' misvaluation. First, the risk explanation states that excess returns are the fair compensation for fundamental risks, such as bankruptcy risk or high information uncertainty. E.g., when information is not easily obtained and investors disagree upon the value of a firm, it is likely that stockholders require a premium

(Dechow and Ge, 2006). In support of this explanation, Fama and French (1992) argue that investing in high BM stocks earns higher excess returns in comparison with other firms, because many of these high BM firms are in financial distress and therefore have a higher fundamental risk. So, risk is priced by the market. However, firm specific risks (e.g., bankruptcy risk) should be diversifiable by taking positions in large, diverse investment portfolios. Hence, in practice this method is employed by many investors (Dechow and Ge, 2006; Palepu et al, 2010).

Moreover, mounting evidence is in support of the second explanation and that is mispricing. Investors fail to correctly value the information conveyed by firm fundamentals. The research in support of the mispricing explanation documents four main market anomalies. These are the accrual anomaly, the value-glamour anomaly, the post-earnings announcement drift (PEAD) and the momentum anomaly (Beaver et al., 2007). Richardson et al. (2010) state in their review that the literature on accounting anomalies has grown differently from research on fundamental analysis. However, they also state that fundamental analysis could be described as subsuming the anomaly literature. This is because of their primary objectives of forecasting earnings and returns. I do agree with both statements. Although the first statement seems to indicate that anomaly literature is no longer related to fundamental analysis, the findings on market anomalies are useful to identify key firm fundamentals. Especially, for the subsets of firms that are likely subject to investor mispricing. Therefore, I discuss the anomaly literature underneath.

2.1.3.1. The Accrual anomaly

First, Sloan (1996) provides evidence on the accrual anomaly. Accruals tend to reverse in future periods and therefore are less persistent than operating cash flows. He finds that investors fail to correctly value the differential in persistence of the separate components of earnings, cash flows and accruals. A trading strategy based on firms reporting high and low levels of accruals generates positive excess returns. Sloan (1996) argues that the results suggest that investors appear to naïvely fixate on bottom line earnings. However, another explanation is provided by Xie (2001) . The accrual anomaly is caused by the overpricing of abnormal or discretionary accruals. Investors overestimate the persistence of these accruals that mainly stem from managerial discretion. On the other hand, the study excludes accrual changes due to major unusual items, such as special items, or unusual business circumstances, for example mergers or divestures.

In contrast to Xie (2001), Dechow and Ge (2006) take these unusual items into account and finds additional evidence on the anomaly. They find that accruals increase earnings persistence in comparison with cash flows in high accrual firms, but decrease the persistence in low accrual firms. This effect is caused by negative special items in low accrual firms which points at investors not understanding the transitory nature of special items.

The accrual anomaly and especially, the effect of special items are the main motivation for the type of firms subject to this thesis, special item-low accrual firms. Later in the literature review, findings on the characteristics of special item-low accrual firms will provide more information on the accrual anomaly apparent in these types of firms.

2.1.3.2. The Value-glamour anomaly

The literature documents a second anomaly between value (high BM) and glamour (low BM) stocks. The value-glamour anomaly is based on findings in the accounting and finance literature. Fama and French (1992) and Lakonishok et al. (1994), among others, document that on average value stocks earn higher future returns than glamour stocks. Next to the respectively high and low BM ratios of these stocks, they are characterized by other measures as well. Value stocks are generally identified by high earnings-to-price (EP) ratios, high operating cash-flow to price (CP) ratios and poor past growth of sales, earnings and/or cash-flows. Meanwhile, glamour stocks show mirrored ratios and growth figures (Desai et al, 2004).

As mentioned earlier, Fama and French (1992) explain the abnormal returns by investors wanting a fair compensation for the fundamental risk of certain stocks. However, Lakonishok et al. (1994) find no support for this risk explanation on misvaluation of value stocks and contradict this statement. They attribute the excess returns to a systematic pattern of errors by investors in assessing the future growth prospects. The market seems to be too pessimistic about the future as a result of weak prior performance and therefore value stocks are underpriced. Thus, when the poor past growth rate mean-reverts, the market is positively surprised by the performance of these stocks. Moreover, Bird and Casavecchia (2007) perform a financial statement analysis to examine the risk based and mispricing explanations for this value-glamour anomaly. The results of their study suggest that the existence of a value premium is more due to judgmental mistakes by investors in the pricing of stocks (mispricing) than to fundamental risks.

Furthermore, accounting researchers have also examined the distinction between the value-glamour and the accrual anomaly. This is because both anomalies are driven by the market extrapolating either past growth in sales, earnings and cash flows or accruals. Thus, market's inability to correctly process accounting information (Desai et al., 2004). Desai et al. (2004) state that when controlling for the CP ratio, a proxy for the value-glamour anomaly, the relation between accruals and future excess returns disappears. Hence, the mispricing of accruals seems to be manifested via the CP proxy of the value-glamour anomaly. However, Cheng and Thomas (2006) examine the same relation and the paper concludes that the accrual anomaly is not subsumed by this CP ratio.

Besides, Duong et al. (2010) investigate whether this anomaly may be explained by theory found in the behavioral finance literature. The researchers argue that many studies that investigate return patterns on trading portfolios do not determine what drives their observations. Value and glamour investors seem to respond to new financial information in two different manners. Value (glamour) investors tend to under react to good (bad) news, but incorporate bad (good) news accurately or even too quickly. Furthermore, their behavior is asymmetric in response to the financial information being released. Value investors appear to be much more pessimistic than growth investors. Overall, these findings are consistent with theory found on people's behavior, the confirmatory bias. People (i.e., investors) tend to react more strongly to information that corresponds to current beliefs and concurrently disregard other news (Rabin and Schrag, 1999).

The value-glamour anomaly is relevant for this study, because special item-low accrual firms show many similarities with value stocks. Typically, special item-low accrual firms have poor performance indicators and investors seem to treat special items as bad news which corresponds with the confirmatory bias. However, special item-low accrual firms also have low BM ratios due to significant negative accrual adjustments (Dechow and Ge, 2006). Hence, the effect of this anomaly on the rewards of this fundamental analysis is ambiguous.

2.1.3.3. The PEAD anomaly

The third anomaly is the PEAD anomaly. Ball and Brown (1968) were also the first to provide evidence on this phenomenon after an earnings announcement. Their evidence suggests that cumulative excess returns continue to drift up (down) for "good news" ("bad news") firms. Bernard and Thomas (1989) examine the reasons for this PEAD drift. Their results suggest that investors incorrectly assess the implications of current earnings for future earnings. This conclusion on investors' behavior has similarities with the explanations of the accrual anomaly. Therefore, Collins and Hribar (2000) investigate whether these two anomalies are measuring the same market inefficiency. They test trading strategies based on unexpected earnings and accruals and find that they capture different phenomenon of mispricing. This study examines a long horizon of one-year-ahead buy and hold abnormal returns and therefore probable excess returns in this study will mostly not be the cause of the PEAD anomaly.

2.1.3.4. The Momentum anomaly

Lastly, the momentum anomaly is based on the short-term failure of the market to recognize a trend (Lakonishok et al, 1994). Hong and Stein (1999) show in a theoretical setting the working of the momentum strategy based on technical analysis. When information is only slowly adopted into the stock price, prices under-react in the short run. This underreaction results temporarily in a market anomaly, because prior stock performance can be used to find certain trends and exploited to earn abnormal returns on short horizons. However, as a result of inherent externalities of this univariate strategy on other momentum traders, the arbitrage eventually disappears and inevitably leads to an overreaction in the long run. Jegadeesh and Titman (1993) find confirm this theory that a relative strength or momentum strategy based on buying (selling) firms with a good (bad) past 6-month stock performance prior to an earnings announcement and a holding period of 6-months, realizes significant abnormal returns. Additional evidence shows that this is indeed due to delayed price reactions to firm-specific information.

The consequences of the momentum anomaly for the fundamental analysis on special item-low accrual firms are hard to predict, because it does not relate directly to typical firm fundamentals and/or firms. Also, earnings announcement dates and prior stock returns are not obtained in this empirical study.

2.1.4. Prior research on fundamental analysis

The evidence on value relevant fundamentals and market inefficiency has led to a stream of research on fundamental analysis. Underneath, I discuss these papers on fundamental analysis in the period prior and beyond the year 2000. The two periods seem to have their unique characteristics.

2.1.4.1. Prior to the year 2000

The first period shows early fundamental analysis which can be described as a search for useful accounting variables to predict future returns. Other research on capital markets research, such as value relevance studies, has been the primary base for these studies (Richardson et al., 2010).

As shown earlier, the accounting literature documents abnormal returns based on one or a few firm fundamentals that are likely to relate to a market anomaly. Most of these studies can be described as univariate (or bivariate) strategies of financial statement analysis. This is because they also support investors' decision making by means of firm fundamentals (Ou and Penman, 1989).

The study of Ou and Penman (1989) was one of the first that combined financial signals (i.e. ratios) in an aggregate measure and tested whether this indicates the direction of future earnings. They identify a set of sixty-eight accounting signals (descriptors) that could predict future earnings and end up with a final indicator (*Pr*) containing binary specifications of sixteen to eighteen variables. Then, a trading strategy is employed taking long and short positions based on this summary measure. The returns indicate that stock prices do not appear to capture these fundamentals and so predictable abnormal returns can be earned. A critique on this method of fundamental analysis is that it uses a huge amount of financial statement information and employs a complex methodology. This makes the usefulness of this strategy questionable (Piotroski, 2000). Also, the final composite measure is significantly reduced due to missing data and the study ends up with different summary measures. This does not suit the main purpose of financial statement analysis that is supporting investment decisions.

The research of Lev and Thiagarajan (1993) takes another approach then Ou and Penman (1989) that uses a statistical search for fundamentals. They describe their method as a guided search procedure. It examines a set of twelve fundamental signals based on analysts' pronouncements and test whether these variables have incremental value-relevance over earnings. This aggregate score is strongly associated with the earnings response coefficient suggesting that the score captures important indicators of earnings quality (i.e. persistence). Their findings show an increase of 70% in explanatory power of earnings pertaining to excess returns. Furthermore, they conclude that macroeconomic variables are important conditions to include in capital market analysis, because this context increases the returns-fundamental relation considerably.

Abarbanell and Bushee (1997) take nine fundamental signals of Lev and Thiagarajan (1993) and test the relation of the individual signals with contemporaneous returns. They state that investors and analysts correctly use these fundamental signals as indicators of a firms' future performance. However, some of these signals capture only information about long-term earnings growth that is not impounded in analysts' forecasts which results in predictable forecast errors. This suggests that investors can benefit from the use of fundamental analysis including these signals even when analysts' forecasts are present.

A follow up study of Abarbanell and Bushee (1998) examines whether an investment strategy based on the nine financial signals composed by Lev and Thiagarajan (1993) can yield significant abnormal returns. In contrast to Ou and Penman (1989), the study, among others, investigates the individual contribution of the signals to the investment strategy. Moreover, they find that these abnormal returns seem to be earned around subsequent earnings announcements. Next to that, they find that the strategy performs better for certain types of firms, for example large firms and firms with prior bad news.

2.1.4.2. *Beyond the year 2000*

The results of Lev and Thiagarajan (1993) and Abarbanell and Bushee (1998) seem to indicate that fundamental analysis should be performed contextually, such as on certain types of firms or macroeconomic conditions. Therefore, the second period is characterized by the focus on more context specific or refined subsets of firms where market inefficiencies are more likely to appear. Hereby, the returns of a fundamental analysis are expected to be the highest (Richardson et al., 2010).

Beneish et al. (2001) make use of a two-stage approach to select the firms for fundamental analysis. The first stage of the analysis selects the likely extreme performers based on a combination of market-related variables (i.e. book-to-price ratio). Next, a strategy is developed based on accounting-based variables (i.e. accruals) to separate potential winners and losers in the selected extreme firms. They find that many fundamental variables differ in explanatory power of returns across the extreme and non-extreme firms. Only the variables of total accruals, earnings surprises and capital expenditures do not seem to be affected. Another prove of the importance of contextual analysis is the study of Soliman (2004). The paper finds that the fundamental variables of profit margin and turnover in traditional DuPont analysis are better valued against an industry-adjusted benchmark.[2]

Next, Piotroski (2000) applies a fundamental analysis on high BM (value) firms and is representative of an analysis on a specific subset of firms. He composes a score (*F-score)* of nine fundamental variables that indicates firm' profitability, capital structure and operational efficiency. The results suggest that an analysis of firm fundamentals can benefit investors in value portfolios. Investing in financially strong high BM firms and employing an investment strategy of buying expected winners and selling expected losers can generate significant annual stock returns. Additional analysis shows that the rewards are found in small and medium-sized firms, firms with low share turnover and no analysts following.

In a similar paper on fundamental analysis, Mohanram (2005) investigates whether a fundamental strategy can separate winners and losers in low BM firms. The strategy on these

[2] A DuPont analysis is a form of fundamental analysis that uses the two components of return on net operating assets, profit margin and asset turnover, to assess future firm performance.

firms does earn significant excess returns and persist after controlling for momentum and accrual anomaly factors. The results could be consistent with the value-glamour anomaly as the mispricing of growth fundamentals seems to be apparent in the findings of Mohanram (2005) as well. Further, the study selects fundamental variables for the summary score (*G-Score*) based on an analysis of the characteristics of low BM firms. This corresponds with the findings of Beneish et al. (2001) that variables can differ in their explanatory power for certain types of firms.

However, Duong et al. (2010) test the scores of Piotroski (2000) and Mohanram (2005) on both high and low BM firms and find that the scores can be used on the two types of firms. Moreover, Duong et al. (2010) provides several reasons for investor' behavior found in the behavioral finance (e.g., confirmatory bias) that can explain the success of the fundamental analyses performed by prior research, such as Piotroski (2000) and Mohanram (2005).

2.1.5. Summary

Investors often use fundamental analysis in equity security analysis to identify mispriced stocks. Accounting research examines the part of traditional fundamental analysis that focuses on the more quantitative measures of financial statements. In this study, fundamental analysis is therefore defined as an analysis of current and past financial statement data to assess underlying firm value to determine when market prices differ. Prior research enhances this research area by means of examining the value relevance of fundamentals and findings on market inefficiency.

First, value relevance studies (i.e. event and association studies) have shown that there is a relation between certain accounting attributes, such as earnings and accruals, and stock prices. Other research on earnings response coefficients has found that the relation is influenced by four main economic determinants: earnings persistence, growth, risk and interest rates. Lastly, research on valuation contributes to this evidence by relating fundamental information to firm value through an accounting-based valuation model.

Secondly, when markets are efficient, the rewards on fundamental analysis are diminished, because the market correctly assesses the information content of financial statements. However, much evidence is found on market inefficiency which is explained in two manners, risk and mispricing. The risk explanation states that this inefficiency is due to investors wanting a fair compensation for the fundamental risks related to the stock. Nonetheless, prior research finds more support for mispricing that argues that investors fail to correctly assess the available information. Investor mispricing is present in four main market anomalies: the accrual anomaly, value-glamour anomaly, PEAD anomaly and the momentum anomaly. Markets inefficiency in special item-low accrual firms is likely to be related to the accrual anomaly and to a lesser extent the value-glamour anomaly.

Research on fundamental analysis can be divided in two main periods, before and beyond the year 2000. The first period is characterized by a search for key firm fundamentals and ways to use these fundamentals to predict future stock returns. In the second period, research on fundamental analysis focuses on more context specific or refined subsets of firms. These firms are more likely to have future price movements and are difficult to assess in different manners (i.e. no analysts forecasts). Hence, market inefficiencies are expected and the returns to a fundamental analysis credibly the highest. This research follows this trend, because a fundamental analysis is possibly useful in taking advantage of the market inefficiencies related to special item-low accrual firms.

2.2. Special items and low accrual firms

The above findings in the financial statement analysis literature indicate that investors are to benefit from financial statement analysis on a subset of firms that have likely future price movements and are difficult to assess in different manners (e.g., analysts forecasts and voluntary disclosure). Therefore, this study chooses to examine special item-low accrual firms in accordance with the recent trend in financial statement analysis. The characteristics of special item-low accrual firms provide a unique opportunity for fundamental analysis to separate the expected winners from losers in future firm and stock performance.

2.2.1. Characteristics of special items

The recognition of special items is no random event, because these items highly relate to economic events and circumstances. These events can cause special item-low accrual firms to be significantly different from other low accrual firms (Dechow and Ge, 2006). In accordance with general accepted accounting principles (GAAP), special items can be described as: *“Material events that arise from a firm’s ongoing, continuing activities, but are either unusual in nature or infrequent in occurrence - but not both - and must be disclosed as a separate line item as part of income from continuing operations, or in footnotes to the financial statements.”* (Revsine et al. ,2005)

Underneath, I further explain these items and their consequences for a firm’s fundamental information.

2.2.1.1. Types of special items

First, the material events of special items can be split up into various types which are, among others, restructuring charges, goodwill impairments, asset write-downs and write-offs and gains or losses from the sale of assets (Fairfield, 2009). The reported special item component can contain positive (i.e. gains on asset sales) and negative special items. Nonetheless, Cready et al. (2012) find that negative special items form a far larger proportion of reported special items. Dechow and Ge (2006) even document that about 55% of low accrual firms report negative special items and 3% positive special items in the period 1988-2002. Furthermore, all types of special items have the similar characteristic that they either are *unusual* or *infrequent*. On the other hand, their underlying economics and meaning for future firm performance can differ substantially.

Firstly, negative special items are indicative of a firm reducing its asset base, downsizing and exiting lines of businesses. It could imply that these measures are necessary because of poor market circumstances. However, it is also possible that management is taking action to improve future firm performance. Thus, the implications of these items are uncertain beforehand (Dechow and Ge, 2006). Furthermore, the implication of a charge could depend on other factors, such as macroeconomic factors and/or current fundamental signals. E.g., restructuring charges often convey information on better future prospects, but it is unsure whether the restructuring will be successful and does indeed reflect this notion.

Secondly, these charges can be due to compliance with accounting regulations. If the fair market value of an asset (e.g., goodwill) on the balance sheet is lower than the book value, accounting standards require the asset to be revalued. This is in conformity with the balance sheet perspective that has the proper valuation of assets and liabilities as the primary objective (Dichev, 2008). The asset impairment can be the result of difficult market circumstances, but the mandatory nature of this charge does complicate assessing the implications for future performance. So, it could be that it still conveys relevant information.

2.2.1.2. Managerial discretion

Second, the uncertain nature of these special items is subject to earnings management. Managers can use their discretion for inter-period transfer of income, expense or classification shifting.

The first method hypothesizes that firms can use either positive or negative special items to transfer current income to future income and vice versa. Cready et al. (2012) states that the special item transfer differs from the use of accruals. Current income is often increased via accruals by borrowing against future earnings. However, a transfer via negative special items decreases current income and transfers this to future income by recognizing future expenses more quickly. Typically, special item transfers are bounded by the amount of the charge (e.g., a restructuring charge is directly linked to the estimated future costs of restructuring), not sustainable in perpetuity and must be eliminated at some point in time.

Burgstahler et al. (2002) state that their findings are consistent with firms shifting expenses from future periods into the current period via negative special items (e.g., restructuring charges). Negative special items are succeeded by earnings of the opposite sign in the subsequent (i.e. four) quarters. However, the research of Cready et al. (2012) performs an additional analysis on this statement. They examine whether earnings are also affected beyond the four quarter period of Burgstahler et al. (2002). The researchers argue that the findings can be explained by the economic consequences of special items. The underlying events can result in real future performance improvements on short and longer horizons. Their findings corroborate this notion. Earnings directly linked to the negative special items represent an increase over the 16 subsequent quarters to more than the original charge (i.e. 130%). The increase is mostly attributable to current activity of a non-transferable nature. The found earnings effect can even be greater, because, as explained below, classification shifting of core expenses to special items could overstate the original charge.

The second method does not transfer income between periods, but instead shifts expenses between the separate line items of the income statement. This is called expense or classification shifting. Accounting standards require to recognize special items as separate, low line items in the income statement. Typically, lower line items are indicators of a less persistent component of earnings. Therefore, management can improve their core earnings by shifting core expenses, such as costs of goods sold and SG&A expenses, to special items. Although total income is not changed or transferred by this method, managers influence analysts and investors by shifting core expenses to a less persistent earnings component. This influences analyst's projections, because generally they exclude special items from pro forma earnings forecasts (McVay, 2006). Bradshaw and Sloan (2002) find that investors react more strongly to pro forma earnings than to GAAP (i.e. bottom-line) earnings. Therefore, managers do appear to emphasize the transitory nature of special items in their voluntary disclosure. However, manager's discretion can cause one firm to exclude a special item and another firm including an identical item in pro forma earnings (Doyle et al., 2003). So, user' assessments are even more negatively influenced by the presence of special items. Thus, managers can meet forecasted earnings benchmarks by means of special items through expense shifting and the voluntary disclosure of pro forma earnings (McVay, 2006).

2.2.1.3. Market responses to special items

Last, the uncertain economic consequences and the possibilities of earnings management are of influence on the behavior of the users of financial statements. Therefore, whether the market reacts correctly to these circumstances of special items has been subject to prior accounting research.

Elliot and Hanna (1996) finds consistent with Bradshaw and Sloan (2002) that investors also attach more weight to unexpected earnings before asset write-offs. This corresponds with investors viewing write-offs as non-recurring events. However, the study also documents that the frequency of large write-offs significantly increased in the period 1975-1994 to over 21% of the firms. Moreover, special items tend to be recurring after a firm has reported a write-off. Thus, investors that do not take this notion into account are likely to misprice firm value. The findings of Doyle et al. (2003) confirm this statement. Management excludes certain expenses from pro-forma earnings and presents them as non-recurring or unimportant for future value. However, these expenses seem to be more recurring. Therefore, investors that focus on pro forma earnings fail to fully appreciate the information contained in other items. Managerial discretion appears to cause this recurrence of typically 'non-recurring' items. E.g., restructuring charges are estimated costs of future cash expenditures. On the other hand, estimates cannot naturally be verified upfront and therefore could also be misestimates. Also, inventory write-downs and asset impairments can be classified as discretionary accruals, because the timing and amount of these charges is subject to managerial discretion (Doyle et al., 2003).

Furthermore, Black et al. (2000) examine whether special items are value relevant for firm valuations of investors. The study states that the recording of special items on a regular basis could indicate that these items have become relevant permanent earning components. They argue that investors appear to value a special item when a firm has reported multiple special items in the past six years, because it generates a negative stock-price effect. Additional analysis shows that this negative reaction of investors is consistent with findings on these firms having higher bankruptcy risks and patterns of earnings management practices.

Besides, Fairfield et al. (1996) investigate whether disaggregating earnings into operating, non-operating and special line-items and weighting them differently in the forecast model improves one-year-ahead forecasts of return on equity. The separated line-items seem to have predictive content for future profitability in line with the classification scheme of accounting standards (i.e. higher line items are more persistent).

On the other hand, Fairfield et al. (2009) state that this relation depends on the current profitability of the firm. Special items are mostly larger and reported more frequently in low profitability firms. However, in these firms they appear to contain no information on future profit margins. On the contrary, in high profitability firms future profit margins are lower when special items are recognized and should therefore be included in analysts' forecasts. Moreover, the findings of Dechow and Ge (2006) are consistent with the transitory nature of special items in low profitability firms. The sample of special item-low accrual firms show typically poor performance measures and are likely to have low profits. However, Dechow and Ge (2006) find that investors do react towards special items and often too negatively, because on average low accrual firms show better future firm performance than is expected by investors.

2.2.2. Characteristics of low accrual firms

Accruals similar to special items are also related to firms underlying business operations. Therefore, the recognition of special items and low accruals both convey information to investors about a firm's business environment. Dechow and Ge (2006) document characteristics of these low accrual firms and in particularly, the ones that recognize special items. These are asset revaluations, decline in investor recognition (i.e. analyst following and institutional investors), poor past performance and financial distress.

2.2.2.1. Low accruals and asset revaluations

First, a type of special item charge is an asset revaluation. These items have various consequences for investors' assessment of accruals and earnings persistence. Sloan (1996) states that investors fail to correctly value the lower persistence of the accrual component in earnings in conformity with the accrual anomaly. In low accrual firms, large negative accrual adjustments appear to bring more noise to the relation with earnings persistence. Dechow and Ge (2006) argue that these adjustments are more likely to be special item charges than large cash inflows that match with related accruals. This is due to the balance sheet perspective of accounting regulations that require a firm to revalue an asset when the market value is lower than its book value. Therefore, not only the magnitude of accruals affects earnings persistence, but also the sign and cause of the accrual adjustments, especially in low accrual firms. This complicates investors' assessment of large negative accruals and could increase the predictable abnormal returns.

Furthermore, the evidence of Bradshaw et al. (2001) appear to correspond with these findings on the effect of the magnitude and sign of accruals on earnings persistence and future stock performance. They form portfolios based on high and low accruals and find that both show strong mean reversion of earnings in the first year and after three years the mean reversion is almost complete. This effect leads to significant forecast errors of earnings and results in high future stock returns. However, in the low accrual portfolios more accruals are non-recurring items, such as special items, which appears to be partly anticipated by the market and leads to lower forecast errors. Nonetheless, these errors remain significant.

2.2.2.2. Declining investor recognition

Next, Dechow and Ge (2006) describe low accrual firms as typically having less analyst following and institutional holdings. Financial analysts do appear to be less interested in firms with poor performance, low trading volume and smaller firms which applies to a large part of low accrual firms. The level of analyst following has important implications for a firms information environment and managers' incentives (Piotroski, 2000).

Firstly, the information environment of (special item-)low accrual firms is uncertain, because information uncertainty decreases with the level of analyst following. Normally, analysts provide investors with valuable forecasts and so convey additional information to firms external reporting. However, analysts seem to move away from low accrual firms that record special items. This is because they are often pessimistic about their future growth rates. Moreover, forward-looking information that is voluntary provided by management is often seen as unreliable in firms that are financially distressed (Koch, 1999). These two findings could cause investors to require a value premium for higher information uncertainty in low accrual firms. On the other hand, Dechow and Ge (2006) find that, although analyst coverage declines with the reporting of special items, it does often remain present in special item-low accrual firms. These firms are generally larger in size than other low accrual firms that is typically related to more analyst following.

Secondly, special items can be subject to earnings management, but management's incentives to perform such actions are highly influenced by analysts coverage. McVay (2006) finds that classification shifting of expenses is more apparent in high growth firms. This is due to its use to meet earnings benchmarks of analysts' forecasts which is less relevant in low growth (i.e. low accrual) firms. This could indicate that recognized special items in low accrual firms are more related to current firm activity and its circumstances than to earnings management.

2.2.2.3. *Poor past performance and financial distress*

Furthermore, low accrual firms reporting special items show on average poor past performance and are financially distressed. The study of Kahn (2005) documents several indicators of low accrual firms typically being bad performers. The sample of low accrual firms from 1971 to 2002 shows on average negative earnings, high leverage, low or negative sales growth and higher bankruptcy risk. Moreover, Kahn (2005) and Dechow and Ge (2006) find no evidence that this fundamental risk on bankruptcy is priced by the market which again contrasts the risk explanation for the misvaluation of firms by investors. Additionally, Dechow and Ge (2006) finds that low accrual firms report a higher percentage of losses and lower asset growth than other accrual firms.

2.2.2.4. *Market responses to special item-low accrual firms*

Besides, Dechow and Ge (2006) find important evidence on investor' behavior to low accrual firms reporting negative special items. Their results of a trading strategy earns on average higher positive returns than other low accrual firms in a sample of US-listed firms in the period 1988-2002. However, the strategy does have specific risks. Although the study uses several screens (e.g., avoiding low stock prices and market values) these firms have a higher chance of bankruptcy and more firms delist because of performance issues. It is therefore relevant for investors to be able to separate these firms from those that have better future stock performance.

2.2.3. Summary

Special items are material events that either are unusual or infrequent, such as restructuring charges, impairment charges and asset write-downs and write-offs. Although special items are unusual or infrequent, these items are not random events, because they highly relate to underlying economics. Negative special items can be caused by poor market circumstances, management taking actions to improve firm' performance or compliance with accounting regulations. Thus, their cause can differ essentially and so, the implications for future firm performance.

Furthermore, special items are subject to earnings management practices, because managers can use discretion in their timing and magnitude. Earnings can be managed by inter-period transfer of income, expense or classification shifting. Mostly negative special items are used to transfer income between periods by decreasing current income and report better income in future periods. The shifting of expenses to special items, or vice versa, is often used to meet forecasted earnings benchmarks, because more value is attached to core and pro forma earnings than the actual earnings figure.

Moreover, financial statement users are influenced by these uncertainties of special items. Managers, analysts and investors view special items as less important than less unusual and more recurring events. Typically, special items are excluded from pro-forma earnings and analyst' forecasts. However, prior literature states that special items tend to recur after firms report a special item which is related to manager' discretion. Evidence is found that the reoccurrence of special items has negative stock price effects. Further, special items are less predictive for future profitability than higher line-items. In low profitability firms, special items even appear to have no informational use to predict future profitability. Nonetheless, prior research on low accrual firms finds that investors react as if special items have more value to predict future earnings. They react often too pessimistically towards the recognition of special items, because on average these firms show better future firm performance.

Further, low accrual firms are characterized by the following: mandatory asset revaluations, decline in investor recognition, poor past performance and financial distress. In low accrual firms, asset revaluations make it more difficult to assess earnings persistence, because these items are likely to be recognized due to compliance with accounting standards. Next, low analyst following and institutional holdings increase information uncertainty, but management has lesser incentives to manage earnings. However, special item-low accrual firms are larger in size and remain a certain level of analyst following. Finally, low accrual firms report losses, have high leverage, higher bankruptcy risk and low or negative earnings, sales and asset growth which indicates their bad performance and financial distress.

The characteristics of low accrual firms and special items make it difficult for investors to assess special item-low accrual firms. Notwithstanding, research finds that on average a trading strategy on special item-low accrual firms earns higher abnormal returns than other low accrual firms. Therefore, a fundamental analysis on special item-low accrual firms can be a useful tool to distinguish the firms that are likely to improve future firm performance from the ones that do not and eventually delist.

3. Hypotheses development

The theory and prior research findings on fundamental analysis and special item-low accrual firms give rise to certain expectations on the main research question. Therefore, this section uses the theoretical background to develop the two main research hypotheses. The first hypothesis states that those firms with high F-Scores are less likely to delist than low F-Score firms. The second hypothesis argues that special item-low accrual firms with a high F-Score have higher abnormal returns than the firms with a low F-Score.

Special items are difficult to assess for investors, because by definition these underlying events are either unusual or infrequent. These charges are therefore unpredictable and likely to have low earnings persistence. This is why analysts and managers typically exclude these items from forecasts and/or pro-forma earnings announcements (Doyle et al., 2003; Fairfield et al., 2009). However, although special items are unusual or infrequent, they do relate to underlying economics and have implications for future firm performance. This notion is important for investors of low accrual firms, because these firms already show poor past performance figures, are in financial distress and have high information uncertainty. Dechow and Ge (2006) find that investors often see negative special items as 'bad news'.

This reaction is consistent with the confirmatory bias. The special items appear to confirm the generally low prospects of low accrual firms. Hence, investors react pessimistically (Duong et al., 2010). However, these special items are not necessarily bad signals for future performance. The underlying events, especially in low accrual firms, frequently do reveal difficulties in the firm's business environment. Special items are recognized due to poor market circumstances, compliance with accounting regulations or earnings management practices (Elliot and Hanna, 1996; Fairfield, 2009; McVay, 2006). On the other hand, although these circumstances seem not favorable for investors, these charges could also indicate a turnaround. Management can be taking actions to improve future firm performance, such as a restructuring charge. The findings of Dechow and Ge (2006) confirm this statement. Low accrual firms show better firm performance at higher rates than expected by investors. So, generally investors react *too* pessimistic to the reporting of special items. As a result, they find that special item-low accrual firms often outperform other low accrual firms in future stock performance. Although special items do seem to have meaning for future firm performance, the uncertainty surrounding these consequences still makes it hard to develop the right expectations. Fairfield et al. (2009) examine whether incorporating special items in the forecasting model can be beneficial for the assessment of a firms' future profitability. The research states that special items have predictive value in high profitability firms, but not in low profitability firms. Low accrual firms are typically firms with poor performance and low profitability figures (Dechow and Ge, 2006). Therefore, using special items in a forecasting model for future firm performance does not appear to improve investor' assessments for this subset of firms. Moreover, managers generally disclose additional information about the recorded special items in pro forma earnings. However, managers have incentives to meet earnings benchmarks in firms with analysts following. When a firm shows poor performance figures, managers can be using special items to manage earnings. Therefore, investors appear to value this information as unreliable in special item-low accrual firms (Doyle et al., 2003).

Another tool that can be used to assess future firm performance is an analysis of a firm's financial statements. Fundamental analysis is an analysis of current and past firm fundamentals to determine the incremental value of a firm. Hereby, it can be used to identify mispriced stocks (Ou and Penman, 1989). The usefulness of a fundamental analysis depends on whether market inefficiencies are apparent and if the fundamental information used in the analysis is value relevant. First, when investors do not (or are not able) to correctly value the information provided to the market, markets are (temporarily) not efficient. This is likely apparent in the case of special item-low accrual firms. These firms show fundamental characteristics, such as extreme (low) accruals, special items and low BM ratios, where market anomalies are likely to be found. Moreover, Dechow and Ge (2006) find evidence of market inefficiencies in their study of special item-low accrual firms.

Furthermore, this thesis performs a fundamental analysis using the same method and firm fundamental information as Piotroski (2000). Piotroski uses an aggregate score of nine firm fundamentals called the F-Score to rank a sample of high BM firms. The firm fundamentals reflect a firm's profitability, capital structure and operational efficiency. A high F-Score indicates that a firm has relatively strong current performance and a low F-Score represents the opposite. Therefore, when a firm's current performance contains information on future firm performance (consistent with link 1 of the three-links framework (Figure 2)), the F-Score is valuable for investors to assess a firm's future firm performance.

Moreover, low accrual firms are generally in financial distress and are more likely to delist for performance related reasons (Dechow and Ge, 2006). This is a typical concern for investors, especially when special items are recognized and their implications are uncertain. While the F-Score is a tool to assess future firm performance, the F-Score can be used to distinguish firms that delist from the ones that turn themselves around. A firm with a low F-Score has only a few good performance signals and therefore is less likely to improve future firm performance. Therefore, when firms have a lower F-Score, it is likely that the probability of delisting due to performance related reasons is higher. Hence, the first hypothesis is as follows:

H1a: Special item-low accrual firms with a high F-Score are less likely to delist than firms with a low F-Score

If the F-Score is able to estimate future firm performance in special item-low accrual firms, it is a valuable tool for investors to use in their firm assessments. However, the question remains whether these investors previously included this information in their decision making concerning the recognition of special items. A sign that investors disregard other fundamental information is that they typically view recorded special items as 'bad news'. This is consistent with the confirmatory bias that people react more strongly towards information that confirms their prior beliefs and herewith disregard other news (Duong et al., 2010). If this applies, special items validate the usually low prospects of future firm performance. As a result, investors react pessimistically towards the recognition of special items and herewith disregard other news, such as other relevant and more reliable fundamental information. Thus, the F-Score should be able to explain, at least partly, the evidence found on the future stock performance of special item-low accrual firms. Subsequently, the mispricing of special item-low accrual firms should be the highest for firms that show good performance signals. These are the firms with the highest F-Scores. Hence, the second hypothesis can be formulated as:

H2a: Special item-low accrual firms with a high F-Score have higher abnormal returns than firms with a low F-Score

Although rewards are expected from a fundamental analysis on special item-low accrual firms, these firms do have several characteristics that counter the feasibility of a fundamental analysis. Therefore, ex ante, the effectiveness of the fundamental analysis is unclear for special item-low accrual firms.

Firstly, analyst coverage is often linked to higher quality of available information and so less mispricing by investors. Although analysts often drop their coverage of low accrual firms due to low future growth prospects, low accrual firms that report special items often sustain longer attention of analysts. This possibly is because these firms are on average larger in size than other low accrual firms. This reduces the possibility of investors mispricing a firm's fundamental value (Dechow and Ge, 2006). The findings of Piotroski (2000) are consistent with a reduction of mispricing in larger firms, because he finds mainly support for small and medium-sized firms in his research on high BM firms.

Secondly, it is unclear whether the current fundamentals aggregated in the F-Score capture all relevant information of a firm's financial statements. First, as inherently related to the use of the F-Score, possible relevant information is lost due to the use of an aggregate score of binary signals instead of the actual firm fundamental values. However, the score is more easily implemented by investors and one measure of a firm's overall financial position is possibly more useful than actual values.

Thirdly, the second concern regarding the use of the F-Score is that it is highly likely that special item-low accrual firms have negative accrual levels; by definition, these firms have low accruals and negative special item charges. It is therefore unclear whether the accrual signal of the F-Score is effective in capturing the possible accrual anomaly. Thus, it is questionable whether the accrual signal contributes to the overall strength of the F-Score.

Finally, the third concern is that the signals of the F-Score are not specifically chosen on their value in assessing the implications of special items. The F-Score is designed to capture the overall strength of a firm's financial position. Therefore, the strength of the F-Score to determine future performance depends on the relation of special items with other firm fundamentals. The strength of the F-Score is enhanced when special items are highly transitory and do not relate to future firm performance. However, Cready et al. (2012) finds that special items can have long term effects. Or, it could be that real improvements of special item charges are more likely to be expected in firms that are financially strong. Meanwhile, as shown by the study of Fairfield et al. (2009), in low profitability firms special items appear to contain no information on future profit margins and have no value for the forecasting model. Therefore, this could imply that the best method to predict future firm performance in special item-low accrual firms is to focus on the key firm fundamentals.

4. Research design

This section is a detailed discussion of the methodology and sample used to test the two main research hypotheses. First, I evaluate the method of the F-Score and describe the proxies of future firm and stock performance. Herewith the equations used to perform the main tests are developed. The section concludes with a description of the steps that are used to obtain the sample of special item-low accrual firms.

4.1. Methodology

The method of financial statement analysis corresponds with the research methodology of Piotroski (2000). He investigates whether an aggregate score of firm fundamentals, named the F-Score, relates to future stock performance in a fundamental analysis of high BM firms. I choose to use the same method, because special item-low accrual firms and high BM firms have similar characteristics. Piotroski (2000) finds that more than half of the high BM firms experience high levels of financial distress and poor profitability which is similar to findings of Dechow and Ge (2006) on special item-low accrual firms. The difference with high BM firms is that special item-low accrual firms usually are larger in size and have low BM ratios. Further, Duong et al (2010) find that the model of Piotroski (2000) is also applicable to low BM firms and therefore appears useful for other types of firms as well. This reduces the likelihood that the model of Piotroski (2000) is misspecified for this study. Hence, it is likely that the method of the F-Score suits the characteristics of special item-low accrual firms.

Furthermore, the method of Piotroski (2000) makes use of an aggregate index score of firm fundamental information in contrast to traditional fundamental analysis. This type of analysis determines the incremental firm value based on actual firm fundamental values. The F-score does not attempt to measure this incremental value, because it only uses indicator variables derived from the underlying firm fundamentals. In this manner the score can be used as a tool to predict future firm performance and identify stocks that are currently mispriced by investors.

On the other hand, the use of an index score inevitably results in the loss of information content. The methodology is also in contrast with the findings of a DuPont analysis of Soliman (2008). Soliman (2008) states that analysts correctly assess the information of a change in asset turnover at least from a directional perspective (positive or negative). This is because this change appears to be associated with contemporaneous forecast revisions. On the other hand, he does find that analysts do not fully use the information of the actual change in asset turnover, because predictable forecast errors are observed. Hence, it could be argued against the method of Piotroski (2000) that actual values should be used for analyzing purposes. However, the DuPont analysis of Soliman (2008) only consists of two firm fundamentals, profit margin and asset turnover. So, this method disregards other useful information of key fundamentals as well.

Moreover, Piotroski (2000), among others, favors an aggregate index score over the use of actual values or complex statistical techniques (e.g., factor analysis), because the method is more easily implemented and still captures the overall financial position. Hence, it has more practical implications for investors, because investor decisions can be based on the strength of one aggregate signal (Duong et al., 2010). This corresponds with the main objective of fundamental analysis that is to identify mispriced stocks to support forecasting and valuation. Next, the F-Score and its fundamental variables are defined and further introduced.

4.1.1. The F-Score

The F-Score can be described as an aggregate signal to measure the overall strength of a firm's financial position. The score consists of binary measures of nine fundamental signals that are indicators of a firm's profitability, capital structure or operating efficiency.[3] These signals are either 'good' or 'bad' based on their implications for future firm performance. The aggregate of the good ('1') and bad ('0') signals results in the final F-Score. The F-Score can be equated as follows:

$$(1) \qquad F_{SCORE} = F_{ROA} + F_{\Delta ROA} + F_{CFO} + F_{ACCRUAL} + F_{\Delta LEVER} + F_{\Delta LIQUID} + F_{EQISS} + F_{\Delta MARGIN} + F_{\Delta TURN}$$

Since there are nine underlying indicator variables, the F-Score can vary from a low of zero to a high of nine, where a high (low) F-Score illustrates a firm with many (a few) good fundamental signals. Hence, a high F-Score is expected to be positively related to changes in future firm performance and stock returns. Underneath, I discuss the nine fundamental variables of the final F-Score that are included by Piotroski (2000). These variables are discussed along three main categories: profitability, capital structure and operational efficiency.

[3] In Appendix A, the definitions of the variables used in this research are tabulated.

4.1.1.1. F-Score signals: Profitability

Piotroski (2000) argues that, as prior research demonstrates, variables that capture accounting returns and cash flows (and their relation to each other) should be central to current financial statement analysis. Therefore, the first four fundamental signals are related to this notion and measure the overall profitability of the firm. These are the return on assets (ROA), change of return on assets (ΔROA), cash flow from operations (CFO) and operating accruals (ACCRUAL). Firms can be classified as financially strong when they are currently profitable. If current profitability relates to future profitability, these firms are more likely to maintain this strength in the future (Mohanram, 2005). This assumption is in conformity with the first link of the three-links framework (Figure 2) that relates current to future earnings.

Furthermore, current profitability and cash flow from operations provide information about a firm's ability to generate funds internally. A firm is financially strong when it is able to continue its business operations without being dependent of outside funds of investors and lenders (Palepu et al, 2010). First, the variables of ROA and CFO are defined as respectively net income before extraordinary items and cash flow from operations scaled by average total assets.[4] Given that special item-low accrual firms generally show poor performance figures, current positive earnings (ROA>0) and cash flows from operations (CFO>0) are good signals for any firm. If the firm's ROA (CFO) is positive, the indicator variable F_{ROA} (F_{CFO}) is equal to one and zero otherwise. Next, ΔROA is the current year's ROA less prior year's ROA. If the earnings trend is positive (ΔROA>0), a firm's underlying ability to generate positive future cash flows is improved as well. If ΔROA is greater than zero, the indicator variable $F_{\Delta ROA}$ is one and zero otherwise (Piotroski, 2000; Palepu et al., 2010).

Moreover, the importance of accruals is shown, among others, by the findings of Sloan (1996). He finds that accruals are less persistent than cash flows. This indicates that a firm with positive accrual adjustments (i.e. earnings are greater than cash flow from operations) is likely to have a negative effect on future earnings and returns. Therefore, it is expected that the effect of firms reporting negative accruals or higher cash flows than their return on assets, CFO>ROA, is positive. In this case, the indicator variable of operating accruals, $F_{ACCRUAL}$, is one and zero otherwise (Piotroski, 2000). One note regarding this signal is that special item-low accrual firms typically have large negative accruals. This significantly reduces or eliminates the variation of the accrual signal and herewith its added value to the overall strength of the F-Score.

[4] I choose to scale all the fundamental variables of this research on average total assets in contrast to Piotroski (2000), but aligned with the computation of the special item-low accrual firms of Dechow and Ge (2006).

4.1.1.2. F-Score signals: Capital structure

The second category of signals relates to the capital structure of a firm and its ability to meet future debt funding obligations. The three related fundamentals are the change in the leverage ratio ($F_{\Delta LEVER}$), change in the liquidity ratio ($F_{\Delta LIQUID}$) and whether or not a firm has issued equity (F_{EQISS}).

First, the leverage ratio is the change in the firm's debt-to-assets ratio during the fiscal year. The debt-to-asset ratio is further defined as the firm's total long-term debt (including the portion of long-term debt classified as current) scaled by average total assets. This change is important for future performance, because special item-low accrual firms are mostly financially constrained and experience financial risks. If the leverage ratio increases, the need to finance the firm's activities with external capital has grown and signals the inability to generate sufficient internal funds. Furthermore, the increase in long-term debt possibly constrains the firm's financial flexibility even more as a result of additional debt covenant restrictions. So, the F-Score variable ($F_{\Delta LEVER}$) is one if the leverage ratio has decreased ($\Delta LEVER<0$) and zero otherwise (Piotroski, 2000; Palepu et al., 2010).

Second, the liquidity ratio (i.e. current ratio) demonstrates the firm's ability to fulfill current debt obligations. An improvement in the firm's liquidity ratio is a good signal for firms that are financially distressed. The F-Score variable measures the change in a firm's current ratio defined as total current assets divided by total current liabilities. A positive change proves that a firm is able to generate a positive overall cash flow and is more able to fulfill its debt obligations. Thus, the indicator variable ($F_{\Delta LIQUID}$) is one if the change in the liquidity ratio is positive and zero otherwise.

Finally, a firm can raise external capital through an increase in long-term debt, but also with an issue of equity. Similar to the leverage ratio, this is a signal that the firm is not able to generate enough internal funds for the firm's future obligations. Furthermore, a firm that chooses to issue equity to generate additional funds when their stock prices are low shows the bad financial condition the firm is in. Besides, investors can interpret an equity issuance as if stock prices are overvalued and therefore the costs of capital are considerably high for special item-low accrual firms. Thus, an equity issuance is seen as a bad signal and then the indicator variable (F_{EQISS}) is zero and one otherwise (Piotroski, 2000; Palepu et al., 2010).

4.1.1.3. F-Score signals: Operating efficiency

The last two variables of the F-Score are profit margin and asset turnover which are indicative for the efficiency of the firm's operations. These two components are also known in the literature as the DuPont components and their product is equal to the return on assets

(ROA). However, Soliman (2008) states that both contain different and valuable information for investor' decision making. This is because evidence is found on predictable abnormal returns caused by investors failing to fully and correctly process the predictive information of these separate components.

A firm's profit margin is measured as a firm's total sales less costs of goods sold divided by total sales. It measures the firm's ability to control the costs of goods sold and illustrates the sensitivity of operating income to product pricing and cost structure. This ratio can differ significantly between firms and industries, because the level depends mainly on a firm's business model. It can be derived from factors such as pricing power, product positioning, brand name recognition, first mover advantage and market niches. The equivalent F-Score signal ($F_{\Delta MARGIN}$) measures the growth in operating income relative to the sales growth. Therefore, the signal demonstrates whether a firm was able to improve the profit margin which could indicate an improvement in factor costs; reduction in inventory costs or a rise in the firm's product prices. If the increase in the profit margin is positive, the signal score is one and zero otherwise (Piotroski, 2000; Soliman, 2008).

Next, asset turnover is the ratio that measures a firm's asset utilization and efficiency which generally is derived from the efficient use of fixed and current operating assets and other forms of working capital management. The change of asset turnover typically measures sales growth relative to the growth in operating assets. An improvement in asset turnover demonstrates that the firm's productivity from its asset base has increased. This can be due to more efficient operations or to improved market conditions for firm' products. If the change of asset turnover is positive, the indicator variable ($F_{\Delta TURN}$) is one or zero otherwise (Piotroski, 2000; Palepu et al., 2010).

Finally, it is important to mention that the effect of many fundamental signals can be ambiguous. E.g., an increase in liquidity can, in theory, be either a positive or negative signal. The increase of liquidity seems positive, but meanwhile could also be negative. This is because an increase could imply that a firm cannot find good investments for their available excess cash. Therefore, the expected consequences for future performance of all F-Score signals are determined assuming that special item-low accrual firms are in some level of financial distress. Thus, an increase in liquidity is assumed to be a positive signal, because in these firms the benefits of being able to generate a positive overall cash flow (e.g., to fulfill debt obligations) seems more plausible than the costs of excess cash. Eventually, the power of the overall measure to separate strong and weak firms depends on whether the implications of these signals for future performance are uniform across the set of special item-low accrual firms (Piotroski, 2000).

Besides, Piotroski (2000) does not pretend that the F-Score is the optimal set of firm fundamentals. The score is designed to be able to measure the overall financial strength of especially, firms that are in financial distress and show poor profitability. It is therefore that some fundamentals overlap with earlier research and others are excluded from the F-Score. Piotroski (2000) typically excludes variables that are expected to be less important (e.g., effective tax rates and qualified audit opinions) than the variables capturing changes in the overall health of firms, such as measures of profitability and the capital structure.

4.1.2. Future firm performance: Probability of Delisting

Further, the first hypothesis states that special item-low accrual firms with a high F-Score are less likely to delist than those firms with a low F-Score. The probability of delisting is measured by means of an indicator variable, DELIST, that is one when a firm delists during the return compounding period and zero otherwise. This period starts the fourth month subsequent to a firm's fiscal year end. Around that time it is likely that all financial statements are made public and therefore have become relevant for investor' decision making. I assume that a firm has delisted when the 1yr BHAR are missing. This is the case when the CRSP database (i.e. the database used to obtain return data) reports missing return data during the return compounding period.

Further, I use a logistic regression to test the relation between the delisting variable DELIST and the F-Score. The delisting variable is the dependent variable and the F-Score is the independent variable. A logistic regression is used because the dependent variable is an indicator or dichotomous variable. Hence, the following equation is tested to address the first hypothesis:

$$DELIST = \alpha + \beta_1 F_{SCORE} + \varepsilon \tag{2}$$

4.1.3. Future stock performance: 1yr BHAR

The tests on future stock performance are designed to address the second hypothesis. That is whether firms with a high F-Score have higher abnormal returns than low F-Score firms. The proxy for future stock performance are the one-year ahead buy-and-hold abnormal returns (1yr BHAR). These future stock returns are the size-adjusted one year buy-and-hold returns calculated from the start of the fourth month subsequent to the end of fiscal year t. These returns are adjusted for size by deducting the value-weighted average return for firms in the same size matched portfolio from the one-year buy-and-hold returns for all available firms. The proxy for firm size is the market value at the beginning of the return window. The return compounding ends the earlier of one year after return compounding started or the last day of CRSP reported trading returns. If the firm delisted during the return compounding period, the 1yr BHAR is assumed to be missing.[5] So, the following equation is used to calculate the 1yr BHAR for each firm:

$$(3) \qquad 1yr\ BHAR = \prod_{t=1/12}^{\min(12, delist)} (1 + r_{i,t}) - \prod_{t=1/12}^{\min(12, delist)} (1 + r_{sp,t})$$

where $r_{i,t}$ is the monthly raw return of firm i in month t, and $r_{sp,t}$ is the monthly benchmark return of the size matched portfolio.

Next, the relation of these future stock returns and the F-Score is empirically tested using an Ordinary Least Squares (OLS) regression. 1yr BHAR is the dependent variable and the F-Score is the independent variable. Hence, the second hypothesis can be examined by the following equation:

$$(4) \qquad 1yr\ BHAR = \alpha + \beta_1 F_{SCORE} + \varepsilon$$

Furthermore, the second hypothesis is addressed by means of an additional test. Herewith, I expand the empirical research to all low accrual firms and interactively test the effect of special items on a broader sample of firms. As shown in the literature review, all low accrual firms have poor performance figures and, because the accrual levels are extremely low, investor mispricing is likely to be apparent as a cause of the accrual anomaly. In this manner, further insight is given on future stock performance and the possibly broader application of the F-Score.

The test is performed using an OLS regression with 1yr BHAR as the dependent variable and as independent variables the F-Score and the interaction term of special items. Thus, the equation with the interaction term of special items is as follows:

[5] This study chooses not to include delisting returns in the 1yr BHAR calculations, because it is easier to implement and treatment of delisting returns varies greatly in the accounting literature. E.g., Piotroski (2000) assumes a delisting return of zero when a firm delists and Dechow and Ge (2006) chooses to take the delisting return of the CRSP database and reinvesting the remaining proceeds in the size-matched portfolio. However, Shumway (1997) points at a bias in the CRSP delisting returns and proposes another method.

$$(5) \qquad 1yr\ BHAR = \alpha + \beta_1 SPI + \beta_2 F_{SCORE} + \beta_3 F_{SCORE} * SPI + \varepsilon$$

, where SPI is one for special item-low accrual firms and zero otherwise.

4.1.4. Special item-Low accrual firms

Finally, to identify low accrual firms, the sample of US firms with sufficient financial statement data is assigned to ten accrual portfolios. I use a firm's operating accruals as the accrual measure which is similar to Dechow and Ge (2006). A firm's operating accruals are equal to the difference between net income before extraordinary items (ROA) and cash flow from operations (CFO) scaled by average total assets. The firms are assigned to an accrual portfolio from low to high accruals separately for each year of the (reduced) sample period.[6] The firms with the two lowest decile ranks (i.e. one and two) are the low accrual firms.

Thereupon, I am interested in low accrual firms that report large negative special items. So, special item-low accrual firms are defined as firms that have negative special items greater than 2% of average total assets.

4.2. Sample Selection

I acquire the sample of special item-low accrual firms from US listed firms for the fiscal years 1988 up to and including 2009. I obtain the necessary fundamental and return data from the CRSP/Compustat Merged (CMM) and CRSP database. The initial sample consists of 162.318 firm year observations. Furthermore, I use the statistical software of STATA to obtain my final sample and eventually perform the empirical analysis. Table I demonstrates the separate steps that are used to obtain the final sample of 5.451 firm year observations including the 899 delisting observations. Next, these separate steps are discussed.

First, I exclude the firm year observations that are known to lead to sample biases. These mutations lead to an US firm sample of 101.827 firm year observations.

The empirical tests require that CRSP has recorded available return data for the whole return compounding period. Therefore, to avoid a bias in the sample, firms that have fiscal year ends in excess of December 31st 2009 are excluded from the sample. Next, also non-US firms are excluded from the obtained sample. It is possible that these firms, especially foreign

[6] The sample period is reduced by two years to a period of 1990 up to and including year 2009 due to the calculation and scaling of the fundamental signals of the F-Score.

private issuers, use accounting standards that are different from the US firms. This may cause firm fundamentals to be measured differently and affect the inferences made in this study (Francis, 2010). I also require firm year observations to have available data on the stock price at year end (Compustat Item #PRCC_F) and the outstanding common shares (Compustat Item #CSHO). Herewith, a firm's market value at year end can be calculated and assures that a firm is still present on a US stock exchange at fiscal year end.

Moreover, I exclude financial firms from the analysis (i.e. firms with SIC codes between 6000 and 6999), because there is no clear distinction between operating and investing activities. This is a primary concern for the variable of operating accruals. This variable is used to divide firms into accrual deciles and also as an indicator variable of the F-Score ($F_{ACCRUAL}$) (Dechow and Ge, 2006). Financial firms are identified using the historical SIC code (Compustat Item #SICH), because current SIC codes can differ as a result of changes in a firm's core business over time. I find that a large proportion of the firm year observations do not have historical SIC codes (20937 of 122.149 observations). For these firm year observations I use their current SIC codes (Compustat Item #SIC).

Next, I identify firms with sufficient fundamental data for the calculation of operating accruals and the F-Score.[7]

I remove firm year observations with missing financial statement data with the exception of the special item (Compustat Item #SPI) and equity issue variables (Compustat Item #SSTK). Special items that are missing are assumed to be zero (Dechow and Ge, 2006). Regardless, these firms remain excluded from the final sample, because special item-low accrual firms have negative special items larger than 2% of average assets. A missing equity issue can occur because equity sales and purchases are already reported on a net basis, since all financial records add up. Hence, a reasonable assumption to avoid further loss of firm year observations is that the issue of equity is zero (Mayer and Sussman, 2002). Further, I exclude firms with total asset values below zero, because these firms and their ratios have low economic meaning. Lastly, the fundamental variables are winsorized on the 1st and 99th percentile to control for outliers.

The remaining sample consists of 72.615 firm year observations. This sample reduction is largely due to the calculation of the F-Score signals that measure change (e.g.,

[7] The calculations of the fundamental variables using the items of the CCM database are found in Appendix B.

$F_{\Delta LEVER}$) and the scaling on (lagged) average assets. These requirements remove the two earliest years of the period under examination (1988 and 1989).

Next, I create the sample of low accrual firms and special item-low accrual firms and obtain the return data that is required to calculate future firm and stock performance.

First, the level of operating accruals is used to assign firms into ten accrual-matched portfolios. Firms that are in the lowest two accrual deciles are classified as the low accrual firms.

Further, I obtain monthly return data from the CRSP database to calculate a firm's 1yr BHAR and create the indicator variable DELIST. First, a firm has delisted if the 1yr BHAR is missing during this return window. To observe only firms that delisted during this period, I exclude firms that have missing return data the month prior to the return compounding period (the third month after fiscal year end). This leads to a drop of 326 firm year observations.

Moreover, I require firms to have a stock price at year end in excess of 1 dollar. This requirement is proposed by Dechow and Ge (2006) to work as a simple screen against the high bankruptcy risk related to firms with very low stock prices. This reduces the likelihood that the risk explanation (i.e. investors requiring a risk premium for high fundamental risk) applies to the observations with significant abnormal returns. This leads to a sample of low accrual firms of 11.855 including 1.822 delisting observations.

Lastly, I determine the sample of special item-low accrual firms that is of interest to the main research question. These are the firms that have negative special items larger than 2% of average total assets. The data computation process results in a final sample of special item-low accrual firms of 5.451 firm year observations including 899 delisting observations.

Table 1 Sample mutations to obtain the final sample of Special Item-Low Accrual Firms

Sample (in firm year observations)	**Dropped***	**Sample size**
Initial sample of fiscal years 1988 to 2009 (of the CCM database)		162.318
Removing datadates in excess of year 2009	*6.172*	156.146
Removing non U.S. firms[a]	*15.188*	140.958
Missing market value (prcc_f and csho) data at fiscal year end	*1.364*	139.594
Removing financial firms ((historical) SIC codes 6000-6999)	*38.562*	101.032
Sample of U.S. firms		101.032
Missing financial statement data for accrual and F_Score variables[a]	*28.417*	72.615
Selecting firms in the two lowest accrual deciles	*58.083*	14.532
Removing firms that delisted prior to return period	*326*	14.206
Removing firms that have share prices less than $1 at fiscal year end	*2.351*	11.855
Sample of Low Accrual Firms		11.855
Selecting firms with negative special items larger than 2% of total assets	*6.404*	5.451
Sample of Special Item Low accrual firms		5.451
Missing one-year buy-and-hold abnormal returns (= DELIST)[b]	*899*	4.552

* The number of firm year observations that are dropped during the sample mutations are presented italic

a Missing financial statement data

Drop duplicate firm year observations to structure panel data	*1.207*	
Calculation of variables for operating accruals and the F-Score	*27.210*	
Adjustments to data that have caused no dropped firm year observations		
Replacing missing SPI variables with zero (Dechow and Ge, 2006)	2.978	
Replacing missing SSTK variables with zero (Mayer, 2002)	2.129	
Winsorize outliers at 1st and 99th percentile		

b The missing one-year buy-and-hold abnormal returns indicate that a firm delisted during the return period

5. Empirical analysis

This section presents the results and findings of the empirical analysis. First, the final samples of low accrual and special item-low accrual firms along descriptive statistics. Secondly, the results of the tests of the two main hypotheses are presented and discussed. Finally, several alternative partitions are presented to analyze the influence of firm characteristics on the relation of the F-Score with future firm and stock performance.

5.1. Descriptive statistics

5.1.1. Fundamental and return characteristics

Table 1 presents summary statistics of the firm characteristics of low accrual firms and special item-low accrual firms. Panel A presents the descriptive statistics of the financial characteristics which are used to determine the fundamental signals of the F-Score. First, this table shows three indicators of firm size that are the market value of equity, assets and turnover. Special item-low accrual firms have mean market values that are lower than the average low accrual firm ($ 718,6 million vs. $ 730,7 million), but the T-statistic shows that these values are not significantly different. However, the size difference of special item-low accrual firms and low accrual firms is present when measured by asset and turnover size (resp. mean values of $ 690,2 million vs. $ 629,1 million and $ 674,7 million vs. $ 594,7 million). Although the market value of equity is not significantly different, the higher asset and turnover size is consistent with the findings of Dechow and Ge (2006). They find that special item-low accrual firms on average are larger in size than other low accrual firms.

Furthermore, the average (median) BM ratio is also reported in Panel A. Both types of firms have low BM ratios[8], but special item-low accrual firms show a higher mean BM ratio than the total of low accrual firms. The low BM ratio is likely due to the recognition of large negative accruals in both samples (on average -0, 288 and -0,245 of total assets). This has a negative influence on the book value and therefore decreases the BM ratio. Moreover, a higher BM ratio shows that investors have lower expectations of future stock performance. This corresponds with the findings of Dechow and Ge (2006) that investors have lower future prospects of firms recognizing special items.

Finally, Panel A presents the fundamentals that are used to determine the signals for

[8] Dechow and Ge (2006) present a mean BM ratio of all US firm year observations between 1988-2002 of 58,84%.

the F-Score. On the left side of the table, the theoretical relation of the fundamentals with future firm performance is shown (which is also the relation that is assumed by Piotroski (2000)). On average, the total of low accrual firms and special item-low accrual firms show poor performance measures with almost all mean values that negatively relate to future performance. Furthermore, special item-low accrual firms have significantly worse mean performance figures than other low-accrual firms. The largest differences between both samples are found in the change of the liquidity ratio (-0,509 vs. -0,375), the mean return on assets (-0,343 vs. -0,0245) and the change in return on assets (-0,182 vs. -0,102). However, the large standard deviations indicate that not all special item-low accrual firms are poor performers. This found variation could imply that the aggregated score of their fundamental signals can be of value for investors.

Panel B of Table 1 shows the one-year ahead buy-and-hold abnormal returns of special item-low accrual firms and the total of low accrual firms. The mean 1yr BHAR for the firms with special items is significantly higher (0,094 vs. 0,053). However, as shown by the distribution of 1yr BHAR, it is mainly due to higher return values in the highest percentiles, the 75% and 90^{th} percentiles. Therefore, a small proportion of special item-low accrual firms outperforms the other low accrual firms. Both results are consistent with the findings of Dechow and Ge (2006). They find that special item-low accrual firms on average outperform the other low accrual firms, but that a large proportion also underperforms. Moreover, these return values also indicate that a fundamental analysis could be useful to distinguish between the high and low 1yr BHAR.

Next, Figure 3 presents further descriptive statistics for the sample of special item-low accrual firms. First, it shows the frequency of observations in the fiscal years of the period 1990 to 2009. The lowest number of special item observations are found in the year 1990 and the highest in 1998, resp. 155 and 384 observations. Secondly, the minimum amount of firms that delist is found in the year 2006 and the maximum in the year 1990, resp. 19 and 126 observations. The delisting observations in the year 1990 are noticeable and unusual. In comparison with the average delisting ratio (delisting observations/total firm year observations) of 16,5% found in Table 3, the ratio is extremely high (81,3%). An economical explanation is not found for this extreme value of delisting observations in the fiscal year 1990.[9] However, although 19 of the 20 fiscal years in the sample period show normal

[9] A possible explanation is that because a delisting observation is equal to missing return data in the return period it is caused by data errors.

Table 2 Summary Statistics for Special Item-Low Accrual Firms between 1990 and 2009

Panel A: Descriptive Statistics of financial characteristics

		Special Item-Low Accrual Firms (n = 5.451)			Low Accrual Firms (n = 11.855)			
Variable	FFP[a]	Mean	Median	Std dev	Mean	Median	Std dev	T-Stat[b]
Market Value of Equity		718,60	84,36	2333,49	730,74	86,02	2310,32	0,53
Assets		690,15	100,02	1952,46	629,07	85,89	1833,39	**-3,35**
Turnover		674,68	104,97	1914,85	594,74	88,88	1759,12	**-4,57**
Book-to-Market Ratio		0,55	0,45	0,74	0,53	0,42	0,68	**-3,12**
Special Items		-0,17	-0,12	0,16	-0,08	-0,01	0,14	**85,92**
Return on Assets	+	-0,34	-0,25	0,33	-0,24	-0,15	0,33	**31,51**
Δ Return on Assets	+	-0,18	-0,16	0,25	-0,10	-0,07	0,24	**37,54**
Cash Flows	+	-0,03	0,03	0,23	0,02	0,07	0,25	**20,07**
Accruals	+	-0,29	-0,23	0,16	-0,25	-0,19	0,14	**32,20**
Δ Leverage	-	0,01	0,00	0,14	0,01	-0,00	0,14	**-8,45**
Δ Liquidity	+	-0,51	-0,25	1,70	-0,38	-0,17	1,68	**7,98**
Equity issuance	-	12,17	0,94	36,48	12,33	0,77	37,34	0,44
Δ Gross Margin	+	-0,00	-0,01	0,54	0,01	-0,00	0,60	**1,97**
Δ Turnover	+	-0,00	0,01	0,28	0,00	0,01	0,28	0,75

Panel B: Descriptive Statistics of One Year Ahead Buy-and-Hold Abnormal Returns

			Percentile						
Variable	n	Mean	10th	25th	Median	75th	90th	% Pos	T-Stat[b]
Special Item-Low Accrual Firms	4.552	0,094	-0,718	-0,463	-0,118	0,324	1,060	41,9%	**-4,36**
Low Accrual Firms	10.033	0,053	-0,696	-0,438	-0,111	0,285	0,905	41,3%	

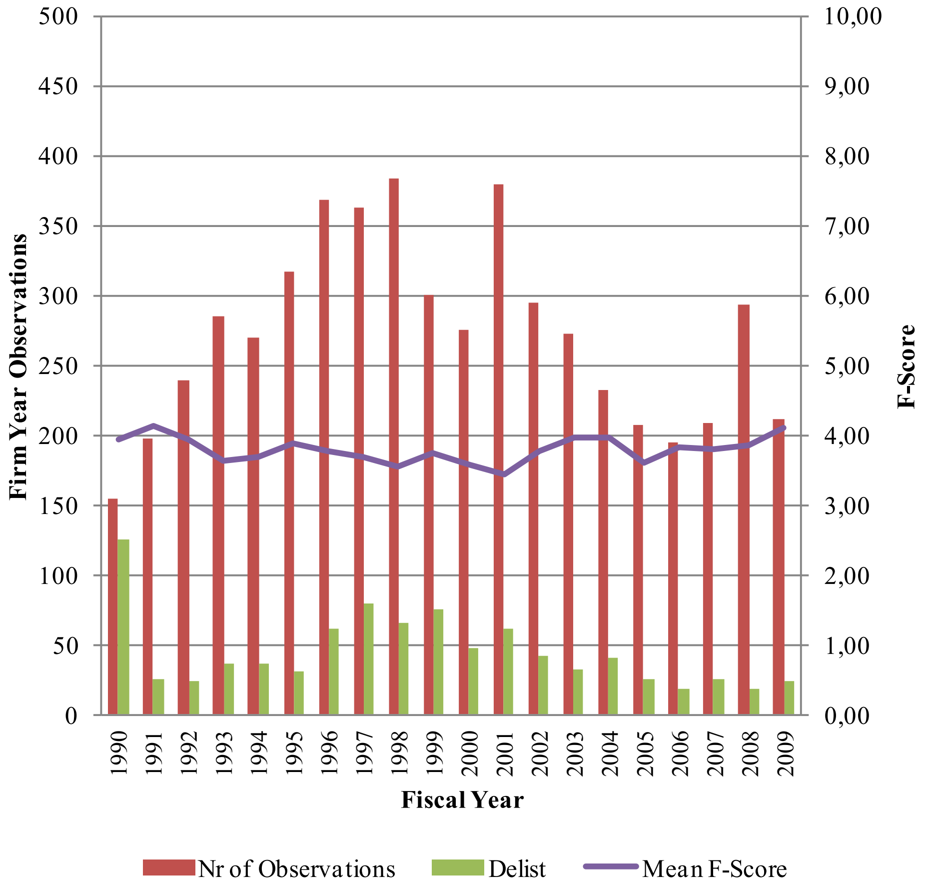
a FFP is the theoretical relation of the variable with future firm performance

b T-Stat is the T-statistic of the two-sample t-test of mean differences of the variables of special item-low accrual firms and low accrual firms with no special items. The value is presented bold when it is significant at a significance level of 5% (p<0.05).

All variables are defined in Appendix A

delisting ratios, the 126 observations are a significant proportion of the total delistings (899). This could be of influence to the results of the main tests. Therefore, I choose to report the results of the regression analysis excluding the year 1990 in Appendix C.[10] Last, the mean F-Score shows no significant outliers and fluctuates between 3,44 and 4,13 across the fiscal years.

Figure 3 Descriptive Statistics of Special Item-Low Accrual Firms (n = 5.451)

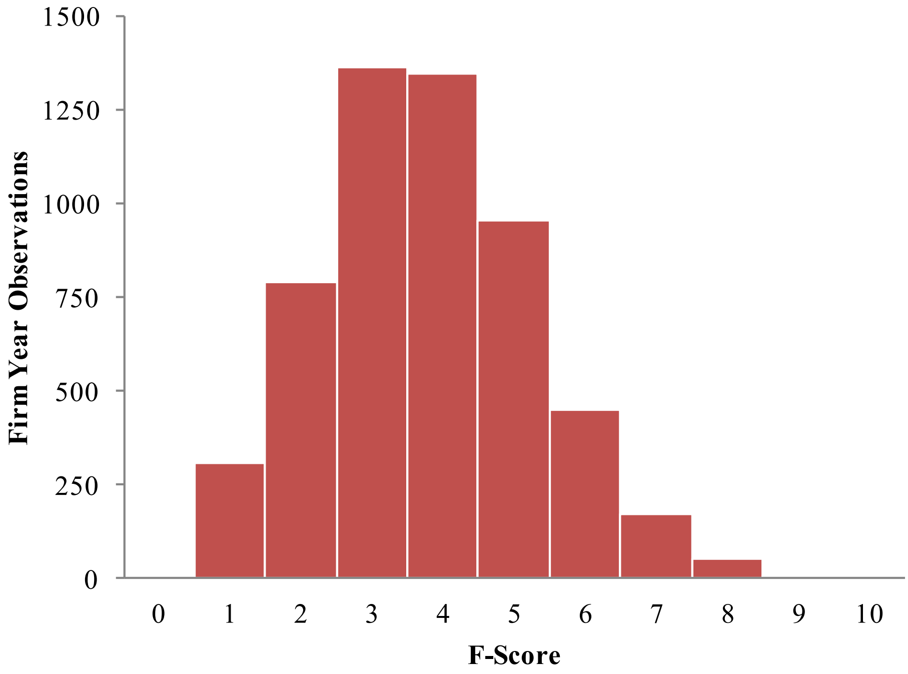


Further, Figure 4 presents the firm year observations partitioned on the F-Score value. The mean F-Score is 3.77 and the median value is 4. The distribution is therefore slightly left skewed. Not surprisingly, no observations are found for a zero F-Score. All special item-low accrual firms have negative accruals and therefore all have one positive signal, the accrual signal (F_{ACCR}). Moreover, the most observations are found for F-scores three and four. This shows that only a small proportion of the special item-low accrual firms show good

[10] The results of the logistic regression analysis without the fiscal year 1990 show a significant support for the first hypothesis as well. The probability of delisting varies here from 8,34% to 18,99%.

performance figures. This is consistent with earlier findings in the literature, especially considered that all special item-low accrual firms already have a positive accrual signal.

Figure 4 Frequency of Firm Year Observations of Special Item-Low Accrual firms by F-Score (n =5.451)



Next, the frequency of negative special items in low accrual firms is presented in Figure 5. The firm year observations are divided by the assigned accrual deciles, either 1 or 2. Further, the figure shows firm year observations of negative special items greater than 1%, 2% and 5% of average total assets. From the figure can be derived that more firms in the lowest accrual decile have negative special items, respectively 58,1% and 35,7% for special items greater than 2%.[11] However, in both deciles special item-low accrual firms (i.e. firms with negative SPI greater than 2%) represent a large proportion. Moreover, the negative special items of the lowest decile appear to be larger than the other accrual decile, because still 50,3% of these firms have negative special items greater than 5% compared to 24,2% in firms of the second accrual decile. [12]

[11] Dechow and Ge (2006) find in their sample of special item-low accrual firms in the period 1988-2002 respectively 55,5% and 32,6% for the lowest two deciles. Therefore, during later years the frequency of special items recognition in the low accrual deciles shows a slight increase.
[12] Elliott and Hanna (1996) find that special items tend to be recurring after their first recognition. In the 20 year-period between 1990 to 2009, I find that on average special item-low accrual firms report negative special items 3,2 years and with a maximum of 15 years.

Table 3 presents further descriptive statistics of these two low accrual deciles. First, the average operating accruals are larger in both accrual deciles for special item-low accrual firms. Next, the percentage of negative special items is on average also larger for the lowest accrual decile which is consistent with the statistics of Figure 5.

Furthermore, the table shows future firm and stock performance of the low accrual deciles measured by the delisting observations and one-year buy-and-hold abnormal returns and. First, the frequency of delisting is higher for decile 1 than decile 2 (resp. 17,8% vs. 13,3%). However, the effect of negative special items seems to vary across the accrual deciles. Negative special items increase the probability of delisting in the lowest decile, but it does not significantly differ in the second decile. Next, the mean 1yr BHAR are similar for both accrual deciles. However, the difference between the mean returns of special item and no special item firms is significant for the lowest accrual decile, a difference of 0,133.

Figure 5 Frequency of Firms with Negative Special Items accross Low Accrual Deciles (*n* = 11.855)

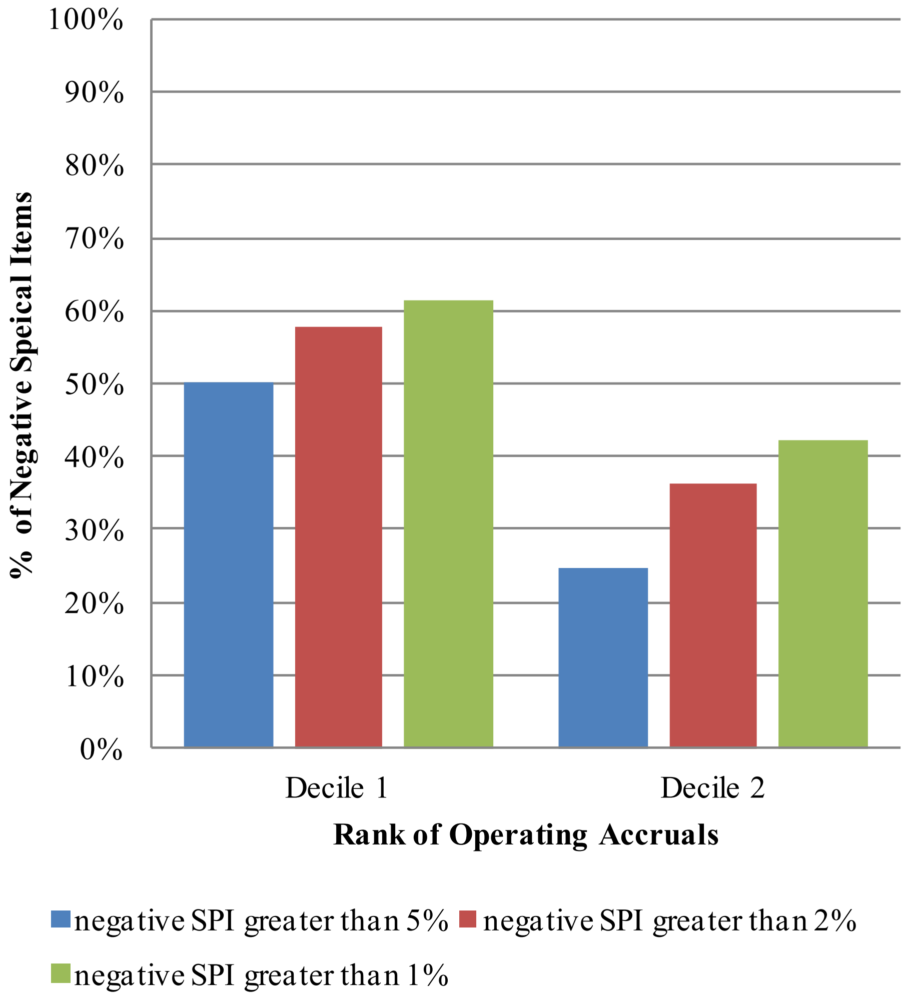


Table 3 Descriptive Statistics of Low Accrual Firms by decile rank and special item recognition (*n* = 11.855)

Decile	% of SPI	Mean of Operating Accruals		Mean of Special Items in SPI Firms	% Delist			1yr BHAR			
		No SPI	SPI		All	No SPI	SPI	All	No SPI	SPI	SPI- No SPI
1	58,1%	-0,305	-0,373	-0,227	17,8%	15,7%	19,3%	0,053	-0,023	0,110	0,133
2	35,7%	-0,155	-0,170	-0,092	13,3%	13,7%	12,6%	0,053	0,042	0,073	0,031
All	46,0%	-0,209	-0,288	-0,171	15,4%	14,4%	16,5%	0,053	0,019	0,094	0,103

Table 4 Spearman correlation analysis between 1yr buy-and-hold abnormal returns, the individual signals of the F-Score and the composite F-Score for Special Item-Low Accrual firms (*n* = 4.552)

Variable	F_{ROA}	$F_{\Delta ROA}$	F_{CFO}	$F_{ACCRUAL}$	$F_{\Delta LEVER}$	$F_{\Delta LIQUID}$	F_{EQ_OFFER}	$F_{\Delta MARGIN}$	$F_{\Delta TURN}$	F-Score
FSP[a]	+	+	+	+	-	+	-	+	+	
1yr BHAR	**0,037**	**-0,041**	**0,150**	-	0,008	**-0,041**	**0,039**	-0,002	0,022	**0,052**
F_{ROA}	1,000	**0,158**	**0,260**	-	**0,058**	**0,074**	**-0,057**	**0,104**	-0,002	**0,356**
$F_{\Delta ROA}$		1,000	-0,024	-	**0,065**	**0,137**	-0,020	**0,266**	**0,124**	**0,424**
F_{CFO}			1,000	-	**0,120**	**0,061**	**0,120**	0,007	0,011	**0,458**
$F_{ACCRUAL}$[b]				-	-	-	-	-	-	-
$F_{\Delta LEVER}$					1,000	**0,168**	0,011	**0,059**	**-0,034**	**0,461**
$F_{\Delta LIQUID}$						1,000	0,005	**0,088**	-0,010	**0,461**
F_{EQ_OFFER}							1,000	0,001	0,024	**0,279**
$F_{\Delta MARGIN}$								1,000	**0,126**	**0,499**
$F_{\Delta TURN}$									1,000	**0,395**
F-Score										1,000

a FSP is the theoretical relation of the variable with future stock performance

b All correlations of the variable $F_{ACCRUAL}$ are missing, because the variable is equal to one for all firm year observations.

The values are presented bold when they are significant on the 5% level ($p<0.05$)

All variables are defined in Appendix A

5.1.2. Characteristics of the F-Score signals

Next, the individual signals of the F-Score and the composite F-Score are discussed with two tables of descriptive statistics.

In Table 4, the Spearman rank correlations between the 1yr BHAR, the individual signals of the F-Score and the F-Score are tabulated. The table presents some expected and obvious relations as well as some interesting patterns. The relative strong positive correlation between return on assets (F_{ROA}) and cash flow from operations (F_{CFO}) is found as expected (0.260). Furthermore, a profitable firm has a higher probability that return on assets (i.e. correlation F_{ROA} and $F_{\Delta ROA}$ of 0.158) and the profit margin (correlation F_{ROA} and $F_{\Delta MARGIN}$ of 0.104) have increased. Next to that the signals of change in return on assets, profit margin and asset turnover show positive correlations amongst each other (resp. 0.266, 0.124 and 0.126). A more exciting pattern is found between the signal of cash flow from operations and the change in leverage ratio. Also, the positive relation between change in liquidity and leverage is not as expected by the theory behind the F-Score. Overall, the correlations amongst the individual signals of the F-Score are low. Therefore, if the individual signals are effective in predicting future returns, the found orthogonality amongst these signals may indicate that an aggregate F-Score is more useful to predict future stock performance than the use of separate individual signals (Mohanram, 2005).

However, the Spearman rank correlations between the 1yr BHAR and these individual signals are all weak with exception of the cash flow signal. For three individual signals the relation is even the opposite from what was expected by the theory behind the F-Score: $F_{\Delta ROA}$, $F_{\Delta LIQUID}$ and $F_{\Delta EQOFFER}$ (resp. -0.041, -0.041 and 0.039). Although these correlations are not strong, this negatively influences the relation of the aggregate F-Score and the 1yr BHAR. Hence, the correlation of the F-Score is also low, 0.052. This is lower than the correlation coefficient of the individual signal of cash flow from operations and 1yr BHAR, 0.150. This is consistent with the findings of Dechow and Ge (2006) that cash flows are more persistent than earnings in extreme low accrual firms.

Furthermore, as mentioned earlier, Piotroski (2000) chose the direction of the individual signals assuming that the firms are in financial distress, typically also the case for special item-low accrual firms. However, although the correlations with 1yr BHAR are small, the observed figures of the change in liquidity and equity issuance are the opposite from what is expected. These firm fundamentals do have an ambiguous nature and therefore it could be that these signals instead have the opposite effect from what is predicted by Piotroski's F-

Score. E.g., a negative change in liquidity could indicate that a firm has chosen to invest which leads to improved firm performance in the future. This is also the case for an issue of equity. A firm was apparently able to obtain funds externally which could mean that it has good prospects.

In Table 5, the relation of the individual signals with future stock performance is further described with a comparison of the mean 1yr BHAR. For each signal the future returns are divided by the value of the individual signal (either "1" or "0") and for each partition the mean 1yr BHAR is presented. It is expected that partitions of the positive signals ("1") have higher mean 1yr BHAR than their counterparts ("0"). This expected difference between the mean future returns is significant for the signal partition of cash flow from operations (F_{CFO}) and change in asset turnover ($F_{\Delta TURN}$), resp. 0.122 and 0.065. However, opposed to what is expected, the mean future returns are higher when the individual signals of the change in return on assets ($F_{\Delta ROA}$) and liquidity ($F_{\Delta LIQUID}$) are negative, resp. -0.095 and -0.100. As seen in Table 4 as well, the liquidity signal is different from the expected direction for future stock returns. This could negatively affect the relation between the overall F-Score and future stock performance.

Table 5 Relation between Individual Signals of the F-Score and 1yr BHAR for Special Item-Low Accrual Firms (*n* = 4.552)

Signal	(1)		(0)			
Variable	N	Mean	N	Mean	(1) - (0)	T-Stat[a]
F_{ROA}	505	0,061	4.047	0,098	-0,037	-0,81
$F_{\Delta ROA}$	750	0,014	3.802	0,110	-0,095	**-2,50**
F_{CFO}	2.950	0,137	1.602	0,015	0,122	**4,13**
$F_{ACCRUAL}$	4.552	0,138	0	-	-	
$F_{\Delta LEVER}$	2.089	0,079	2.463	0,107	-0,027	0,96
$F_{\Delta LIQUID}$	1.530	0,028	3.022	0,128	-0,100	**-3,35**
F_{EQ_OFFER}	742	0,119	3.810	0,089	0,029	0,77
$F_{\Delta MARGIN}$	1.803	0,090	2.749	0,097	-0,006	-0,22
$F_{\Delta TURN}$	2.403	0,125	2.149	0,060	0,065	**2,30**

a T-Stat is the T-statistic of the two-sample t-test of mean differences of the variables of special item-low accrual firms and low accrual firms with no special items.
The value is presented bold when it is significant at a significance level of 5% (p<0.05)
All variables are defined in Appendix A

5.1.3. Summary

The sample of special item-low accrual firms has on average larger total assets and turnover, but no higher market values, than other low accrual firms. As expected, both types of firms show poor performance measures. However, special item-low accrual firms do have significantly higher mean 1yr BHAR, but this is mainly caused by a small proportion of firms with high 1yr BHAR. Next, the mean F-Score does not show any outliers across the years and most observations are found of firms with an F-Score of three and four. Lastly, the delisting ratio shows an unusual peek in the year 1990 which cannot be explained in a logical manner.

Next, several differences are found across the two lowest accrual deciles. Firms in the lowest accrual decile show significantly larger negative special items than the other low accrual decile. For both accrual deciles, special item-low accrual firms show larger negative operating accruals. However, the frequency of delisting and the mean 1yr BHAR of firms with special items are only significantly larger in the lowest accrual decile in comparison with the other low accrual firms. Overall, these fundamental and return characteristics are consistent with the findings of Dechow and Ge (2006).

Lastly, the correlations among the individual signals of the F-Score are generally low with the exception of the ROA and CFO signals. This could motivate the use of an aggregate F-Score to predict future stock returns. However, the individual signals are not effective in predicting the change in 1yr BHAR. Moreover, the F-Score signals of the change in liquidity and equity issuance show weak, but opposite relations with future returns of what is expected. This negatively affects the overall strength of the F-Score. The low Spearman rank correlation of the aggregate F-Score confirms this notion. Finally, the mean future returns based on individual signal partitions show expected positive relations for the signals of CFO and ΔTURN. On the other hand, an unexpected, significant relation is once more found for the liquidity ratio. The partition of a positive change in liquidity shows significantly lower mean 1yr BHAR than its counterpart.

5.2. Empirical Results

The descriptive statistics show interesting characteristics and patterns in the sample of special item-low accrual and other low accrual firms. This section continues with the empirical results of the regressions that test the main hypotheses. Moreover, a partition analysis on the F-Score and firm size is performed to examine their effect on future firm and stock performance.

5.2.1. Results of the test of H1

The results show significant support for the first hypothesis. Special item-low accrual firms with a high F-Score are less likely to delist than firms with a low F-Score.

Table 6 reports the results of the logistic regression performed with DELIST as the dependent delisting variable and the F-Score as the independent variable. DELIST is one if a firm delisted during the return compounding period and zero otherwise. Therefore, the expected coefficient of the F-Score is negative. I find support for this expectation, because the negative logit coefficient of the F-Score shows that the probability of delisting decreases with the increase of the F-Score. This effect is significant at the significance level of 1% which is illustrated by a z-value of -3.89. However, the reported logit coefficients are not easily interpreted, because they do not represent the coefficients of Equation 2. This is because these obtained coefficients are equal to the natural log of the odds of delisting. This is the probability that delisting will occur divided by the probability that delisting will not occur (Pr (success)/Pr (failure)).

To show the economic significance of the results shown in the logistic regression, Figure 6 illustrates the predicted probabilities of delisting across the F-Score values. The figure shows a decline in the probability of delisting as the F-Score value increases. This probability decreases from 20,39% to 10,60%. This result indicates that the F-Score is a meaningful predictor for the probability of delisting. Thus, high F-Score firms are less likely to delist than low F-Score firms.

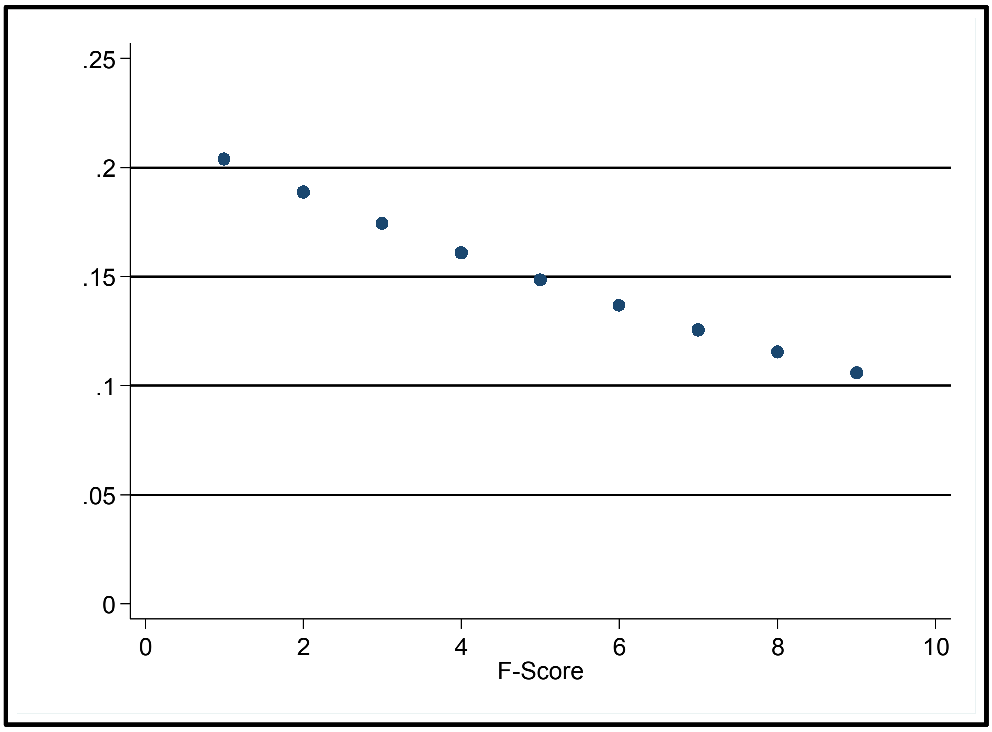
Table 6 Results of the Logistic Regression of Future Delisting on the F-Score of Special Item-Low Accrual Firms (n = 5.451)

$$(2)\quad DELIST = \alpha + \beta_1 F\text{-}SCORE + \varepsilon$$

Dependent variable:	DELIST	
	Logit Coefficient	Std. Err.
F-Score	-0,0963***	0,0247
	(z = -3,89)	
Constant	-1.2660***	0,0969
	(z = -13,07)	
n	5.451	
χ^2 (df=1)	15.37	
Odds ratio	0,9082	
Pseudo R^2	0,0031	

*** Significant at 1% level (p<0.01) ** Significant at 5% level(p<0.05) * Significant at 10% level (p<0.10)

Figure 6 Predicted Probability of a firm delisting for the DELIST and F-Score variable for Special Item-Low Accrual firms (n = 5.451)



5.2.2. Results of the test of H2

The empirical tests of the second hypothesis show that the F-Score has no predictive value (i.e. a zero effect) for the future abnormal returns of special item-low accrual firms. On the contrary, the results suggest that investors already incorporate the fundamental information of the F-Score in their assessment of low accrual firms that report special items. On the other hand, market mispricing appears to be highly related to the reported special items.

Table 7 shows the results of OLS regression that examines the fourth equation of this study.[13] The regression estimates the coefficient of the F-Score on the future return variable of 1yr BHAR. The 1yr BHAR vary heavily among special item-low accrual firms. As shown in Table 2, across the 25th and 75th percentile the 1yr BHAR varies from -0.463 to 0.324. Therefore, it is expected that the higher F-Scores lead to larger abnormal returns. However, the coefficient of the F-Score shows a zero effect ($\beta 1$ = 0.0003) and is also not significant.

[13] I find that the residuals of the regression of equation four show heteroskedasticity. This is illustrated by the plot of Appendix D. Additionally, a Breusch-Pagan test finds a chi-statistic of 60.17 that indicates that the residuals do not have constant variances. Therefore, I choose to perform the OLS regressions with robust standard errors and clustering by firm, as a current F-Score can relate to a subsequent F-Score within each firm.

Thus, the results indicate that high F-Score firms do not earn significant higher abnormal returns than lower F-Score firms.

Table 7 Results of the Ordinary Least Squares Regression of 1yr BHAR on the F-Score of Special Item-Low Accrual Firms (n = 4.552)

$$(4)\ \ 1yr\ BHAR = \alpha + \beta_1 F\text{-}SCORE + \varepsilon$$

Dependent variable:	1 yr BHAR	
	Coefficient	Std. Err.
F-Score	0,0003	0,0091
	(t = 0,03)	
Constant (= α)	0,0928**	0,0394
	(t = 2.36)	
n	4.552	
R^2	0,0000	

*** Significant at 1% level (p<0.01) ** Significant at 5% level(p<0.05) * Significant at 10% level (p<0.10)
The OLS Regression is with robust standard errors adjusted for heteroskedasticity and clustered by firm

However, the OLS regression with the use of special items as the interaction term provides further insight in the relation of the F-Score and future stock performance.[14] Table 8 reports significant regression coefficients on all independent variables of the equation. The use of an interaction term provides two separate regression lines for low accrual firms with and without special items. First, the OLS regression shows the same constant of 0.0928 (i.e. α + β1) and an F-Score coefficient of 0.0003 (i.e. $\beta_2 + \beta_3$) as observed by the prior regression of Equation 4. These are now significant at the 1% level, because the regression is performed on the full sample of low accrual firms and show coefficients highly deviant from zero. Therefore, the conclusions that the F-Score has zero predictive value for the 1yr BHAR does remain intact. On the other hand, the significance of the interaction term shows that the effect of the F-Score on 1yr BHAR is different for low accrual firms with ad without special items. Hence, the fitted line for low accrual firms with no special items starts at a constant value α of -0.1523 and a coefficient of the F-Score (β_2) of 0.0345. This shows that the F-Score is able to predict future abnormal returns low accrual firms different from special item-low accrual firms.

Moreover, these results suggest that investors use the fundamental information of the

[14] The test of heteroskedasticity of Equation 5 shows the same results of Equation 4, as shown in Appendix D. The Breusch-Pagan test shows a chi-statistic of 51.89.

F-Score differently for special item-low accrual firms and other low accrual firms. When special items are recognized, investors appear to use the fundamental information contained in the F-Score to assess future firm performance. Meanwhile, investors fail to use this information in other low accrual firms and as a result, the F-Score shows a significant positive relation with 1yr BHAR. Furthermore, the results suggest that market mispricing is still mainly due to inefficiencies related to the assessment of special items and their consequences. Thus, other omitted variables relevant to the implications of special items could explain these abnormal returns better than the information provided by the F-Score.

Table 8 Results of the Ordinary Least Squares regression of future stock performance and the F-Score of Low Accrual Firms with the interaction of special Items or no special Items (n = 10.033)

$$(5)\quad 1yr\ BHAR\ = \alpha\ + \beta_1 SPI + \beta_2 F\text{-}Score + \beta_3 F\text{-}Score{*}SPI\ + \varepsilon$$

Dependent variable:	1yr BHAR	
	Coefficient	*Std. Err.*
Constant (= α)	-0.1523***	0,0321
	(t = -4,75)	
SPI	0,2452***	0,0513
	(t = 4,78)	
F-Score	0,0345***	0,0059
	(t = 5,88)	
F-Score*SPI	-0,0342***	0,0110
	(t = -3,11)	
n	10.033	
R^2	0.0049	

*** Significant at 1% level (p<0.01) ** Significant at 5% level(p<0.05) * Significant at 10% level (p<0.10)
The OLS Regression is with robust standard errors adjusted for heteroskedasticity and clustered by firm

5.2.3. Partition analysis

Last, Table 9 shows an additional empirical test examining the relation between the F-Score and future stock performance. The test consist of two partitions, on the F-Score and on firm size. Prior research on fundamental analysis examines whether the relation between the aggregate fundamental scores and future returns can be used for a trading strategy. E.g., Piotroski (2000) creates low and high F-Score firms and bases the fundamental trading strategy on these two types of firms. The low F-Score firms have F-Scores of zero, one or two and high F-Score firms an F-Score of eight and nine. Therefore, I also choose to create groups of special item-low accrual firms and low-accrual firms based on the F-Score and examine their future firm and stock performance. The distribution of the F-Score of special item-low accrual firms of Figure 4 shows that the F-Scores three and four are medium scores. Hence, I choose to define the special item-low accrual firms that have F-scores lower than three (<3) as low F-Score firms. The high F-Score firms are firms that have F-Scores higher than four (4<).

Next, I examine whether the influence of firm size on the relation between the F-Score and future firm and stock performance is significant. I perform this additional test, because the findings of Dechow and Ge (2006) show that special item-low accrual firms are on average larger in size and therefore remain longer analyst following. Although the descriptive statistics of this study do not show this difference, firm size can still have a significant influence on the examined relations. Hence, I create three partitions: small, medium and large firms. This is done by ranking special item-low accrual firms and low accrual firms on their market value of equity at fiscal year end separately for each year.

Table 9 shows the results of these partitions of special item-low accrual firms and low-accrual firms. First, future firm and stock performance are partitioned on the low, medium and high F-Score firms. Panel A reports the probability of delisting among these partitions. The observed pattern is as expected. The highest delisting ratios are found in the special item-low accrual and low accrual firms with low F-Scores (resp. 19,4% and 20,6%) and the lowest in high F-Score firms (resp. 14,6% and 13,4%). Furthermore, the left side of Panel B shows an interesting pattern in the mean future returns of all special item-low accrual firms. The medium F-Score firms show the highest mean 1yr BHAR instead of the high F-Score firms (resp. 0.109 vs. 0.086). However, for the total sample of low accrual firms the pattern of future returns is found as expected, the highest for high F-Score firms.

Next, the analysis based on the size partition reveals that size influences the relation of the F-Score with future firm and stock performance in both firm types. Panel A reports the frequencies of delisting by size partition. Large firms are less likely to delist than small firms in both special item-low accrual firms and low accrual firms. Furthermore, only in small firms and medium firms the difference between the delisting ratios across the F-Score partitions is significant.

Finally, Panel B shows that for both firm types the future returns are the lowest for the large firms and the highest for the small firms. This is consistent with the findings of Piotroski (2000) on high BM firms that show that the excess returns are the lowest for the largest firms. Both can be explained by the positive correlation of firm size and analyst following as found by Dechow and Ge (2006). More analysts following results in lower information uncertainty and negatively influences the possibility of excess returns. Moreover, the size partition shows further insight in the return patterns of the low, medium and high F-Score firms. The F-Score partitions appear to have only the expected patterns (i.e. low to high returns) for the small special item-low accrual firms and the small and medium low accrual firms.

5.2.4. Summary

First, the empirical analysis starts with a test of the first hypothesis. The results suggest that high F-Score firms are less likely to delist than low F-Score firms. For special item-low accrual firms the probability of delisting decreases from 20,39% for firms with the lowest F-Score to 10,60% for the highest F-Score firms. This shows that the F-Score is a meaningful predictor of a firm's probability of delisting.

Secondly, two OLS regressions test the second hypothesis of this study. These examine whether special item-low accrual firms with a high F-Score have higher abnormal returns than low F-Score firms. On the other hand, the interaction effect of special items provides additional insight. The results suggest that the F-Score is used by investors to assess special item-low accrual firms. However, investors fail to correctly use the information in other low accrual firms. This suggests that investors' mispricing still mainly relates to the recognized special items. Thus, other variables omitted from this fundamental analysis can better predict future stock performance than the F-Score in special item-low accrual firms.

Besides, the analysis on the F-Score and firm size partitions finds interesting patterns in the relation between the F-Score and future firm and stock performance. First, although not significantly different in large firms, the probability of delisting is the lowest for high F-Score firms. In both firm types and across the F-Score partitions, larger firms are less likely to delist than smaller firms. Secondly, the expected pattern of high F-Score firms outperforming the lower F-Score firms is only found in small special item-low accrual firms and small and medium low accrual firms. Moreover, 1yr BHAR are the lowest for large firms and the highest for small firms for both types of low accrual firms. This is consistent with more analyst following causing market mispricing to decrease for larger firms.

Table 9 Future Firm and Stock Performance based on F-Score and Size Partitions

Panel A: Probability of Delisting

	Special Item-Low Accrual Firms								Low Accrual Firms							
	All Firms		Small Firms		Medium Firms		Large Firms		All firms		Small Firms		Medium Firms		Large Firms	
F-Score	% Delist	*n*	% Delist	*n*	% Delist	*n*	% Delist	*n*	% Delist	*n*	% Delist	*n*	% Delist	*n*	% Delist	*n*
Low	19,4%	1.101	26,1%	399	17,7%	424	12,6%	278	20,6%	1.743	27,6%	702	17,9%	675	12,0%	366
Medium	16,4%	2.710	24,6%	897	14,5%	932	10,1%	881	15,6%	4.759	23,7%	1.627	12,6%	1.678	10,1%	1.454
High	14,6%	1.640	20,6%	525	14,4%	464	10,0%	651	13,4%	5.353	18,2%	1.628	12,5%	1.600	10,5%	2.125
All	16,5%	5.451	23,8%	1.821	15,2%	1.820	10,4%	1.810	15,4%	11.855	22,1%	3.957	13,5%	3.953	10,5%	3.945

Panel B: Mean 1yr BHAR

	Special Item-Low Accrual Firms											
	All firms		Small Firms			Medium Firms			Large Firms			
F-Score	Mean	*n*	Mean	Median	*n*	Mean	Median	*n*	Mean	Median	*n*
Low	0,068	887	0,106	-0,174	295	0,079	-0,238	349	0,005	-0,095	243
Medium	0,109	2.265	0,143	-0,090	676	0,101	-0,156	797	0,088	-0,080	792
High	0,086	1.400	0,183	-0,054	417	0,082	-0,132	397	0,021	-0,080	586
All	0,094	4.552	0,147	-0,116	1.388	0,091	-0,164	1.543	0,051	-0,084	1.621

	Low Accrual Firms										
	All firms		Small Firms			Medium Firms			Large Firms		
F-Score			Mean	Median	*n*	Mean	Median	*n*	Mean	Median	*n*
Low	-0,002	1.384	0,025	-0,234	508	0,004	-0,266	554	-0,055	-0,135	322
Medium	0,054	4.015	0,067	-0,150	1.242	0,048	-0,158	1.466	0,047	-0,103	1.307
High	0,070	4.634	0,104	-0,097	1.332	0,068	-0,100	1.400	0,047	-0,048	1.902
All	0,053	10.033	0,076	-0,135	3.082	0,049	-0,146	3.420	0,037	-0,070	3.531

6. Conclusions

The final section of this thesis starts with a summary of the main findings and the answer to the main research question. Further, the limitations of the study are discussed and the section ends with several recommendations for further research.

6.1. Main findings

The objective of this thesis is to provide an answer to the main research question which is whether a fundamental analysis is able to separate special item-low accrual firms that delist from the ones that turn themselves around and herewith can improve investors' assessment. I find that a fundamental analysis using the method of the F-Score is able to distinguish between a firm's probability of delisting in special item-low accrual firms. Moreover, investors do appear to include this fundamental information in their assessment of special item-low accrual firms. However, market mispricing is still apparent for negative special items. Furthermore, this market mispricing appears to be negatively related to firm size which corresponds with less information uncertainty due to the presence of more analyst following. Although the F-Score is useful to assess future firm performance in special item-low accrual firms, the F-Score does not explain market inefficiency in special item-low accrual firms.

Special items are material events that either are unusual or infrequent and usually recorded in firms that show poor performance figures and are in financial distress. These are the main characteristics of low accrual firms. Further, the cause of a special item recognition can differ heavily. Negative special items can be due to poor market circumstances, managers' actions to improve firm performance or compliance with accounting rules. Moreover, these items are also subject to earnings management practices. Therefore, the implications of special items are highly uncertain. Besides, prior research finds that in low accrual firms investors often react too pessimistically towards the recognition of special items. Hence, evidence is found that special item-low accrual firms outperform low accrual firms in future stock performance. Thus, a tool that is able to support investors in their assessment of special item-low accrual firms is of value to investors. However, the literature documents that the inclusion of special items in the forecasting model of future profitability does not improve the model in low profitability firms. Furthermore, managers' voluntary disclosure on the recording of special items is often seen as unreliable due to earnings management motives.

Hence, another method that uses relevant and more reliable information is a fundamental analysis. This tool uses firm fundamentals to assess firm value to determine when stock prices differ. The usefulness of such an analysis depends on the relevance of the firm fundamentals used for analysis and the presence of market inefficiencies, such as the accrual anomaly and the value-glamour anomaly. Recent research on fundamental analysis has focused on firms where inefficiencies are likely to be apparent and the rewards of the analysis the highest. Hence, an analysis of special item-low accrual firms follows this trend, because these firms are likely to have future price movements and show market mispricing. Besides, investors appear to react in conformity with the confirmatory bias. If this applies, special items confirm the low prospects of low accrual firms and herewith other fundamental information is possibly disregarded. This could enhance the value of a fundamental analysis on special item-low accrual firms.

This thesis employs the method of fundamental analysis of Piotroski (2000) that makes use of the F-Score. This is a summary score of nine fundamental signals that measures a firm's profitability, capital structure and operation efficiency. The use of an index score instead of actual values is advantageous, because it is easily implemented by investors and captures the overall strength of a firm's financial condition in one single measure. So, a high (low) F-Score indicates that a firm has many (a few) good performance signals and therefore likely shows better (worse) future firm performance.

Hence, the first hypothesis to address the main research question is whether special item-low accrual firms with high F-Scores are less likely to delist than firms with low F-Scores. The logistic regression that tests this hypothesis provides significant evidence that a higher F-Score reduces the probability of delisting. The probability of delisting decreases from 20,39% for firms with the lowest F-Score to 10,60% for the highest F-Score firms. Thus, special item-low accrual firms with high F-Scores are less likely to delist than firms with low F-Scores.

The second hypothesis states that special item-low accrual firms with high F-Scores have higher abnormal returns than firms with low F-Scores. The results provide no support on the F-Score being able to predict future stock performance in special item-low accrual firms. This is because the F-Score shows a zero effect on the prediction of 1yr BHAR. Nonetheless, a follow up test shows that investors appear to use the fundamental information of the F-Score in their assessment of special item-low accrual firms. This shows the use of the F-Score in investors' assessment of future firm performance. However, investors fail to use the information correctly in other low accrual firms. Moreover, the results suggest that the abnormal returns are still mainly caused by incorrect assessments of negative special items and their consequences. Thus, other omitted variables are possibly better able to explain the market mispricing of investors than the F-Score.

Finally, a partition analysis finds that firm size influences the relation of the F-Score with future firm and stock performance. First, large firms are less likely to delist than smaller special item-low accrual firms. Further, high F-Score firms show only higher future stock returns than lower F-Score firms in small special item-low accrual firms. Moreover, the future abnormal returns are the lowest for large firms and the highest for small firms in both special item-low accrual firms and low accrual firms. This market mispricing can be in conformity with larger firms having less information uncertainty as a result of more analyst following.

6.2. Limitations

One of the limitations of this research concerns the calculations related to delisting. In this thesis firms are assumed to be delisted due to performance related reasons when returns are missing during the return compounding period. However, whether these missing data are indeed caused by this type of delisting is questionable. The missing return data can be caused by errors in the database or by other types of delisting activities, such as a merger. On the other hand, special item-low accrual firms have typically poor performance figures. So, any delisting activity is expected to be somehow related to these financial circumstances.

The second issue relates to exclusion of delisting returns for the calculation of the 1yr BHAR. Several studies include actual delisting returns in the compounding of future stock returns. However, the actual delisting returns are not easily measured and usually are subject to researcher's discretion. E.g., Piotroski (2000) assumes the delisting return is zero when a firm delists and Dechow and Ge (2006) takes the delisting return reported by the CRSP database and reinvesting the remaining proceeds in the size-matched portfolio. Moreover, Shumway (1997) argues that a delisting bias is present in the CRSP database and propones an alternative method to calculate delisting returns. Hence, a generally accepted treatment of delisting returns is not found in the literature. Thus, I choose to exclude these delisting returns

Lastly, the F-Score of Piotroski (2000) is an aggregate score of nine fundamentals. However, whether this score is the optimal set of variables to measure the overall strength of special item-low accrual firms is not proven. Although Duong et al. (2010) shows the broad application of the F-Score, it could be that the F-Score leaves out key firm fundamentals that are relevant for special item-low accrual firms. Moreover, the ambiguous nature of some individual signals could have misspecified F-Score signals from a directional perspective.

6.3. Recommendations

This research has shown that the F-Score is a useful (and used) method to predict future firm performance. However, it was not (significantly) able to predict the future stock performance in a sample of special item-low accrual firms. Moreover, firm size negatively effects market mispricing. These findings leave room to directions for future research.

First, this study can be followed by further research on the relation of firm fundamentals with future firm performance in special item-low accrual firms. This research examines only one measure of future firm performance that is the probability of delisting. So, other measures of future firm performance, such as future profitability, can increase insight in the applicability of the fundamental information. Moreover, although the F-Score proves useful to predict future firm performance, other methods of fundamental analysis and fundamentals may improve the relation with future firm performance in special item-low accrual firms. E.g., Mohanram (2005) uses a similar method as Piotroski (2002), but aims at some other types of firm fundamentals, such as. R&D and advertising costs.

Secondly, the F-Score was not able to predict future stock performance in special item-low accrual firms. Nonetheless, it could be that other, omitted variables or firm fundamentals relate to market's mispricing of special items. Thus, further research on the relation of special items with other (fundamental) variables can be highly beneficial to investor' assessments. Furthermore, the mispricing of the fundamental information in low accrual firms is remarkable and is interesting for future studies on low accrual firms. Moreover, a fundamental analysis or other method that is successful to assess future stock performance in both types of low accrual firms can be of great value. This is because a trading strategy that can be applied on a wide set of firms and can circumvent pitfalls like uncertain special items is better implementable in practice.

Finally, this thesis examines the total of recognized special items instead of individual components of the special item figure. However, the recorded special items are expected to be a collection of different types of special items. As shown before, underlying economics can differ heavily between special items. Hence, the consequences will also greatly depend on the special item composition. So, more insight on the implications of certain types of special items can enhance future research. Especially, because fundamental information is previously used to assess future firm performance and appears not to solve market's mispricing.

7. References

Abarbanell, J. and Bushee, B. 1997. Fundamental Analysis, Future Earnings, and Stock Prices. *Journal of Accounting Research* 55 (1): 1-24.

Abarbanell, J. and Bushee, B. 1998. Abnormal returns to a fundamental analysis strategy. *The Accounting Review* 73: 19-45.

Ball, R. and Brown, P. 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research* 6: 159-177.

Beaver, W. 1998. Financial Reporting: An Accounting Revolution. Upper Saddle, NJ: Prentice Hall, Third Edition.

Beaver, W., McNichols, M. and Price, R. 2007. Delisting returns and their effect on accounting-based market anomalies. *Journal of Accounting and Economics* 43: 341-368.

Beneish, M., Lee, C. and Tarpley, R. 2001.Contextual Fundamental Analysis Through the Prediction of Extreme Returns. Review of Accounting Studies 6: 165-189.

Bernard, V. and Thomas, J. 1989. Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting Research* 27: 1-48.

Bird, R. and Casavecchia, L. 2007. Sentiment and Financial Health Indicators for Value and Growth Stocks: The European Experience. *European Journal of Finance* 13 (8): 769-793.

Black, E.L., Carnes, T.A. and Richardson, V.J. 2000. The Value Relevance of Multiple Occurrences of Nonrecurring Items. *Review of Quantitative Finance and Accounting* 15: 391-411.

Bradshaw, M. T., Richardson, S.A. and Sloan, R.G. 2001. Do analysts and auditors use information in accruals? *Journal of Accounting Research* 39 (1): 45-75.

Burgstahler, D., Jiambalvo, J. and Shevlin, T. 2002. Do stock prices fully reflect the implications of special items for future earnings? *Journal of Accounting Research* 40: 585-612.

Chen, H.Y., Chen, S.S., Hsin, C.W. & Lee, C.F. 2010. *Price, Earnings and Revenue Momentum Strategies*. Working Paper, Rutgers University.

Cheng, C.S. and Thomas, W.B. 2006. Evidence of the abnormal accrual anomaly incremental to operating cash flows. *The Accounting Review* 81: 1151-1168.

Collins, D. and Hribar, P. 2000. Earnings-based and accrual-based market anomalies: one effect or two? *Journal of Accounting and Economics* 29: 101-123.

Cready, W.M., Lopez, T.J. and Sisneros, C.A. 2011. *Negative Special Items and Future Earnings Expense Transfer or Real Improvements?* Working paper, University of Texas.

Dechow, P.M. 1994. Accounting earnings and cash flows as measures of firm performance: the role of accounting accruals. *Journal of Accounting and Economics* 18: 3-42.

Dechow, P.M. and Dichev, I. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (Supplement): 35-59.

Dechow, P.M. and Ge, W. 2006. The persistence of earnings and cash flows and the role of special items: Implications for the accrual anomaly. *Review of Accounting Studies* 11: 253-296.

Dechow, P.M., Ge, W. and Schrand, C. 2010. Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics* 50: 344-401.

Desai, H., Rajgopal, S. and Venkatachalam, M. 2004. Value-glamour and accruals mispricing: one anomaly or two? *The Accounting Review* 79 (2): 355-385.

Dichev, I. 2008. On the Balance Sheet-Based model of Financial Reporting. *Accounting Horizons* 22 (4): 453-470.

Doyle, J.T., Lundholm, R.J. and Soliman, M.T. 2003. The Predictive Value of Expenses Excluded from Pro Forma Earnings. *Review of Accounting Studies* 8: 145-174.

Duong, C.M., Pescetto, G. and Santamaria, D. 2010. *How value-glamour investors use financial information: UK evidence of investor's confirmation bias*. Working paper, University of Portsmouth: 1-41.

Elliott, J.A. and Hanna, J.D. 1996. Repeated accounting write-offs and the information content of earnings. *Journal of Accounting Research* 34: 135–155.

Fairfield, P., Sweeney, R. and Yohn, T. 1996. Accounting classification and the predictive content of earnings. *The Accounting Review* 71: 337–355.

Fairfield, P., Kitching, K. and Tang, V. 2009. Are special items informative about future profit margins?. *Review of Accounting Studies* 14: 204-236.

Fama, E. and French, K. 1992. The cross-section of expected stock returns. *Journal of Finance* 46: 427-466.

Francis, R.N. 2010. The presence of foreign private issuers in the North American Compustat Database: A note for empirical research in accounting and finance. *Advances in Accounting, incorporating Advances in International Accounting* 26: 221–226.

Frankel, R. and Lee, C.M.C. 1998. Accounting valuation, market expectation, and cross-sectional stock returns. *Journal of Accounting and Economics* 25: 283-319.

Holthausen, R. and Verrechia, R. 1988. The effect of sequential information releases on the variance of price changes in an intertemporal multi-asset market. *Journal of Accounting Research* 26: 82-106.

Hong, H. and Stein, J. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance* 54: 2143–2184.

Jegadeesh, N. and Titman, S. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance* 48 (1): 65-91.

Khan, M. 2005. *Are Accruals Really Mispriced? Evidence from Tests of an Intertemporal Capital Asset Pricing Model*. Working paper, Massachusetts Institute of Technology.

Koch, A. 2002. *Financial distress and the credibility of management earnings forecasts*. Working paper, University of Texas at Austin.

Kothari, S. 2001. Capital markets research in accounting. *Journal of Accounting and Economics* 31: 105-231.

Lakonishok, J., Shleifer, A. and Vishny, R. 1994. Contrarian investment, extrapolation and risk. *The Journal of Finance* 49: 1541-1578.

Lee, C.M.C., Myers, J. and Swaminathan, B. 1999. What is the intrinsic value of the Dow? *The Journal of Finance* 5: 1693-1741.

Lev, B. and Thiagarajan, R. 1993. Fundamental information analysis. *Journal of Accounting Research* 31: 190- 215.

Libby, R., Bloomfield, R. and Nelson, M.W. 2002. Experimental research in financial accounting. *Accounting, Organization and Society* 27: 775-810.

Mayer, C. and Sussman, O. 2002. *Projects are Largely External and Mostly Debt Financed: A New Approach to Testing Capital Structure*. Working paper, University of Oxford.

McVay, S. 2006. Earnings management using classification shifting: An examination of core earnings and special items. *The Accounting Review* 81: 501-32.

Mohanram, S.P. 2005. Separating Winners from Losers among Low Book-to-Market Stocks Using Financial Statement. *Review of Accounting Studies* 10: 133-170.

Nichols, C.D. and Wahlen, J.M. 2004. How Do Earnings Relate to Stock Returns? A Review of Classical Accounting Research with Updated Evidence. *Accounting Horizons* 18 (4): 263-286.

Ou, J. and Penman, S. 1989. Financial statement analysis and the prediction of stock returns. *Journal of Accounting and Economics* 11: 295–329.

Palepu, K.G., Healy, P.M. and Peek, E. 2010. Business Analysis and Valuation. Cencage Learning EMEA, IFRS Edition: Text Only, Second Edition.

Piotroski, J.D. 2000. Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers. *Journal of Accounting Research* 38 (Supplement): 1-41.

Rabin, M. and Schrag, J.L. 1999. First Impressions Matter: A Model of Confirmatory Bias. *Quarterly Journal of Economics* 114 (1): 37-82.

Revsine, L, Collins, D. and Johnson., W. 2005. Financial Reporting and Analysis. Upper Saddle River, NJ: Prentice Hall.

Richardson, S., Tuna, I. and Wisocki, P., 2010. Accounting Anomalies and Fundamental Analysis: A Review of Recent Research Advances. *Journal of Accounting and Economics* 50: 410-454.

Shumway, T. 1997. The Delisting Return Bias in CRSP Data. *Journal of Finance* 52: 327-340.

Sloan, R. G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71 (3): 289-315.

Soliman, M.T. 2004. *Using Industry-Adjusted DuPont Analysis to Predict Future Profitability*. Working paper. Stanford University.

Soliman, M.T. 2008. "The use of DuPont Analysis by market participants", *The Accounting Review* 83 (3): 823-853.

Xie, H. 2001. The mispricing of abnormal accruals. *The Accounting Review* 76: 357-373.

Appendices

Appendix A

Variable definitions

Year t	The fiscal year of observation preceding the return compounding period.
Market value of equity	The market value of equity at the end of year t.
Book-to-Market ratio	The book value of equity divided by the market value of equity at the end of year t.
Average total assets	Average of total assets reported during the period between the beginning and end of year t.
SPI	An binary variable that indicates whether a firm recognized negative special items larger than 2% of total assets ('1') or not ('0') in year t.
ROA	Net income before extraordinary items of year t scaled by average total assets.
ΔROA	Change in annual ROA between the end of year t and year t-1. ΔROA is calculated as ROA for year t less the firm's ROA for year t-1.
CFO	Cash flow from operations for the year t scaled by average total assets.
ACCRUAL	Net income before extraordinary items less cash flow from operations scaled by average total assets.
ΔLEVER	Change in the firm's debt-to-assets ratio between the end of year t and year t-1. The debt-to-assets ratio is the firm's total long-term debt (including the portion of long-term debt classified as current) scaled by average total assets.
ΔLIQUID	Change in the firm's current ratio between the end of year t and year t- 1. Current ratio is defined as total current assets divided by total current liabilities.
EQ_OFFER	A binary variable that indicates whether a firm issued equity ('1') or not ('0') in year t.
ΔMARGIN	Gross margin (net sales less costs of goods sold) for the year t scaled by net sales for year t, less the firm's gross margin (scaled by net sales) from year t-1.
ΔTURN	Change in the firm's asset turnover ratio between the end of year t and year t-1. The asset turnover ratio is defined as net sales scaled by average total assets for year t.
1 yr BHAR	One year ahead buy-and-hold abnormal return that is a firm's one year buy-and-hold return minus the buy-and-hold return on the value-weighted average return of all available firms in the size-matched portfolio. The proxy for firm size is the market value at the beginning of the return period. Return compounding ends the earlier of one year after return compounding started or the last day of CRSP reported trading.
DELIST	A binary variable that indicates whether a firm delisted ('1') during the one year return accumulation period or not ('0').

Appendix B

Fundamental Variable Calculations

Variables	**Compustat Item #**	**Description**	**Calculation**
Market value of equity	PRCC_F	Price Close - Annual - Fiscal Year	$PRCC\_F_t \times CSHO_t$
	CSHO	Common Shares Outstanding	
Book-to-Market Ratio	CEQ	Common/Ordinary Equity - Total	$CEQ_t/(PRCC\_F_t \times CSHO_t)$
	PRCC_F	Price Close - Annual - Fiscal Year	
	CSHO	Common Shares Outstanding	
Average Total Assets (AAT)	AT	Assets - Total	$AT_t+AT_{t-1}/2$
SPI	SPI	Special Items	SPI/AAT_t
ROA	IBC	Income Before Extraordinary Items (Cash Flow)	IBC_t/AAT_t
ΔROA	IBC	Income Before Extraordinary Items (Cash Flow)	$(IBC_t/AAT_t) - (IBC_{t-1}/AAT_{t-1})$
CFO	OANCF	Operating Activities – Net Cash Flow	$OANCF/AAT_t$
ACCRUAL	IBC	Income Before Extraordinary Items (Cash Flow)	$(IBC-OANCF)/AAT_t$
	OANCF	Operating Activities – Net Cash Flow	
ΔLEVER	DLTT	Long-Term Debt - Total	$(DLTT_t+DLC_t/AAT_t) - (DLTT_{t-1}+DLC_{t-1}/AAT_{t-1})$
	DLC	Debt in Current Liabilities - Total	
ΔLIQUID	ACT	Current Assets - Total	$(ACT_t/LCT_t) - (ACT_{t-1}/LCT_{t-1})$
	LCT	Current Liabilities - Total	
EQ_OFFER	SSTK	Sale of Common and Preferred Stock	$SSTK_t$
ΔMARGIN	GP	Gross Margin (Sales less Costs of Goods Sold)	$GP_t - GP_{t-1}$
ΔTURN	SALE	Sales/Turnover (Net)	$(SALE_t/AAT_t) - (SALE_{t-1}/AAT_{t-1})$

Appendix C

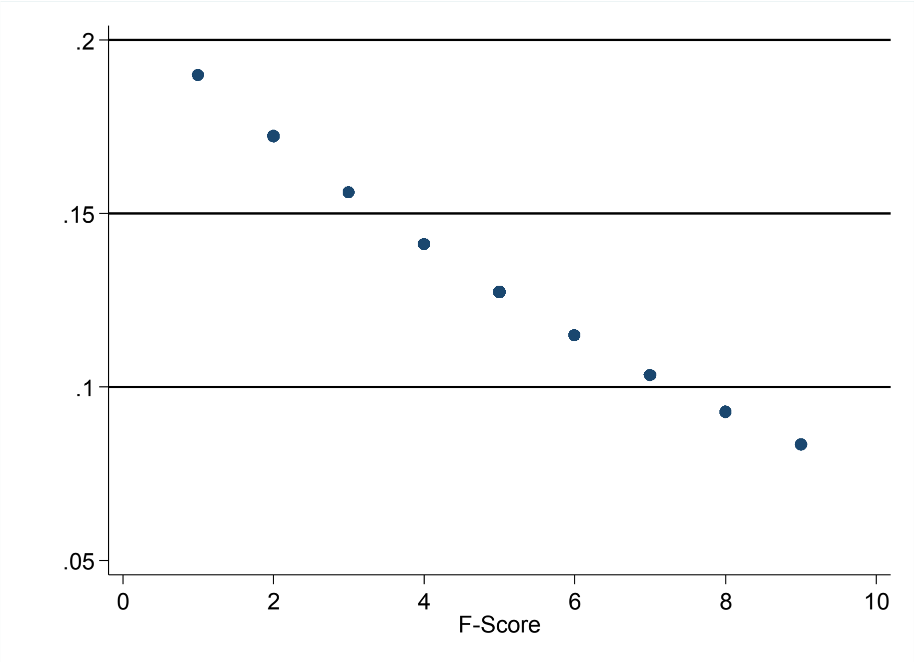
Logistic Regression without the "unusual" year 1990(*n* = 5.296)

$$(3) \quad DELIST = \alpha + \beta_1 F\text{-}SCORE + \varepsilon$$

Dependent variable:	DELIST	
	Logit Coefficient	Std. Err.
F-Score	-0,1183***	0,0266
	(z = -3,89)	
Constant	-1.3322***	0,1027
	(z = -13,07)	
n	5.296	
χ^2 (df=1)	20.24	
Odds ratio	0,8884	
Pseudo R^2	0,0046	

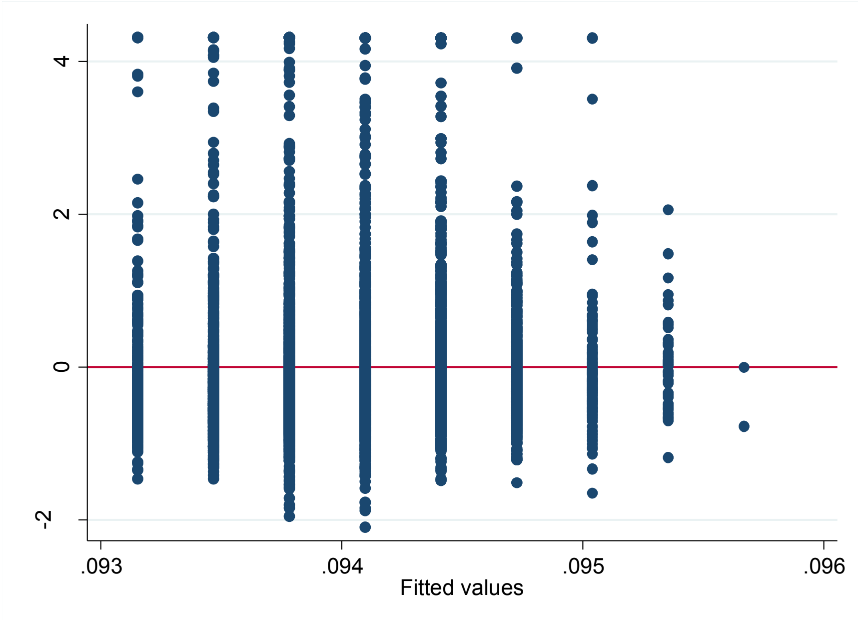
*** Significant at 1% level (p<0.01) ** Significant at 5% level(p<0.05) * Significant at 10% level (p<0.10)

Predicted Probability of a firm delisting without the "unusual" year 1990



Appendix D

Equation 4 Plot of Residuals versus Fitted values to test heteroskedasticity



Equation 5 Plot of Residuals versus Fitted values to test heteroskedasticity