Accounting Research Journal

Abnormal Returns Using Accounting Information within a Value Portfolio

Pradip Banerjee Soumya G Deb

Abnormal Returns Using Accounting Information within a Value Portfolio

Abstract

Purpose: This paper investigates whether a simple accounting information based fundamental analysis strategy could identify winners from losers within a portfolio of high book to market (value) stocks, over the last decade in the Indian equity market, where historically information disclosure and transparency levels have been on the lower side.

Design/Methodology/Approach: Using a sample of 'value' firms, we formulate an 'F-score' for each firm, as the sum of binary signals (favourable and unfavorable) with respect to nine key variables. We then form ten equal size F-score portfolios within the value band, each year, and track the performance of robust high F score firms vis-à-vis that of weaker low F score firms.

Findings: We highlight, that the historical success of a value strategy in general, relies on the strong performance of few firms while 'tolerating the poor performance of many deteriorating companies' within the broad value group and show that firms with strong fundamentals within the value group outperform their less robust counterparts, based on absolute as well as risk adjusted measures.

Practical Implications: Our results show that strong performers can indeed be distinguished from underperformers within the broad category of value stocks. This can have significant implications for investors at large in the Indian equity market.

Originality /Value: The study suggests an approach to identify potential winners within a broad 'value' portfolio using an array of accounting information even in a relatively less transparent Indian equity market.

Key Words: F-score, Value stock, book-to-market, Abnormal returns

Paper Type: Research Paper.

1. Introduction

This paper investigates whether a simple accounting based fundamental analysis strategy can help investors identify superior performers within a portfolio of low market-to-book (value)[1] stocks in the Indian equity market over the last decade. One of the most contentious issues of discussion among researchers for many years is the empirical evidence that value stocks generate higher average returns than growth stocks. A significant amount of research in this area (Chan et al., 1991, Fama and French, 1992; Rosenberg et al., 1985; Deb et al., 2006 and Deb, 2012), demonstrates evidence towards the same in various markets across the globe, including Indian equity markets. Prior literature attributes this superior performance to both market efficiency and inefficiency. Fama and French (1992) argue that value stocks typically represent distressed firms and are hence more risky. The subsequent superior performance of these firms thus represents a fair compensation for incremental risk. This interpretation is also reflected in other contemporary works (Penman, 1991). Another explanation towards this superior return performance is believed to be 'market mispricing'. This theory postulates that value firms are actually 'neglected firms', where the market overshoots and forms 'too pessimistic' expectations about future performance of these firms based on some poor prior performance (Lakonishok et al., 1994). This leads to 'positive return surprises' in the subsequent periods causing superior performances (La Porta et al., 1997). Historically, however, it is seen that analysts typically tend to recommend glamour stocks and strong momentum companies (La Porta, 1996). One possible explanation for this is probably their belief that on an individual stock basis a typical value firm underperforms the market and the success of the value strategy is exhibited only at a portfolio level.

Piotroski (2000) explores further into this issue and highlights that success of value strategy relies on the strong performance of a few firms within the group while "tolerating the poor

[1]Value stocks are stocks with low ratios of price to some fundamental parameter like book-value of equity, cash flow, sales, earnings etc.

performance of many deteriorating companies" within the same. He also points out that given the diverse outcomes realized within the same portfolio of value stocks, investors could benefit, ex–ante, by distinguishing between potentially strong and weak companies within the high book-to-market band. This can be done by following a simple accounting based fundamental analysis strategy that he calls 'F-SCORE'. Working on a sample of around 14000 US value stocks over a period of 21 years between 1976 to 1996, he demonstrates that this F score strategy can "shift the distribution of returns earned by an investor" positively and significantly differentiates winners from losers within a generic value portfolio. He argues that this strategy will be especially efficient in case of value stocks for three reasons : i) value firms are often ignored by market participants and are not adequately followed by analysts, ii) for value firms, most informal information dissemination channels are difficult to access and hence financial statements represent the most reliable and most accessible source of information, iii) from a valuation perspective also, growth stock valuations are typically based on long term performance expectations, with investors relying mostly on non-financial information. On the other hand valuation of value stocks, with little current expectation in place, typically focuses more on the firm's fundamentals. To the extent investors can use financial information and fundamental analysis to identify strong value companies, a high return value investment strategy can be devised. Some similar approaches, attempting to establish the usefulness of fundamental analysis are not uncommon. Mohanram (2005) combines traditional fundamentals, such as earnings and cash flows, with measures tailored for growth firms, such as earnings stability, growth stability, intensity of research and development, capital expenditure and advertising, to create an index called GSCORE. He reports significant excess returns to a long short strategy based on G Scores. Ou and Penman (1989) demonstrate that certain financial ratios can be useful in predicting future changes in earnings. Abarbanell and Bushee (1997) show that an investment strategy based on financial signals earn significant abnormal returns. Lev and Thiagarajan (1993) analyze 12 financial signals that are used by financial analysts, and show that these signals are correlated to contemporaneous returns. Sloan (1996) shows that firms with a higher proportion of accruals in their earnings underperform in the future.

A fundamental analysis based strategy, should work at least as well in emerging markets where efficiency tends to be lower. Harvey (1995) shows that the amount of predictability found in emerging markets are greater than found in developed markets. The objective of this study is to investigate whether a simple fundamental analysis based strategy, can separate winners from losers within a portfolio of value stocks in an emerging market like India. The choice of only value stocks arises out of the notion that, inefficiency, if any, in incorporating financial information in the stock prices are to be expected more in case of value or 'distressed' stocks rather than highly followed growth or glamour stocks. In India, transparency and disclosure levels are not very high. The country ranking on Transparency International, India's overall rank is quite low (94/177) as compared to US (19/177) and India's rank on financial secrecy is also stand much lower (25/71) as compared to US (5/71)[2]. Khanna, Palepu and Srinivasan (2004) analyze the firm level disclosure data of S&P[3]and show the average score on overall transparency and financial transparency and disclosure of India is a meagre 4.5 and 5.7 respectively (on a 10 point scale). Despite having such low levels of transparency and financial disclosure for Indian companies, our results show that an 'F score strategy' derived from historical accounting information, is strong enough to earn consistent positive superior returns, both on absolute and risk adjusted basis, within a value portfolio.

In this study we use a sample all firms listed in NSE and identify those with sufficient stock price and accounting data during our study period. In line with Piotroski (2000), we develop an

---

[2]http://www.transparency.org/country

[3] The transparency and disclosure survey developed by Standard and Poor's (S&P) contains 98 questions for scoring process, segmented into three different categories namely ownership structure, financial transparency and disclosure and Board and management structure. All these questions included for scoring purpose are benchmarked with U.S. best practices.

F-score of each firm each year within our study period by combining nine binary fundamental signals pertaining to three broad areas: (i) profitability, (ii) leverage & liquidity and (iii) efficiency. We then form two broad groups of value and growth stocks based on the P/B ratios of the firms each year. We select the firms only within the value subgroup for our final analysis. Within the value group we arrange the firms in an ascending order of their F scores and form 10 portfolios of equal number of stocks, name the lowest F score portfolio as F1 and the highest F score portfolio as F10. The performance of the high F score (HFS henceforth) portfolios vis-à-vis the low F score (LFS henceforth) portfolios is then checked through a number of absolute and risk adjusted return measures. Our hypothesis is that if the market puts a value to robust fundamentals within the value band, HFS portfolios should outperform the LFS portfolios.

We also check the performance after controlling for the impacts of size and book-to-market effect using the 3 factor model of Fama and French (1993)(FF henceforth) . We repeat the entire procedure across a number of sub-periods within our overall time horizon to check if any time specific pattern is observable. Our results indicate that HFS value firms with robust fundamentals indeed earn a superior return based on both absolute and market risk adjusted measures over their LFS counterparts in the overall period, as well as in most sub-periods. This indicates that the success of the F score strategy is not limited to any particular time band .

There is a possibility that this differential performance between the HFS portfolios vis-à-vis the LFS portfolios could be potentially typical within some very low priced or illiquid stocks. This would jeopardize the universal applicability of the strategy and adversely affect the investor's ultimate experience. To address that concern, we carry out some robustness checks by creating partitions within our sample based on share price and turnover (trading volume) and explore the effectiveness of the F score strategy within such partitions. Our results indicate that the F score strategy is not typical to any particular price or turnover groups.

A concern expressed by Piotroski (2000) and some subsequent researchers (Anderson and Draskovic 2011; Mohanram 2005) in this area is that the translation of accounting numbers into binary signals could potentially eliminate useful information evident in the magnitude *per se* of the measures. We address that concern in this study, by using a Rank-Sum-Score (RSS) which would capture the continuous representations of the fundamental measures to form portfolios and explore the performance of high RSS portfolios and low RSS portfolios. We find that the results from the RSS analysis reinforce the findings of the F score strategy. Anderson and Draskovic (2011) suggest further improvement to the F score strategy by weighting the importance and the strength of the nine signals. In line with their suggestion, we further develop a Correlation Weighted F Score (CORFS) and explore performances of portfolios based on CORFS. Our results again substantiate our previous findings.

We are aware of only a couple of related studies in the Indian context by Venkatesh, *et al.,* (2013), which use a G-Score in analyzing the financial position of thirty stocks in IT, pharmacy and banking sectors. However, the studies suffer from a small sample size and the firms in the sample are also not sorted by book-to-market ratio. We intend to address both these issues in our study. The remaining portion of the study is organized as follows. The next section discusses the data and methodology adopted for F-score calculation and performance evaluation of the F-score portfolios. Section 3 presents the results obtained and the inferences thereon. Section 4 concludes the paper followed by the references and tables.

2. Data and Methodology

Our study period is from March, 2003 to March, 2013. We start by including all firms listed in NSE for each year and get all data for each company on the chosen nine accounting variables. All firm level accounting information related to calculation of F score is collected from the CMIE Prowess database. Methodology of calculating F scores is detailed in the next subsection. We also collect the monthly return data (dividend adjusted) for each stock for analysis of the absolute and risk adjusted performance of F score portfolios, and turnover (trading volume) and closing price data of each for partition analysis, from CMIE Prowess. We use the monthly returns from NIFTY Total Return Index as the proxy for the market return Rm and the 91-D Treasury bill yields from Reserve Bank of India website[4]as the proxy for risk free rate.

We include only those firms in the final sample which has data on all the required variables and monthly return data for at least two consecutive years, as we monitored performance of F-score portfolios for at least two years after portfolio formation. Accordingly the number of firms in our sample varies from 800 to around 1300, detailed in Table 1. We then proceed to calculate the F-score of each firm in our sample at the beginning of each financial year based on the previous year's financial information and signals. That is, the F-scores for the firms are calculated as on March of year 't' based on the financial information provided by the firm from April of year t-1 to March of year t, where 't' is from 2003 to 2011. The accounting year in India is typically from April of year't-1' to the March of year 't' and hence the choice. As we measure the performance of the portfolios for over the next two years after portfolio formation, our total study period is up to March 2013. After finding F-scores for all firms across all years, we arrange our sample each year based on a price to book ratio (P/B) the firms as on 31st March of every year, into three groups: a value group comprising the bottom 30% the growth group comprising the top 30% and a median group comprising the remaining 40% of the firms in between. The cut off percentages chosen for the groups are in line with FF. For our final analysis we select the year-wise value group only, which we divide further into ten portfolios based on their F scores, as mentioned before and explore their relative performance. We elaborate the processes in greater detail hereunder.

[4] Reserve bank of India Website :www.rbi.org.in for the yields on 91 days T Bills .

Calculation of F-scores

We closely follow the variables and the methodology used by Piotroski (2000) in calculating the F-scores. We first choose nine variables to measure three areas of the firm's fundamental robustness: i) profitability, ii) leverage, liquidity and source of funds and iii) operating efficiency. From these variables, nine binary signals are derived, which are then classified as either 'favourable' or 'unfavourable' depending on their implication for future performance in terms of firm profitability and returns. We assign a value of 1 if the signal is favourable and '0' otherwise. We finally define the sum of these binary signals as the F-score. We describe these steps in detail below.

Step 1: Identifying the variables relevant for assessing the firm's fundamental robustness:

We choose 4 variables as proxies of the firm's robustness in the profitability area. These are ROA, ΔROA, CFO and ACCRUAL. We define them as follows:

i) $ROA = \dfrac{Net\ Income / PAT_{31st\ March,t}}{Total\ \ Assets_{\ 31st\ March,\, t-1}}$, where t = 2003, 2004 ….. , 2013.

ii) $\Delta ROA = ROA_{31st\ March\ ,t} - ROA_{31st\ March\ ,t-1}$

iii) $CFO = \dfrac{Cash\,Flow\ from\,Operations\ _{31st\ March,t}}{Total\ \ Assets\ _{31st\ March,\, t-1}}$

iv) $ACCRUAL = \dfrac{(PAT - CFO)_{31st\ March\,,t}}{Total\ \ Assets\ _{31st\ March,\, t-1}}$

We choose 3 variables in the leverage, liquidity and sources of funds area as proxies for the firm's robustness. ΔLEVERAGE, ΔLIQUIDITY, and ΔEQUITY.

We define them as follows:

v) $\Delta LEVERAGE = \dfrac{Total\ \ Borrowings_{31st\ March,\, t} - Total\ \ Borrowings_{31st\ March,\, t-1}}{Total\ \ Assets\ _{31st\ March,\, t-1}}$

where total borrowings = short term borrowing + long term debt

vi) $\Delta LIQUIDITY = Current\ Ratio_{31st\ March\ ,t} - Current\ Ratio_{31st\ March\ ,t-1}$

vii) $\Delta EQUITY = Equity\ Capital_{31st\ March\ ,t} - Equity\ Capital_{31st\ March\ ,t-1}$

We choose 2 more variables in the operating efficiency area. They are ΔMARGIN and ΔTURNOVER which ~~are~~we define as follows:

viii) $\Delta MARGIN = \dfrac{Gross\ Margin_{31st\ March,\ t} - Gross\ Margin_{31st\ March,\ t-1}}{Sales_{31st\ March,\ t}}$

Where, gross margin is sales minus cost of goods sold.

ix) $\Delta TURNOVER = \dfrac{Sales_{31st\ March,\ t} - Sales_{31st\ March,\ t-1}}{Total\ \ Assets_{31st\ March,\ t}}$

Step 2: Assigning the binary signals

We then assign binary signals of 'Favourable' (= 1) and 'Unfavourable' (= 0) against observed values of each variable mentioned above for calculating the F-Score for each firm. The process is detailed hereunder:

i) F_ROA = 1, if ROA > 0, 0 otherwise.

ii) F_CFO = 1, if CFO > 0, 0 otherwise

iii) F_ΔROA = 1, if ΔROA > 0, 0 otherwise

iv) F_ACCRUAL = 1, if ACCRUAL < 0, 0 otherwise

Reasons for i), ii) and iii) are easily understandable. A negative accrual implies a CFO greater than PAT which would in turn imply that the firm has achieved some efficiency in realizing previous accruals, which we thought should be a good sign for the firm.

In the next area, we assign,

v) F_ΔLEVERAGE = 1, if Δleverage < 0 , 0 otherwise

vi) $F\_\Delta LIQUIDITY = 1$, if Δliquidity > 0, 0 otherwise.

vii) $F\_\Delta EQUITY = 1$, if $\Delta EQUITY <= 0$, 0 otherwise

The arguments here are as follows: since our sample consists primarily of value stocks, which are apparently 'financially distressed' firms, an increase in leverage for those firms should be a worrying signal. An improvement in liquidity is a good signal about the firm's ability to service debt obligations and vice-versa. The general finding in literature is that an equity issue is a bad signal for a typical firm due to the information asymmetry (Myers and Majiluf, 1984). This would be even truer for typical high book- to market financially distressed firms since there is more information asymmetry for these firms.

Finally in the Operating Efficiency area:

viii) $F\_\Delta MARGIN = 1$, if $\Delta MARGIN > 0$, 0 otherwise

ix) $F\_\Delta TURNOVER = 1$, if $\Delta TURNOVER$ is positive, 0 otherwise

Here again the argument is that an improvement in the gross margin is a good signal and an improvement in turnover, should also be a good signal for the firm signifying greater productivity from the asset base.

Step 3: Finding the F Score and forming the F score portfolios for tracking performance:

We define the F-Score for a firm in a particular year as the sum of these nine binary signals. The expression for F score is: as follows:

$$\begin{aligned} F\_SCOREfirm = {} & F\_ROA + F\_CFO + F\_\Delta ROA + F\_ACCRUAL + F\_\Delta LIQUIDITY + \\ & + F\_\Delta LEVERAGE + F\_\Delta EQUITY + F\_\Delta MARGIN + F\_\Delta TURNOVER \end{aligned}$$

Once the F scores for all firms across all years are found, we sort the firms in our sample in ascending order of their P/B ratios on 31st March, and segregate our sample into three groups of value, growth and median, each year. The value group consists of the bottom 30% of the firms, the growth group comprises the top 30% and the median group comprises the median 40%. For our final analysis we select the value group only each year. Within the value group, we form ten equally weighted portfolios as F1, F2,.....F10 etc. on 1st of April of each year 't' based on F score calculated as on 31st March of the year. F10 includes firms with the highest F-scores, while F1 includes the firms with the lowest F-scores. We do not form F-score portfolios after 2011, in order to ensure that we have at least two years of return data following portfolio formation to track the performance of the portfolios. Each portfolio contains equal number of firms which keeps on varying across different portfolio formation years as our sample size is also varying every year.

Preliminary Evaluation of performance of F-score portfolios:

We collect monthly dividend adjusted return data against each firm in our sample for the period from April 2003 to 2013 from Prowess database. After formation of the F score portfolios we calculate the monthly returns of each F score portfolio for the next two years, as an equally weighted average of the monthly returns of its constituent stocks. To have a first glimpse of our hypothesis that the relative performance of the HFS portfolios could be different from that of the LFS portfolios we look at the simple mean monthly raw returns of the individual F score portfolios averaged over all portfolio formation years. We find that the HFS portfolios generate higher returns than the LFS ones.

We then look at the differential average monthly raw returns for the HFS portfolios (F7 through F10) vis-à-vis the LFS portfolios (F1 through F4) over the next 1 year and 2 year period, keeping F5 and F6 as the median portfolios. A similar approach is adopted to explore the differential raw buy and hold returns (BAHR),if any, between the high and low F score groups over next one and two year periods. The BAHR of a portfolio is taken as the value weighted average BAHR of the individual stocks in the portfolio. The results are detailed in table 3. Here again we find that HFS portfolios outperform LFS ones.

To check , if the differential returns persist even after controlling for (i) the market risk factor and (ii) the market risk factor along with two other FF risk factors SMB and HML. We run regressions, using the differential average monthly returns of high F-score portfolios (F7,F8,F9,F10) over the average monthly returns of the low F-score portfolios (F1,F2,F3,F4) as the dependant variable and i) Rm-Rf only and ii) the three FF factors Rm-Rf, SMB, HML as the independent variables.

The regression models estimated are as follows:

$$\mathrm{R(HFS)}_{t} - \mathrm{R(LFS)}_{t} = \alpha + \beta(\mathrm{Rm - Rf})_{t} + \varepsilon_{t} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad (1)$$

$$\mathrm{R(HFS)}_{t} - \mathrm{R(LFS)}_{t} = \alpha + \beta(\mathrm{Rm - Rf})_{t} + \mathrm{s(SMB)}_{t} + \mathrm{h(HML)\,t} + \varepsilon_{t} \quad \ldots\ldots\ldots\ldots \qquad (2)$$

In this regression, HFS (t) is the return on high F-score portfolio group for month t, LFS is the return of the low F score portfolio group for month t, $(\mathrm{Rm\text{-}Rf})_t$ is the market risk premium for the month t, SMB_t is the difference between the returns on diversified portfolios of small stocks and big stocks, and HML_t is the difference between the returns on diversified portfolios of value stocks and growth stocks. As mentioned before, the monthly SMB, and HML factors for our study period were generated following the procedure adopted by FF. We realize that our study period from 2003 to 2013 can be broadly divided into the following three sub periods (SPs) based on the overall stock market movement[5] during these periods:

i) SP1= 2003 -2007: bull period with overall market movement = 434%

[5]The market here is represented by the NSE Nifty total return, which reflects a combination of the capital gains yield as well dividend yield of the constituent stocks. The returns during the subperiods are calculated over the first trading-date of the beginning year to the last trading-date of the closing year.

ii)SP2= 2008 : the global meltdown year of 2008 with overall market return = -52%

iii) SP3= 2009-2013: the recovery period with overall market = 94%

To check whether there are any differential patterns observable across these different sub periods because of potentially different market sentiments existing in each of them, we estimate the regression models (1) and (2) above separately over the entire period and the three sub periods.

Testing Robustness of the F score strategy: Addressing a few concerns:

A. Partition Analysis:

Piotroski (2000) and Mohanram (2005) express the concern that the success of the F score strategy could be potentially arising out of a 'liquidity premium' and could be typical to some very 'low priced' or 'illiquid' stocks which jeopardizes the universal applicability of the strategy and adversely affect the investor's ultimate experience. To address this concern, we carry out a robustness check of the F score strategy within turnover (trading volume) as well as price 'partitions'. The process adopted is as follows: we first divide our sample into three broad partitions: small (bottom 30%), median (40% in between) and large (top 30%), based on their turnover. We then create the F-score portfolios within each turnover partition based on the F-scores of the constituent firms in each partition. We then look at the one year and two year BAHR of the high F-score portfolios and LFS portfolios and their differential return, if any within each turnover partition. A similar process is repeated by creating partitions with respect to closing price as well.

B. RankSum Score (RSS) analysis :

The translation of profitability, liquidity, capital structure and operating efficiency measures into binary signals (of 0 and 1) can eliminate useful information evident in the magnitude per se of the measures. Piotroski (2000), prescribes a 'Rank Score' approach whereby the binary signals are extended to capture the continuous representations of the financial performance factors. We also perform a robustness check for the F score strategy with Piotroski's rank score approach with some modifications. Piotroski (2000) relied on a relative rank score between 0 and 1. We on the other hand apply a 'Rank Sum Score' (RSS henceforth). Every year, end of March, we arrange our sample firms in ascending order of the magnitude of each of the variables used to calculate the F-score (except Δequity because of its binary nature). We then assign a rank to each firm based on the value of the concerned variable among all firms and repeat the procedure for all other eight variables. We then find the sum of the ranks against all eight variables for each firm in that year which we define as RSS. A high RSS firm in this process is expected to have strong fundamentals than a low RSS firm and hence correspond to a high F-score firm. We repeat the procedure for all firms every year. With the yearly rank sum scores generated we then proceed to arrange our sample of firms every year into ascending order of their RSS. The RSS sorted firms are then grouped into quintiles Q1, Q2, Q3, Q4 and Q5 every year end of March, with Q1 including firms with lowest RSS and Q5 including firms with highest RSS. With the return figures of each individual firm in each quintile available we then find the one year and two year BAHR for each quintile. High RSS quintiles Q4 and Q5 should correspond primarily to the HFS portfolios while the low RSS quintiles Q1 and Q2 should correspond primarily to the LFS portfolios. We then move on to explore the marginal difference in one year and two year BAHRs (if any) between the high RSS quintiles and the low RSS quintiles. High RSS quintiles outperforming the low RSS quintiles would imply robustness of the F score strategy.

C. Correlation Weighted F score (CORFS) analysis:

Piotroski (2000) employs equal weights to each of the nine binary signals, even when the corresponding variables exhibit different correlations with future returns. This is criticized in some works (Anderson and Draskovic, 2011). We try to address that issue by a correlation weighted F score (CORFS) approach. We first find the Spearman's correlation coefficients of the nine signals with one year and two year returns and use these correlation weighted sum of the signals as the modified F-score which we call 'Correlation Weighted F score' or CORFS. By this approach the relative importance of each of the signals is incorporated in the F-score calculation rather than employing equal weights for each signal, which can have important consequences. Once the CORFS for each firm is found every year end of March, we group the CORFS sorted firms into quintiles Q1, Q2, Q3, Q4 and Q5, with Q1 including the firms with lowest CORFS and Q5 including the firms with highest CORFS. We then find the one year and two year BAHR for each quintile, and check if there are any marginal difference in that between high CORFS quintiles (Q4 and Q5) and low CORFS quintiles (Q1 and Q2). The way we define CORFS, a high CORFS firm should typically have stronger fundamentals than a low CORFS firm. If the fundamental analysis strategy is robust then we should expect the high CORFS quintiles to outperform the low CORFS quintiles.

3. Results and Inference

Table 1 (Panel A) shows the year wise breakup of the entire sample by the total number of firms for which we have data to calculate the F-scores and the number of value stocks. Table 2, Panels A and B shows the future return realizations vis-à-vis the individual F score signals. To provide preliminary evidence as to whether the signals used are effective, we examine the relationship between the individual signals and the future one-year and two-year BAHRs for our sample of firms. We find that firms with positive ROA (F_ROA=1) have significantly higher one and two year BAHR. Similar results are obtained for the ΔROA and Δleverage variables indicating that firms with positive ROA changes and reducing net debt exposure over the last one year are more prone to generate higher returns over the next one year as well as two years However, we find slightly counterintuitive results as far as ΔACCRUAL is concerned. We find that firms with higher accruals (F_ΔACCRUAL=0) also have higher returns, inconsistent with our conjecture that more accruals are detrimental for future returns.

Table 3 reports differential mean monthly returns and one and two year BAHRs between the HFS (F7 through F10) and LFS (F1 through F4) portfolios. We find that the differential mean monthly returns and BAHR between the HFS and LFS portfolios for the next one and two years are all positive and statistically significant although the magnitude per se is small (about 2% for 1 year and 2 year BAHRs and less than 1% for monthly average).These findings thus definitely indicate that HFS firms with robust fundamentals outperform the LFS firms with weaker fundamentals on the average, within a generic band of value firms, although by a small margin.

Tables 4 and 5 shows the results of the regression models (1) and (2) discussed in the previous section. The regression models test if the strategy of long HFS and short LFS portfolio position earns abnormal returns even after controlling for (i) the market risk factor and (ii) the three FF risk factors. Table 4 shows the results of the single factor (CAPM) model and table 5 shows the results of the FF three factor model. We run the models for the overall period 2003-2012, and also over three sub-periods: SP1, SP2 and SP3, to check differential patterns, if any, in the marginal returns between HFS and LFS portfolios. From table 4 we find that the 'abnormal return' generated by this hypothetical long HFS – short LFS portfolio captured by the intercept 'α' is positive and significant over the entire period, and also the three sub periods. It is negative and significant during the meltdown year which was the period when everything in the market went down. We find almost exactly similar patterns using the three factor model (Table 5). The three factor alphas, capturing the abnormal returns generated by the long HFS and short LFS portfolios across all the sub-periods are positive significant except for the meltdown year. The abnormal return generated by the F score strategy is thus significant even after controlling for the market risk, the size and the book–to-market effect. This indicates that the F-score strategy works quite well even in an emerging market like India, where financial transparency and disclosure is relatively low.

Table 6 shows the results of the RSS approach. We find a positive and statistically significant differential return between fundamentally robust firms vis-à-vis fundamentally weaker firms,(as evident from the 'High-Low' and 'High-All' numbers in the table) at least when the two year BAHR is considered. In case of one year BAHR, the differential return is insignificant although the magnitude is positive. As high RSS quintiles correspond to the HFS portfolios and low RSS quintiles correspond to the LFS portfolios, this observation also substantiates the robustness of F-score strategy to identify winners from a generic portfolio.

Table 7 represents the results of the robustness test vide partition analysis. We observe that , the F-score strategy is effective across price and turnover partitions. The differential one year BAHR between HFS and LFS portfolios is positive and significant in small, medium as well as large price and turnover partitions, while the differential two year BAHR is positive and significant in all but the small price partition. This re-emphasizes our general observation that the F-score strategy indeed works well in the Indian equity market.

Finally, table 8 shows the results of the robustness test vide CORFS approach. We find that the one year and two BAHRs of the high CORFS quintiles exceed the corresponding numbers for the low CORFS quintiles. The future returns earned by a typical high CORFS quintile are higher than an average quintile or a low CORFS quintile, particularly over a two year holding period. This again substantiates the strength of the F score strategy.

Conclusions

In this paper, we test whether a simple accounting information based fundamental analysis strategy can identify winners from losers within a broad portfolio of value stocks. The motivation primarily comes from Piotrosky (2000) who test a similar strategy for the US markets and reports that there could be a few superior performers and a large number of underperformers within an overall portfolio of value stocks, and prescribes an accounting information based strategy to identify potential winners within the portfolio. We highlight the fact that levels of transparency and financial information disclosure are significantly lower in India compared to US or other developed markets. As such a question naturally arises: will a similar strategy also work in India with such low levels of disclosure and transparency?

We broadly follow Piotrosky's (2000) basic 'F score' approach, although we extend it in several ways. We carry out an RSS approach to incorporate the information content in the magnitude per se of the accounting variables and a "partition analysis", to test is the F score strategy's effectiveness is limited to a small group of low priced and low liquidity stocks. We also carry out a Correlation Weighted F-score (CORFS) approach to test whether weighing the fundamental signals with their respective observed correlations with future returns could change the results significantly.

Our results show that the high F-score portfolios significantly outperform the low F-score portfolios, on a risk adjusted basis, overall, as well as across all subgroups or partitions. This finding is strongly substantiated by the RSS and the CORFS extensions of the basic approach. This suggests that Indian firms with strong fundamentals within the value group earn a superior return over their less robust counterparts, based on absolute as well as risk adjusted measures, and the superior performance persists even after controlling for time, size, book to market, price and turnover. The F score strategy based on accounting information thus works even in an apparently less transparent financial disclosure environment like India. The ability to distinguish future successful and unsuccessful firms and marginal abnormal returns from the strategy indicates that the Indian equity market could not efficiently incorporate past signals into present stock prices, at least for the less followed and out of favour value stocks. These findings, we believe, should have significant implications in the Indian equity market for the investors at large.

References:

Abarbanell, J. and B. Bushee. (1997), ''Financial Statement Analysis, Future Earnings and Stock Prices.'' *Journal of Accounting Research*, Vol. 35, pp.1–24.

Anderson, E. and Draskovic, D. (2011), " Dreaming of Beating the Market : A Fundamental Analysis Study on the Stockholm Stock Exchange" , Bachelor Thesis , Uppsala University, Department of Business Studies, extracted from http://www.divaportal.org/smash/record.jsf?pid=diva2:427729. (accessed 17 August, 2014).

Chan, K.C; Y Hamao and J Lakonishok. (1991), "Fundamentals and Stock returns in Japan", *Journal of Finance*, Vol. 46, pp.1739-1789.

Deb,S.G, (2012) "Value Versus Growth: Evidence from India", *IUP Journal of Applied Finance*, Vol.18, No.2, pp.48-62.

Deb, S G, Banerjee A, Chakrabarty, B, (2006), "Value Premium In Indian Equity Market During 1990 To 2005: Market Evidence", *IUP Journal of Applied Finance*, Vol.10, No.2, pp. 55-72.

Fama E, and K French (1992) ,'The Cross Section of Expected Stock Returns', *Journal of Finance*, Vol.47, pp.427-65.

Fama, Eugene F.; French, Kenneth R. (1993). "Common Risk Factors in the Returns on Stocks and Bonds". *Journal of Financial Economics*, Vol.33, No. 1, pp.3–56.

Harvey C R., (1995) "Predictable Risk and return in Emerging Markets", *Review of Financial Studies,* Vol.8, pp. 773-816.

Khanna T, Palepu K, Srinivasan S, (2004), "Disclosure Practice of Foreign Companies Interacting with U.S. Markets", *Journal of Accounting Research*, Vol.42(2), pp.474-508.

La Porta, R. (1996), "Expectations and the Cross-Section of Stock Returns", *Journal of Finance*, Vol.51, pp. 1715–1742.

Lakonishok J, A Shleifer and R Vishny. (1994), “Contrarian Investment, Extrapolation and Risk”, *Journal of Finance*, Vol.44, pp. 1541-78.

Lev, B. and R. Thiagarajan, (1993), ‘‘Fundamental Information Analysis”. *Journal of Accounting Research*, Vol.31, pp.190–214.

Mohanram, P.S. (2005), “Separating Winners from Losers among Low Book-to-Market Stocks using Financial Statement Analysis”, *Review of Accounting Studies*, Vol.10, pp.133-170.

Myers, S. C., &Majluf, N. S. (1984). “Corporate Financing and Investment Decisions When Firms Have Information that Investors Do Not Have”, *Journal of Financial Economics*, Vol. 13, No.2, pp. 187-221.

Ou, J. and S. Penman. (1989), “Accounting Measures, Price-Earnings Ratio and the Information Content of Security Prices”, *Journal of Accounting Research*, Vol. 27, pp.111–143.

Penman, S (1991), “An Evaluation of Accounting Rate of Return”, *Journal of Accounting, Auditing and Finance*, Vol. 6, pp.233-55.

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

Rosenberg B, K Reid and R Lanstein. (1985), “Persuasive Evidence of Market Inefficiency”, *Journal of Portfolio Management*, Vol.11, pp. 9-17.

Sloan, R. (1996), ‘‘Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings?”, *The Accounting Review*, Vol.71, pp. 289–316.

Venkatesh C. K, M Tyagi, and Ganesh (2013), “Analyzing The Performance Of High And Low Book-To-Market Ratio Firms With Specific Reference To Indian It, Pharmacy And Banking Stocks”, *Innovative Journal of Business and Management*, Vol.2, pp.40-43.

Table 1: Year-wise distribution of firms in our sample

This table shows the year wise breakup of the entire sample by the number of firms for which we have data to calculate the F-scores, and also by the number of value stocks (lowest 30% of firms when sorted by price-to-book ratio), growth stocks (highest 30% of firms when sorted by price-to-book ratio), and median stocks (middle 40% of firms when sorted by price-to-book ratio).

Year	Total Number of Firms (with F scores calculated)	Total Number of Value Stocks
2003	783	235
2004	783	235
2005	796	239
2006	846	254
2007	939	282
2008	1087	326
2009	1212	363
2010	1256	377
2011	1333	400
Total	**9035**	**2710**

Table 2: Future Returns and Individual Signals

This table reports the relationship between the individual signals and the future one-year BAHR and two-year BAHRs for the sample of value firms. The indicator variables take a value of 0 if unfavorable and 1 if favourable. Detailed explanation of the variables is given in Methodology section and Appendix. *** indicates significant at 1% while ** indicates significant at 5%.

Panel A : One year BAHR

	variable value =1	variable Value =0		
Indicator Variable	Mean one year Return (a)	Mean one year Return (b)	Differential return (a)-(b)	Significance of differential return
F_ROA	0.02	-0.001	0.021	.000***
F_CFO	0.016	0.016	-0.001	0.874
F_ΔROA	0.02	0.011	0.009	.038***
F_Accrual	0.011	0.025	-0.013	.004***
F_ΔLeverage	0.02	0.012	0.008	.059**
F_ΔLiquidity	0.018	0.014	0.004	0.406
F_ΔMargin	0.017	0.015	0.002	0.642
F_Δturnover	0.014	0.016	-0.002	0.671
F_Δ Equity	0.015	0.018	-0.003	0.57

Panel B : Two year BAHR

	variable value =1	Variable Value =0		
Indicator Variable	Mean Two-year Return (a)	Mean two year Return (b)	Differential return (a)-(b)	Significance of differential return
F_ROA	0.058	0.017	0.041	.000***
F_CFO	0.05	0.048	0.001	0.861
F_ΔROA	0.057	0.04	0.018	.008***
F_Accrual	0.045	0.058	-0.013	.061**
F_ΔLeverage	0.058	0.041	0.018	.008***
F_ΔLiquidity	0.055	0.045	0.01	0.139
F_ΔMargin	0.047	0.049	-0.002	0.753
F_Δturnover	0.05	0.039	0.011	0.129
F_DeltaEquity	0.048	0.057	-0.01	0.209

Table 3: Differential average monthly returns and buy and hold returns of HFS and LFS portfolios.

The averages are calculated over all portfolio formation years. Every year once the portfolios are formed their monthly average returns over the next one and two years and BAHR over next one and two years are found and averaged . The t-stats with *** are significant at 1% while the ones with ** are significant at 5% level of significance.

Average Monthly returns of the F score portfolios over the next one year after portfolio formation				Average 1 year BAHR of the F score portfolios		
	F7 through F10 (HFS)	F1 through F4 (LFS)	HFS minus LFS	F7 through F10 (HFS)	F1 through F4 (LFS)	HFS minus LFS
Mean	0.0030	0.0015	0.0015	0.0367	0.0189	0.0178
t-stat	2.737***	1.309	3.231**	3.151**	1.542	4.262***
Average Monthly returns of the F score portfolios over the next two year after portfolio formation				**Average 2 year BAHR of the F score portfolios**		
	F7 through F10 (HFS)	F1 through F4 (LFS)	HFS minus LFS	F7 through F10 (HFS)	F1 through F4 (LFS)	HFS minus LFS
Mean	0.0029	0.0022	0.0008	0.0721	0.0525	0.0196
t-stat	3.74***	2.62***	2.41**	6.964***	4.534***	3.975***

Table 4 : Regression of average returns of HFS minus LFS portfolio on the market risk factor Rm-Rf
Dependent variable: Average monthly returns of HFS portfolios (F7, F8,F9,F10) minus the average monthly returns of the LFS portfolios (F1, F2,F3,F4). The independent variable is the monthly returns of the market risk factor Rm-Rf. The regression equation estimated is :

$$R(HFS)_t - R(LFS)_t = \alpha + \beta(Rm\text{-}Rf)_t + \varepsilon_t$$

	Overall Period (2003-2012)			**Sub period I(2003-2007)- Boom period**		
Variable	**Coefficient**	**t-stat**	**p-value**	**Coefficient**	**t-stat**	**p-value**
Rm-Rf	-.0379197	-1.12	0.266	-.0222316	-0.42	0.678
α	.0014248	3.13***	0.002	.00173	2.37***	0.021
	Sub period II(2008)- meltdown			**Sub period III(2009-12)- recovery**		
Variable	**Coefficient**	**t-stat**	**p-value**	**Coefficient**	**t-stat**	**p-value**
Rm-Rf	-.1156752	-2.66***	0.024	-.0451006	-0.88	0.384
α	-.002243	-2.77***	0.020	.0019957	3.60***	0.001

Table 5 : Regression of average returns of HFS minus LFS portfolio on the market risk factor Rm-Rf, SMB and HML.

Dependent variable: Average monthly returns of HFS portfolios (F7, F8,F9,F10) minus the average monthly returns of the LFS portfolios (F1, F2,F3,F4). The independent variable is the monthly returns of the market risk factor Rm-Rf and the monthly returns of HMB and SML . The model estimated is as follows

$$\mathbf{R(HFS)_t - R(LFS)_t = \alpha + \beta(Rm\text{-}Rf)_t + s(SMB)_t + h(HML)_t + \varepsilon_t}$$

In this regression, HFS(t) is the return on high F score portfolio for month t, LFS is the return of the low F score portfolio for month t.

	Overall Period (2003-2012)			**Sub period I(2003-2007)- Boom period**		
Variable	**Coefficient**	**t-stat**	**p-value**	**Coefficient**	**t-stat**	**p-value**
Rm-Rf	-.0081007	-0.23	0.816	.0399762	0.74	0.463
SMB	-.05919	-1.43	0.155	-.137283	-1.91*	0.061
HML	-.1948593	-2.35***	0.020	-.2072143	-1.69*	0.096
α	.0013765	3.08***	0.003	.0015928	2.35***	0.022
	Sub period II(2008)- meltdown			**Sub period III(2009-12)- recovery**		
Variable	**Coefficient**	**t-stat**	**p-value**	**Coefficient**	**t-stat**	**p-value**
Rm-Rf	-.1874989	-3.42***	0.009	-.032609	-0.46	0.649
SMB	-.1283637	-2.49***	0.037	-.0047022	-0.05	0.957
HML	-.0647515	-0.42	0.684	-.04293	-0.30	0.765
α	-.0032695	-4.18***	0.003	.0020384	3.17***	0.003

Table : 6
Robustness test based on portfolio RSS

The figures in the cells below indicate the percentage BAHR of the rank score quintile portfolios over 1 year and 2 years from the time of quintile formation. All represents the one year BAHR for ALL firms in the sample. High and low respectively indicate the mean BAHRs of Q4 plus Q5 and Q1 plus Q2. The table also shows the mean values of the BAHRs across all portfolio formation years and the corresponding t-statistics. The t-stats with *** indicates significance at 1%, ** indicates significance at 5% and * indicates significance at 10% respectively.

	RSS Based Portfolio performance Based on 1 year BAHR					**RSS Based Portfolio performance Based on 2 years BAHR**				
Year	**All**	**High**	**Low**	**High - Low**	**High-All**	**All**	**High**	**Low**	**High - Low**	**High-All**
2003	-0.40%	-0.11%	-0.37%	0.26%	0.29%	6.09%	6.58%	5.79%	0.79%	0.49%
2004	5.80%	5.34%	6.09%	-0.76%	-0.47%	5.84%	5.78%	6.06%	-0.28%	-0.06%
2005	0.69%	0.96%	1.14%	-0.18%	0.27%	0.03%	0.68%	0.83%	-0.16%	0.65%
2006	-1.51%	-2.53%	-0.60%	-1.94%	-1.02%	5.11%	4.52%	6.28%	-1.76%	-0.60%
2007	7.35%	7.63%	5.78%	1.86%	0.28%	9.85%	10.74%	7.40%	3.34%	0.89%
2008	1.14%	1.46%	1.10%	0.36%	0.32%	8.76%	9.70%	8.73%	0.97%	0.94%
2009	7.69%	9.35%	6.26%	3.09%	1.66%	9.29%	10.82%	7.68%	3.15%	1.53%
2010	0.78%	1.44%	0.20%	1.23%	0.66%	4.26%	4.24%	3.43%	0.81%	-0.02%
2011	3.35%	4.59%	2.67%	1.92%	1.24%	5.59%	7.42%	4.45%	2.97%	1.83%
	Mean	**3.13%**	**2.48%**	**0.65%**	**0.36%**	**Mean**	**6.72%**	**5.63%**	**1.09%**	**0.63%**
	t-stat	**2.43****	**2.61****	**1.27**	**1.36**	**t-stat**	**5.98*****	**6.98*****	**1.87***	**2.43****

Table 7: Robustness test for One year and Two year Buy and Hold return(BAHR) for an F score strategy across Turnover and Price partitions

The numbers in the cells indicate the mean one year and two year BAHRs for the F score portfolios constructed within price and turnover partitions. The mean is taken across all portfolio formation years. The t stats with *** indicates significance at 1% , with ** indicates significance at 5% and * indicates significance at 10%

Panel A : Across Price Partitions

	1 Yr BAHR			2 Yrs BAHR		
	Small Price	Medium Price	Large Price	Small Price	Medium Price	Large Price
All firms	0.021	0.034	0.040	0.048	0.075	0.085
LFS	0.009	0.025	0.024	0.042	0.065	0.066
HFS	0.035	0.046	0.054	0.063	0.095	0.096
High - low	0.026	0.020	0.030	0.022	0.028	0.027
t-stat	1.95*	2.84**	4.86***	1.04	2.36**	2.18*

Panel A : Across Turnover Partitions

	1 Yr BAHR			2 Yrs BAHR		
	Small Turnover	Medium Turnover	Large Turnover	Small Turnover	Medium Turnover	Large Turnover
All firms	0.027	0.036	0.035	0.061	0.075	0.078
LFS	0.013	0.026	0.020	0.039	0.068	0.052
HFS	0.047	0.052	0.043	0.079	0.090	0.089
High - low	0.035	0.026	0.023	0.039	0.023	0.037
t-stat	2.52**	3.76***	2.28*	3.64***	2.20*	2.22*

Table 8
Robustness test based on correlation weighted F score (CORFS)

The numbers in the cells indicate the 1 year and 2 years BAHRs of the CORFS sorted quintiles, Q1 through Q5. Q1 is the quintile with the lowest CORFS while Q5 is the quintile with highest CORFS. High indicates average of Q4 and Q5 and low indicates average of Q1 and Q2. All stands for average of Q1 through Q5. The t stats with *** indicates significance at 1% , with ** indicates significance at 5% and * indicates significance at 10%

CORFS Based Portfolio performance based on 1 year BAHR										
Year	CORFS Based Portfolio performance on 1 year BAHR					CORFS Based Portfolio performance on 2 years BAHR				
Year	All	High	Low	High - Low	High- All	All	High	Low	High -Low	High- All
2003	-0.004	-0.002	-0.007	0.005	0.002	0.061	0.167	0.079	0.087	0.106
2004	0.058	0.107	0.122	-0.015	0.049	0.058	0.128	0.071	0.057	0.070
2005	0.007	0.019	0.023	-0.004	0.012	0.000	0.025	-0.045	0.070	0.024
2006	-0.015	-0.051	-0.012	-0.039	-0.036	0.051	0.122	0.091	0.031	0.071
2007	0.074	0.153	0.116	0.037	0.079	0.098	0.205	0.178	0.027	0.107
2008	0.011	0.029	0.022	0.007	0.018	0.088	0.165	0.159	0.006	0.077
2009	0.077	0.187	0.125	0.062	0.110	0.096	0.177	0.198	-0.021	0.081
2010	0.008	0.029	0.004	0.025	0.021	0.043	0.131	0.047	0.084	0.089
2011	0.033	0.059	0.076	-0.018	0.026	0.056	0.093	0.121	-0.028	0.038
	Mean	**0.059**	**0.052**	**0.007**	**0.031**	**Mean**	**0.135**	**0.100**	**0.035**	**0.073**
	t-stat	**2.31****	**2.71****	**0.66**	**2.17***	**t-stat**	**7.59*****	**4.01*****	**2.42****	**7.96*****