Fundamental Analysis: Evidence from India

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Abstract

This paper investigates whether fundamental analysis using accounting numbers can generate abnormal returns in the Indian stock market, focusing on both high and low book-to-market firms. Drawing on Piotroski [2000], the study constructs fundamental signals from financial statements to distinguish winners from losers. Using firm-level data from the Prowess database for 2013–2022, the findings reveal that the portfolios based on strong fundamental signals earn a mean market-adjusted buy and hold return of 17.6%, while a long–short strategy between winners and losers yields a mean market-adjusted buy and hold return of 14.2%. Employing Fama–MacBeth regressions, the analysis shows that each one-point increase in F-SCORE is associated with a 3.7% increase in one-year market-adjusted buy and hold returns. The return premium remains robust after controlling size, book-to-market and market beta. Further analysis shows that the return predictability weakens for firms with higher institutional ownership and multinational status but strengthens for smaller firms facing greater information asymmetry. These results highlight market inefficiencies and suggest that Indian markets underreact to fundamental signals. The study contributes to the literature by demonstrating the predictive power of fundamental analysis in an emerging market with distinct institutional structures, regulatory frameworks, and accounting standards.

Keywords: Fundamental Analysis, Value Investing, Growth Stocks, Market Anomalies, Emerging Markets

JEL Codes: G11, G12, G14, M41, O16

1. Introduction

This paper examines whether a fundamental analysis strategy using accounting numbers from financial statements generates abnormal returns in India for high and low book-to-market ratio firms. Prior literature identifies several anomalies, including the accrual anomaly (Sloan [1996]), underreaction to earnings news, leading to Post-Earnings Announcement Drift (PEAD) (Bernard and Thomas [1989]), and anomalies related to momentum, pricing multiples, and value (Basu [1977]; Fama and French [1992, 1995]). Research also highlights abnormal returns for high book-to-market firms (Fama and French [1992]). Interpretations of this effect differ: Fama and French [1992] attribute it to unobservable risk factors, while Lakonishok, Shleifer, and Vishny [1994] argue it stems from mispricing.

Building on these insights, this paper explores whether a fundamental analysis strategy can effectively exploit market inefficiencies in the Indian context. The Indian market, characterized by emerging-market dynamics, concentrated ownership and relatively lower analyst coverage, offers a unique setting to test whether accounting-based signals can generate abnormal returns. By employing a comprehensive set of fundamental signals, including profitability, earnings quality, and leverage, we evaluate whether market participants underreact to publicly available accounting information. Our analysis contributes to the ongoing debate on the relative importance of risk-based versus mispricing explanations for return anomalies. Additionally, by focusing on a major emerging market, we assess the generalizability of these anomalies beyond developed markets, providing new insights into the role of accounting information in investment decision-making.

Penman and Reggiani [2010] emphasize that a strong understanding of accounting information can help predict relationships between returns, pricing multiples, and earnings

growth. The literature on fundamental analysis highlights that financial statement information is essential for estimating a firm's intrinsic value, which can subsequently influence share prices. Investor sophistication plays a critical role in how this information is interpreted. For example, Sloan [1996] observes that naïve investors overemphasize bottom-line earnings, causing a negative relationship between returns, future earnings, and accruals. In contrast, sophisticated investors account for accrual properties, resulting in differing conclusions. Many foundational studies, such as PEAD documented in 1989, were conducted in eras of limited information access. As a result, their applicability in today's digital information landscape is uncertain.

Piotroski [2000] applies fundamental analysis using accounting metrics to differentiate winners and losers among high book-to-market (value) firms. Such firms, typically referred to as value stocks, often suffer from limited analyst coverage and poor information dissemination due to their recent underperformance. However, their future performance can vary significantly based on their financial fundamentals. Piotroski highlights how accounting-based analysis can uncover undervalued firms and identify profitable investment opportunities, reinforcing the value of financial statement analysis in predicting stock performance.

In contrast, Mohanram [2005] highlights low book-to-market firms known as growth stocks, which would have experienced strong performance in the previous periods. These stocks attract sophisticated investors such as institutional investors and attract financial intermediaries such as analysts. This results in multiple channels of information dissemination other than financial reports. This might diminish the importance of fundamental analysis. Dechow and Sloan [1997] highlight that markets often extrapolate current fundamentals into future earnings, ignoring the impact of conservative accounting (Penman and Zhang [2002]). To address this limitation, Mohanram [2005] introduces the GSCORE metric, which incorporates signals from conservative accounting practices and naive extrapolation to evaluate profitability and

earnings. Using the GSCORE, he distinguishes between winners and losers, with the strategy delivering a mean adjusted return of 3.1%.

Most of the studies including Piotroski [2000] and Mohanram [2005] provide evidence of fundamental analysis in the developed markets (US). There is very little evidence or no evidence in how fundamental analysis eventuates in an emerging economy. India is the world's third-largest economy when measured by gross domestic product (GDP) based on purchasing power parity (PPP), which adjusts for differences in price levels between countries. This metric reflects the country's significant economic size and purchasing power on a global scale. India offers a unique and valuable setting to study fundamental analysis due to its distinct institutional features and evolving capital markets. As one of the largest emerging economies with a rapidly growing investor base, India provides insights that extend beyond developed market frameworks. The market is characterized by concentrated ownership, with promoters and family-controlled firms playing a central role in corporate decision-making. This ownership structure, coupled with the prevalence of related party transactions within business groups, highlights the importance of fundamental analysis in assessing corporate performance and governance practices. Additionally, India's evolving financial intermediation landscape, marked by relatively lower analyst coverage, especially for small and mid-cap firms, creates opportunities for fundamental analysis to uncover mispriced stocks and address information asymmetry.

India's regulatory landscape, shaped by reforms such as SEBI's Listing Obligations and Disclosure Requirements (LODR), has improved transparency, yet differences in accounting standards and disclosure practices offer a rich ground for examining how accounting information is incorporated into market prices. Market characteristics, such as segments with lower liquidity and less efficient price discovery, further underscore the value of fundamental analysis in identifying intrinsic value. Additionally, India's diverse investor base, comprising a

growing number of domestic retail investors and mutual funds, brings distinct behavioral patterns compared to institutional-heavy markets. Studying fundamental analysis in this context not only enhances understanding of how accounting fundamentals drive market behavior in emerging economies but also provides broader insights into global market anomalies and investment strategies.

External market imperfections can exacerbate the information problems (Khanna, and Palepu [2000]). The level of protection of investors against insider expropriation and the quality of enforcement can determine the size of the capital markets. The countries that offer better security laws and enforcement can motivate more entrepreneurs to seek external finance thereby broadening the capital markets and resulting in higher valuations (La Porta, Lopez-De-Silanes, Shleifer, and Vishny [1997]). The financial development in any country can result in the reduction of transaction costs of investments and savings thereby decrease in cost of capital. The developed financial markets help firms mitigate problems such as adverse selection and moral hazard which can have direct effect on the firm's revenue such as cash flows (Rajan, and Zingales [1996]). Therefore, we test if the trading strategy based on fundamental analysis shifts the distribution of returns in emerging economy firms.

To address the research question, we sourced data from; the Prowess database, curated by the Centre for Monitoring Indian Economy (CMIE) offering firm-specific details. This database is widely utilized in research on Indian capital markets (Bertrand, Mehta, and Mullainathan [2002], Gopalan, Nanda, and Seru [2007], Manchiraju and Rajgopal [2017], Agrawal, Manchiraju and Rajput [2025]). Our sample period spans from 2013-2022. The final sample consists of 13,258 firm-year observations, representing 2,474 unique firms. We use Fama- MacBeth [1973] regression model to capture the association between buy-hold returns and F_SCORE.

In this study, we investigate the effectiveness of a fundamental investment strategy based on fundamental signals in the Indian capital market. First, we use the F-SCORE methodology to classify firms into high, medium, and low F-SCORE groups to assess their ability to distinguish between future winners and losers. Next, we compare the returns of these portfolios and find that high F-SCORE firms generate 17.6% market-adjusted buy-and-hold returns (BHR), significantly outperforming low F-SCORE firms, which generate only 3.4% market-adjusted BHR. This results in a statistically significant return differential of 14.2%. We then test whether this return differential persists after controlling for well-known factors such as size, accruals, book-to-market, and leverage. Our results show that the difference remains significant. Further, we find that each one-point increase in F-SCORE is associated with a 3.7% increase in one-year market-adjusted returns and a 4.4% increase in raw returns. Over a two-year horizon, a one-point increase in F-SCORE leads to a 13.2% rise in market-adjusted returns and a 17.5% increase in raw returns, highlighting the predictive power of fundamental signals.

Next, we explore how information frictions influence the effectiveness of fundamental analysis. We examine whether institutional ownership, multinational status, and firm size affect the relationship between F-SCORE and returns. We find that the association between F-SCORE and returns weakens for firms with higher institutional ownership and multinational status, likely due to more efficient information environments. Specifically, a one-unit increase in the interaction term between institutional ownership and F-SCORE is associated with a 2% lower return, statistically significant at the 5% level. In contrast, we observe a stronger association for smaller firms, which typically face greater information frictions due to limited analyst coverage and lower voluntary disclosures. Overall, our findings suggest that fundamental analysis is more effective when information asymmetry is higher, underscoring its value in identifying mispriced stocks in markets with varying levels of transparency and investor attention.

This paper contributes novel insights to the finance and accounting literature by demonstrating how accounting fundamentals forecast stock returns in the emerging Indian market, a context distinct from developed markets due to differences in market structure and information frictions. First, we advance beyond Piotroski [2000] by applying the F-SCORE methodology to both high and low book-to-market firms, revealing that fundamental signals from historical accounting data effectively predict future performance in an emerging market with limited analyst coverage. Second, unlike prior studies that focus on value or growth strategies independently, we integrate insights from both Piotroski [2000] and Mohanram [2005] to show that fundamental analysis drives return across value and growth firms, highlighting its broad applicability. Third, we uncover that high F-SCORE firms consistently earn superior market-adjusted returns, demonstrating that the predictive power of accounting fundamentals persists despite the informational inefficiencies' characteristic of emerging markets.

Moreover, our study offers a new perspective on why fundamental investment strategies succeed. We establish that the market's inability to fully incorporate accounting signals, compounded by information frictions unique to the Indian context, creates opportunities for investors. First, we show that, even amid known anomalies such as those identified by Lakonishok, Shleifer, and Vishny, [1994], historical accounting information effectively differentiates future winners from losers. Second, we highlight that both value and growth firms benefit from fundamental analysis, extending beyond prior single-segment approaches. Finally, we show that the underreaction to accounting signals is most pronounced for small and less-followed firms, offering new evidence on the relationship between information frictions and market inefficiencies. Collectively, our findings contribute to the literature by illustrating how fundamental analysis interacts with market structure to drive returns, offering a fresh lens on market efficiency and anomalies in emerging markets.

The following paper is organized as follows, section 2 covers the literature review including market anomalies, such as PEAD, momentum, accrual anomalies, fundamental analysis, and context of Indian markets. Section 3 presents the research design with variable definitions and research methodology. Section 4 and 5 presents the sample data description followed by empirical results. Section 6 concludes the paper with future research directions.

2. Literature Review

2.1 Market Anomalies

Several studies in the extant literature explain seeking "abnormal" returns using markets' incapability to completely incorporate the implications of financial information. Some of those include Post Earnings Announcement Drift where the stock prices drift in the direction of the good/bad news post-earnings announcement, momentum strategies indicate that the stocks performing well will continue to perform well and stocks performing poorly will continue to perform poorly until the returns are reversed and accruals anomaly is based on the two components of earnings namely cash flows and accruals. Investors overprice accruals and firms with high accruals will yield lower returns subsequently.

2.1.1Underreaction to Accounting Information (PEAD, Momentum)

Post Earnings Announcement Drift (PEAD) is a major market anomaly pertaining to accounting-based information documented by Bernard and Thomas, [1989]. PEAD showcases the underreaction of the investors to the earnings news and how the stock prices drift in the direction of news (upward drift in prices for good news and vice versa). This explains the inability of the market to incorporate all attributes of earnings. Although, this behavior of abnormal returns in the direction of news was initially observed by Ball and Brown [1968], Bernard and Thomas [1989] provide with various explanations that can cause this behavior

such as delayed price response to information or misestimated Capital Asset Pricing Model (CAPM). A long position in the decile with the highest unexpected earnings and a short position in the low decile would yield a return of 4.2% approximately over 60 days. Also, the absolute magnitude of unexpected earnings and drift are inversely related to the firm size. Most of the drift in prices occur within 60 days after the announcement of earnings and there was no statistical evidence beyond 180 trading days. Bartrov, Radhakrishnan, and Krinsky [2000] investigate if the drift is a result of inefficient processing of earnings information by investors. They use institutional investors as proxy for sophisticated investors and find a negative correlation with the abnormal returns post the earnings announcement. They attribute this drift to being prominent within unsophisticated investors and the magnitude of abnormal returns being much lower when investors are sophisticated or institutional owners.

Jegadeesh, and Titman [1993] have showcased that by buying stocks that performed well and selling the stocks that performed poorly would yield positive returns over the holding periods of 3- 12 months. By adopting momentum strategies, by buying the stocks with high returns over the prior 3 to 12 months and selling stocks with low returns in the previous months will earn a return of 1 percent per month for the following year. The abnormal returns realized during the first year are dissipated in the subsequent two years. Although the findings are widely accepted, the interpretation of these results are contested. Some conceive it as an illustration of "market inefficiency" while other explanations include compensation for risk or the issues related to data mining (Jegadeesh, and Titman [2001])

2.1.2. Accruals/Investment-related Anomalies:

Sloan, [1996] helps us understand the information contained in the accrual and the cash flow components of current earnings. The cashflows and the accruals have different implications for assessing future earnings. The investors fixate on the earnings failing to fully understand the information embedded or differentiate between the accrual and cashflow flow components of

current earnings until it affects future earnings. He finds that the accrual component exhibits a lower persistence of earnings performance compared to that of the cash flow component. Firms with high levels of accruals are overestimated thus yielding negative future abnormal returns and vice versa. Specifically, accruals are subjected to reversal and investors do not understand the time series properties. Richardson, Sloan, Soliman, and Tuna [2005] extend the findings presented by Sloan, [1996] by showcasing that less reliable accruals drive the lower persistence of earnings. Collins, and Hribar [2000] tries to determine if PEAD and the accruals anomaly capture the same inefficiency of the market or if they represent different anomalies representing a much bigger market mispricing/anomaly. They confirm that accrual mispricing is distinct from Post-Earnings Announcement Drift and the market tends to overprice accruals. The strategies based on unexpected earnings and accruals capture distinct phenomena. The magnitude of drift is conditioned by the accruals. When accruals and the earnings surprise are in the same direction, the drift is decreased, whereas when they are in the opposite direction, the drift is much greater. Xie, [2001] finds that the accruals anomaly is related to the mispricing of discretionary/ abnormal accruals and underestimation of their reversal in the future. The market misprices the abnormal accruals but does not misprice normal accruals. Rangan, [1998] finds that managers can opportunistically utilize abnormal accruals to improve their earnings which are overpriced before IPOs or seasoned equity offerings.

Several studies have also established the relationship between the accrual anomaly and earnings management. Beneish, and Vargus [2002] suggest an explanation of earnings management to the accruals anomaly. They find that the lower persistence of income-increasing accruals combined with abnormal insider selling signals earnings management. As all market participants overprice the accruals as they are of high quality, the manager's trading helps investors and researchers in assessing the quality of accruals. In addition to market anomalies,

there exists a stream of research that focuses on earning abnormal returns based on financial signals.

2.2 Fundamental Analysis:

Fundamental analysis helps us understand the determinants of the intrinsic value of the firms. This helps in making better forecasts of earnings or stock returns and to identify mispriced securities (Kothari [2001]). It is independent of the market efficiency hypothesis thereby making it appealing to both believers and non-believers of market efficiency and helps investors, lenders make better decisions (Richardson, Tuna, and Wysocki [2010]).

Ou and Penman, [1989] establish that financial statements contain information in stock prices that lead to earnings in the future. They demonstrate that these inputs from financial statements can be summarized into a single measure (e.g. P/E) that predicts future earnings and filter out the transitory components of earnings. The contemporaneous price changes with respect to earnings showcase only the transitory earnings making them poor predictors of earnings in the future compared to information in financial statements. The ratios such as P/E corrects current earnings as it differentiates the earnings that is persistent in the future compared to those of earnings that occurred due to temporary phenomenon. The variation in the cross-section of P/E is explained in the financial statements.

Ohlson [1995] builds a model to establish the relationship between the market value of the firm and earnings (contemporaneous and future), dividends and book values and conceptualizes the association between the market value and the accounting data. The model begins with the assumption that the present value of the expected dividends is equal to the value of the firm. Using the clean surplus relation (the difference between earnings and dividends results in the change in book value), dividends are replaced by earnings/book value in the formula and showcase abnormal or residual earnings as a variable influencing firm value.

Feltham, and Ohlson [1995] build a model to demonstrate the relationship between market value and the accounting data comprising of financial and operating activities. Book value equals market value for financial activities whereas discrepancy arises in operating activities. For example, accrual accounting for financial activities can be redundant whereas operating earnings with adjusted accruals can address concerns as the assets are not traded in perfect markets, this leads to the difference between market and book values.

Determining the value of equity involves forecasting payoffs such as dividends, earnings and cash flows in future and discounting them to present value. Although dividend, earnings and cashflow methods of valuation are equivalent when the payoffs are predicted to infinity, in practice, the forecasts are made over finite horizons. Penman, and Sougiannis [1998] examine how dividends, cashflow, and earnings perform in finite horizon analysis. They find that accrual earnings forecasted via GAAP result in lower valuation errors compared to those of forecasting dividends or cash flows. The accrual accounting provides correction for the cashflow valuation by incorporating anticipated receipts and investments and recognizes non-cash related value changes.

Fama, and French [1993] present the three-factor model for asset pricing. The model includes a market factor and factors related to size and BE/ME that captures the cross-section of average returns in stocks. Fama and French [1995] try to study whether these factors size and book-to-market ratio reflect the earnings behavior to present the complete economic story. They examine if the stock price reflects the differences in profitability when the stocks are sorted on size and BE/ME. They find that BE/ME showcases the persistent properties in earnings. Low book-to-market firms had lower earnings persistently and vice versa. Low book-to-market firms remained more profitable compared to high book-to-market firms for the subsequent quarters. Similarly, size is also associated with profitability. Later, a five-factor

model is proposed by Fama and French [2015] capturing value, size, profitability, B/M, and investment patterns which performs better than the three-factor model.

Fama annd French [2006] using valuation theory tries to determine the variables that can predict the stock returns such as the B/M ratio, expected profitability, and investment where the accounting fundamentals are used to build the proxies for expected values of profitability and investment. However, all these variables are correlated such as earnings and book values are both affected by the growth of the firm. The primary focus of the Fundamental Analysis includes predicting the stock returns, earnings, and firm cost of capital. Extending fundamental analysis, the researchers have constructed several scores using the information in financial statements to build scores.

2.2.1 Scores using information in Financial statements:

The main value drivers in predicting the value of an organization include earnings, growth, risk associated, and competitive position. Lev and Thiagarajan [1993] identified fundamental signals that can assess the persistence in earnings (quality) and the growth of earnings. They find a strong association between the fundamentals and earnings response coefficient and the growth of future earnings. The fundamental signals they use include inventory captured as the difference between the change in inventory and sales, Accounts receivable measured as change in accounts receivables less change in sales, capital expenditure (R&D) as change in industry capital expenditures, gross margin, Sales and Administrative Expenses, provision for doubtful receivables, effective tax, backlog of orders, labor force, LIFO earnings and whether or not a firm is qualified for audit. The fundamental signals demonstrate a strong correlation to returns after controlling for earnings innovations, size, and macroeconomic conditions.

Piotroski [2000] applies an investment strategy based on accounting numbers specifically on high BM firms and finds that there is a 7.5% increase in mean returns by selecting high BM firms that are financially strong. He also finds an underreaction to historical accounting

information and this information is not completely embedded into stock prices in a timely manner. The three main areas of financial performance include namely profitability, liquidity, and operating efficiency. Profitability becomes crucial to assess the firm's ability to generate money through its operating activities. Variables such as return on assets, cash flow from operations and accruals indicate the profitability of the firm. To understand the capital structure of the firm, leverage, liquidity, and source of funds become valuable. The variables such as the firm's long-term debt levels, current ratio and equity offerings helps us understand the capital structure of the firm. The underlying driver of profitability being operational efficiency, it is captured through the gross margin ratio and asset turnover ratio.

While Piotroski [2000] examines the high BM firms which are value firms, Mohanram [2005] focuses on low BM firms which are referred as growth or glamour stocks. The low BM firms would have reaped the benefits of strong performance in the prior periods and attracted the following of analysts and institutional investors. Naïve extrapolation of the past returns to the future will diminish the inferences of conservative accounting for future earnings (Penman, and Zhang [2002]). Therefore, Mohanram [2005] builds G score and the long-short strategy yields significant abnormal returns, especially from the short side. G score comprises of profitability signals from the ROA (Compared to other low BM firms in the market), Cashflow ROA as earnings are usually overrepresented in low BM firms, cash flow from operations, naïve extrapolation signals including variability in earnings, growth variability and conservative accounting signals such as R&D, capital expenditure and advertising intensity, etc.

All the studies discussed previously are based on the context of developed markets. It is a general consensus that emerging markets are not as efficient as developed economies. It is unclear if the results pertaining to fundamental analysis still hold in an emerging economy context. Indian markets exhibit distinct characteristics compared to developed markets, shaped

by differences in institutional structures, ownership patterns, and information environments. Agency issues and information asymmetry are heightened by limited disclosures and corporate governance practices tailored to concentrated ownership and family-controlled businesses. Additionally, the financial ecosystem is influenced by relatively fewer financial intermediaries, such as analysts, investment bankers, and venture capitalists, which affects capital allocation and market efficiency. This limited intermediation extends beyond capital markets, impacting labor and product markets and, consequently, firm productivity. Furthermore, regulatory frameworks differ, with challenges in consistent enforcement and evolving market oversight. The equity market, though expanding, has lower liquidity, and banking systems remain dominated by nationalized institutions (Khanna and Palepu [2000]).

In the developed market context such as the US, diversified firms are known to underperform due to inefficiencies in decision rights, allocation of capital, and weak internal governance structures. However, in the emerging economy context, the business group can fill the void of the absence of an intermediary between independent entrepreneurs and the markets which are imperfect. Lack of intermediary can be costly for the firms to access requisite inputs for the firm such as financing, technology, skilled workers, etc. Therefore, the firms affiliated with business groups can leverage their networks and resources to overcome the failures in the markets. Khanna, and Palepu [2000] find that there is an initial decline in firm performance after group diversification, however, the firm performance improves after the diversification surpasses a certain threshold.

On the other hand, wealthy families controlling large public listed firms can give raise to many principal- principal agency conflicts between family (controlling) and non-family shareholders (non-controlling). Amidst poor governance structures, wealthy families may exploit minority shareholders through tunnelling behavior (Chen, Chittor, and Vissa, [2018]).

In Indian Labor market, the prevalence of informal work has emerged as one of the key characteristics. While the informal sector accounts for roughly half of the country's GDP, it dominates employment, with around 90% of the entire workforce employed in the informal economy (Economic Survey, [2022]).

The difference in accounting standards will also play a role when using fundamental analysis to predict returns. India has adopted Indian Accounting Standards (IndAS) effective from 1 April, 2016 starting with companies with net worth of 500 crore INR. The companies that are not covered under IndAS can use Indian GAAP or adopt IndAS voluntarily (PwC [2017]). The differences between the Ind AS, US GAAP can affect the studies based on fundamental analysis. For example, contingency pricing and the revenue recognition models vary across US GAAP and Ind AS. In US GAAP, the contingency amounts are not commonly recognized as revenue until the resolution of contingency. However, under Ind AS, the probability of benefits related to the transaction are considered, and with reliability on measurement, the contingent revenue is included. This can result in timing differences where revenue under Ind AS is recognized earlier than US GAAP.

Harvey [1995] finds that the asset pricing models that are used commonly cannot explain the cross-section of returns in emerging economies. However, Griffin, Kelly, and Nardari [2010] analyzed 56 markets and find that there is no difference between returns earned in developed markets and emerging markets when adopting strategies such as PEAD, short-term reversal, and momentum. There are mixed results on the informational efficiency and the results pertaining to fundamental analysis in emerging markets such as India. Therefore, we examine if the fundamental signals are relevant in India to obtain abnormal returns given its distinct institutional context, information environment and accounting practices.

3. Research Design

We follow the F-score model by Piotroski [2000] containing 9 fundamental signals in the areas of profitability; leverage, liquidity, and source of funds; and operating efficiency. To measure the financial performance of the firms the variables ROA, ΔROA, CFO, ACCRUAL are considered as positive trends in earnings forecasting the ability of the firm to generate positive cashflows. ROA is calculated as net income divided by total assets and CFO is cash flow from operations divided by total assets. Correspondingly, indicator variables F_ROA, and F_CFO are created and equal to 1 if ROA and CFO are positive otherwise 0. ΔROA is the change in ROA compared to the previous year and a positive ΔROA results in F_ΔROA as 1. We also consider accrual adjustments considered by Sloan [1996] as earnings dominated by high accruals yield negative subsequent returns, we include the accrual component in performance measures. It is calculated as the difference between net income and cash flow from operations scaled by total assets. F_ACCRUAL is 1 if cashflow from operations is greater than ROA.

To gain insights into the firm's capital structure and its ability to meet its debt obligations, we include variables ΔLEVER, ΔLIQUID, EQ_OFFER. We consider increase in financial leverage, decrease in liquidity and external financing as a signal to the risk involved. ΔLEVER is captured as an annual change in the ratio of long-term debt to average total assets. F_ΔLEVER is 1 if the leverage has decreased compared to the previous year otherwise 0. ΔLIQUID captures the change in the current ratio. If the firm's liquidity increases (ΔLIQUID>0) then it is a good signal and F_ΔLIQUID is 1 else 0. EQ_OFFER indicates if a firm has issued any equity in the previous year. EQ_OFFER is 1 if the firm does not issue any equity.

ΔMARGIN, ΔTURN captures the efficiency in operations and are the drivers of ROA. ΔMARGIN is calculated as the difference between current gross margin ratio and the previous year's gross margin ratio. Positive ΔMARGIN yields F_ΔMARGIN as 1 and negative

ΔMARGIN results in F_ΔMARGIN of 0. ΔTURN is the difference between the current and previous years asset turnover ratio (total sales scaled to total assets in the beginning of the year). Positive ΔTURN will result in F_ΔTURN 1 otherwise 0. Finally, using all the binary variables, the composite score is calculated as sum of all the indicator variables. The composite F_SCORE can range between 0 and 9 with 0 being the lowest and 9 being highest. The high F_SCORE firms with strong fundamentals are expected to have higher returns compared to that of firms with low F_SCORES.

The firm-specific returns are calculated as one-year/two-year buy-and-hold returns (BHR-12 Month, BHR-24 Month) earned from the third month of the fiscal year-end to 12 or 24 months post the beginning of return compounding. In case of delisting of a firm, the return is considered as 0. The third month is chosen to ensure that relevant financial information is accessible to the investors for the formation of portfolios.

The research methodology includes formation of portfolios based on the composite F_SCORE. The firms with F_SCORE of 0,1,2 are considered as low F_SCORE firms with weak fundamentals and the firms with high F_SCORE of 7, 8 or 9 are the firms with strong fundamentals. The medium F_SCORE firms include the firms with scores 3,4,5 and 6. We expect the high F_SCORE firms to outperform the low F_SCORE firms.

We use Fama- MacBeth [1973] regression model to capture the association between buy-hold returns and F_SCORE.

$$BHR_{it} = \alpha_0 + \beta_1 * F\_SCORE_{it} + \beta_2 * SIZE_{it} + \beta_3 * ln\ (BM) + \beta_4 * BETA + \varepsilon_{it}$$

The dependent variable is BHRit, Buy-hold return for the firm i in time period t (12 months or 24 months), the independent variable is F_SCORE which is the composite F_SCORE ranging from 0-9 for the firm i in time period t, SIZE, natural log of market value of equity and market BETA are used as control variables and εit captures the error term.

4. Sample Data Description

Our starting sample comprises 68,100 firm-year observations spanning from 2011 to 2022, sourced from the Prowess database maintained by CMIE (Centre for Monitoring Indian Economy). This database is widely accepted in academic research on Indian markets, as evidenced by prior studies (Khanna, and Palepu [2000], Gopalan, Nanda, and Seru [2007], Manchiraju and Rajgopal [2017], Li [2021]). To arrive at our final sample, we apply certain filters. Firstly, we exclude observations with missing financial data such as sales, profit after tax, total assets and liabilities, cash flow from operations, reducing our initial sample size by 31,964 firm-year observations. Secondly, we retain only firms with fiscal year-ends in March, resulting in the removal of 718 firm-year observations. For our empirical analysis, we require F-SCORE, a sum of nine binary signals representing three aspects of a firm's financial condition: profitability, financial leverage/liquidity, and operating efficiency (Piotroski, [2000]). These signals are chosen for as summary performance measures. We drop observations with missing F-SCORE. This step leads to the exclusion of 5,330 firm-year observations. Essential aspect of our analysis is the calculation of buy-and-hold returns (BHR). To achieve this, we utilize stock prices from the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE), focusing primarily on NSE data and resorting to BSE data where NSE data is unavailable due to its wider listing. For our returns test, we compute BHR (buy-and-hold return), comprising one-year and two-year market-adjusted buy-and-hold returns, initiated in the third month after the fiscal year-end and extending to the earliest subsequent date within either 12 or 24 months (Hsu, and Kross [2011]). To ensure a minimum of 12 months of data for BHR calculation, we exclude values with less than 12 months of returns data. We incorporate size, book-to-market, momentum, and market beta as controls in our return test. The three-year market beta is calculated, using NIFTY 500 as the benchmark index. Momentum is determined by the six-month market-adjusted buy-and-hold return over the six

months preceding the third month after the fiscal year-end. We eliminate observations with missing values of stock returns, index returns, market capitalization, beta, momentum, and book-to-market ratio. This process results in the loss of 16,829 firm-year observations, yielding a final sample of 13,258 firm-year observations, representing 2,474 unique firms. Table 1 provides a summary of our sample selection criteria.

<<< Table 1>>>

Table 2 presents the distribution of our sample across years and industries, comprising 13,258 firm-year observations from 2,474 unique firms. Panel A displays the year-wise distribution, showing that observations are relatively balanced across the nine-year period from 2013 to 2021. The sample ranges from 1,399 observations in 2019 (10.55%) to 1,568 observations in 2021 (11.83%), indicating consistent data coverage over time.

Panel B presents the industry-wise distribution based on the Fama-French 12 industry classification. The sample covers a diverse range of industries, with manufacturing firms constituting the largest share (23.71%), followed by firms classified under 'Other' industries (16.67%) and non-durable consumer goods (15.58%). Chemicals (9.00%) and shops (7.81%) also represent significant portions. Industries such as telecom (5.95%), health (5.72%), and money finance (5.32%) contribute moderately to the sample. In contrast, durable consumer goods (3.58%), utilities (1.25%), and energy (0.91%) comprise relatively smaller shares. This distribution highlights the broad sectoral representation, ensuring that our analysis captures variations across different segments of the Indian economy.

<<< Table 2>>>

Table 3 Panel A presents descriptive statistics for key firm characteristics based on 13,258 firm-year observations from 2,474 unique firms. The table displays the mean, median (p50), standard deviation (SD), and interquartile range (p25 to p75) for each variable. Firm size, measured by market capitalization, shows high variability, as indicated by large standard

deviations. For example, the mean market capitalization is INR 45.791 billion, but the median is significantly lower at INR 1.560 billion, highlighting the skewed distribution. Similarly, profitability metrics such as return on assets (ROA) and cash flow from operations (CFO) show modest averages (0.021 and 0.064, respectively), with accruals averaging -0.043, suggesting conservative earnings management practices. Additionally, the composite F-score, a measure of financial strength, has a mean of 5.066, with most firms scoring between 4 and 6.

Panel B displays the correlation matrix, examining the relationships between 12-month and 24-month buy-and-hold returns (BHR) and fundamental signals, including ROA, accruals, leverage, liquidity, and the F-score. Notably, 12-month market-adjusted returns are highly correlated with raw returns (0.949), indicating that market trends significantly drive short-term performance. Longer-term returns (24 months) show weaker correlations with short-term metrics but are more closely related to improvements in fundamentals, such as ROA (0.128) and CFO (0.117). The F-score, which aggregates multiple financial signals, is positively correlated with both 12-month (0.069) and 24-month (0.216) market-adjusted returns, underscoring its predictive power for future performance. Conversely, accruals have a negative relationship with returns, consistent with the accrual anomaly literature. Overall, these results highlight the importance of fundamental signals in predicting long-term stock performance.

<<< Table 3>>>

5. Empirical Results:

Table 4 presents the returns generated by a fundamental investment strategy based on fundamental signals, presenting both raw and market-adjusted buy-and-hold returns over a one-year period. The sample is classified based on F-SCORE, categorizing firms with an F-SCORE

less than or equal to 2 as low F-SCORE firms, those with an F-SCORE between 3 to 6 as medium, and those with an F-SCORE greater than 6 as high F-SCORE firms. 70.86% of the observations exhibit conflicting firm performance signals. Therefore, we use extreme portfolio of firms to examine ability of fundamental signals to distinguish between future winners and loser stocks (Piotroski [2000]). Our findings reveal that high F-SCORE firms (17.6% market adjusted BHR) outperform their low F-SCORE counterparts (3.4% market adjusted BHR), with a statistically significant mean market-adjusted return difference of 14.2% at the 1% significance level. These results collectively suggest that investors can utilize relevant historical information to strategically select firms with promising prospects while eliminating those with less favorable future outlooks.

<<<Table 4>>>

Table 5 presents descriptive statistics comparing key firm characteristics between portfolios of high and low F-Score firms. The F-Score, a composite measure of financial strength, is defined based on criteria from Table 4. The table reports the mean and median values of size (SIZE), accruals (ACCRUAL), book-to-market ratio (BTM), and leverage (LEVERAGE), along with their differences between high and low F-Score portfolios.

High F-Score firms, which exhibit stronger financial fundamentals, are generally larger, with a mean size of 7.907 compared to 6.773 for low F-Score firms, resulting in a significant difference of 1.134. In terms of accruals, high F-Score firms have more negative accruals (-0.056) compared to low F-Score firms (-0.021), with a difference of -0.035, indicating more conservative earnings practices. High F-Score firms also tend to have lower book-to-market ratios (BTM), with a mean of 0.377 compared to 1.237 for low F-Score firms, suggesting they are often growth-oriented, whereas low F-Score firms are more likely to be value stocks. Additionally, high F-Score firms carry lower leverage (0.131) than low F-Score firms (0.231), with a significant difference of -0.099, indicating stronger financial health and less reliance on

debt. Overall, these results align with the F-Score framework, highlighting that firms with high F-Scores tend to have better financial profiles than those with low F-Scores.

<<< Table 5>>>

Table 6 presents the results of regressions examining the effect of F-SCORE on stock performance, measured using buy-and-hold returns (BHR). Columns 1 and 2 report results for one-year returns, while columns 3 and 4 show results for two-year returns. Raw returns are in columns 1 and 3, while market-adjusted returns are in columns 2 and 4. The regressions control for firm size (SIZE), book-to-market ratio (ln(BM)), and market beta (BETA). All regressions are estimated using the Fama-MacBeth [1973] method with Newey-West [1987] corrections for standard errors, and t-statistics are shown in parentheses.

The results indicate that F-SCORE is a significant predictor of stock performance. A one-unit increase in F-SCORE is associated with a 4.4% increase in one-year raw BHR (column 1) and a 3.7% increase in one-year market-adjusted BHR (column 2). The effect is stronger over two years, with a 17.5% increase in raw BHR (column 3) and a 13.2% increase in market-adjusted BHR (column 4). All these relationships are statistically significant at the 1% level, highlighting that high F-SCORE firms outperform low F-SCORE firms over both short and long horizons.

Among the control variables, SIZE is negatively associated with BHR, suggesting that smaller firms tend to generate higher returns. The relationship is significant for one-year returns (columns 1 and 2) and marginally significant for two-year raw returns (column 3). However, ln(BM) and BETA do not show significant associations with returns. Overall, these findings align with the F-SCORE framework, showing that high F-SCORE firms deliver superior long-term returns.

<<< Table 6>>>

The relevance of fundamental analysis as a method for distinguishing firms suggests that the ability to earn above-market returns might be linked to information-processing limitations within companies. Firms with higher institutional ownership and multinational status are likely to possess a more efficient information environment due to enhanced monitoring and broader market scrutiny. Conversely, small-sized firms may face information-processing limitations, as they receive less attention from the investment community. Their voluntary disclosures may lack credibility, and they often have fewer channels for informal information dissemination. Hence, we argue that fundamental analysis proves more effective when information frictions are higher, allowing investors to capitalize on mispricing.

Table 7 investigates how information frictions, measured through institutional ownership, multinational status, and firm size, influence the relationship between F-SCORE and buy-and-hold returns (BHR). Columns (1) and (2) explore the impact of institutional ownership, showing that while higher institutional ownership is positively associated with returns, its interaction with F-SCORE is negative, suggesting that the benefits of fundamental analysis diminish in firms with efficient information environments. Columns (3) and (4) examine multinational status, where a similar pattern emerges—multinational firms have higher returns, but the interaction with F-SCORE is negative, indicating that enhanced information flows in these firms reduce opportunities for excess returns from fundamental signals.

In contrast, columns (5) and (6) highlight the role of firm size, showing that smaller firms, which are more prone to information frictions, exhibit a stronger relationship between F-SCORE and returns. The significant positive interaction term indicates that fundamental analysis is more valuable when information gaps are greater. Across all columns, the control variables behave as expected, and the results are consistent under both raw and market-adjusted returns. Overall, these findings support the hypothesis that the effectiveness of fundamental

analysis is contingent on the degree of information frictions, with the strongest effects observed in firms facing greater information asymmetry.

<<<Table 7>>>

6. Conclusion

This paper examines whether a fundamental analysis strategy based on accounting signals can generate abnormal returns in the Indian equity market. By employing the F-SCORE methodology and analyzing a comprehensive sample of Indian firms from 2013 to 2022, we provide robust evidence that high F-SCORE firms consistently outperform their low F-SCORE counterparts. Specifically, we document a significant return differential of 14.2% in market-adjusted buy-and-hold returns, reinforcing the predictive power of fundamental signals in an emerging market context. Our findings remain robust after controlling well-known risk factors, such as firm size, accruals, book-to-market ratio, and leverage.

Additionally, we highlight the role of information frictions in shaping the effectiveness of fundamental analysis. The relationship between F-SCORE and returns weakens for firms with higher institutional ownership and multinational status, where information environments are more efficient. In contrast, smaller firms with limited analyst coverage exhibit a stronger association, underscoring the value of fundamental analysis in identifying mispriced stocks when information asymmetry is high.

This research contributes to the literature in several ways. First, we extend Piotroski [2000] and Mohanram [2005] by demonstrating the applicability of fundamental analysis strategies in an emerging market with distinct institutional features, such as concentrated ownership and evolving regulatory frameworks. Second, we provide new evidence that accounting-based

signals are effective in predicting returns for both value and growth stocks, highlighting the broad applicability of fundamental analysis beyond developed markets. Third, we illustrate how information frictions influence the effectiveness of accounting-based strategies, offering insights into the interaction between market structure and investment performance.

Overall, our findings underscore the importance of accounting fundamentals in investment decision-making and highlight the continued relevance of fundamental analysis in an era of digital information dissemination. The results have practical implications for investors and portfolio managers, suggesting that accounting-based signals remain valuable for identifying mispriced stocks, especially in markets with limited analyst coverage and higher information asymmetry. Future research could explore how other emerging market characteristics, such as regulatory changes or behavioral biases, further shape the performance of fundamental analysis strategies.

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Table 1: Sample Selection

Sample Criteria	Observations
Starting sample firm-year observations from 2011-2022	68,100
Drop firms with missing sales, COGS, Profit after tax, borrowings, total assets, liabilities, cash flow from operations	31,964
Drop firms without march year end	718
Drop observations with missing F-score	5,330
Drop observations with missing market data	16,825
Drop observation with missing controls variables	4
Drop observation with missing industry classification	1
	13,258

Note: We retain firm year observations with non-missing values of sales, total assets, net income, assets, liabilities and cash flow from operations. We retain stock return data with non-missing values of Beta, Book to Market ratio and Buy hold return (BHR).

Table 2: Distribution of sample across years and industries

Panel A: Year-wise Sample distribution

Year	Freq.	Percent
2013	1,431	10.79
2014	1,512	11.4
2015	1,498	11.3
2016	1,495	11.28
2017	1,465	11.05
2018	1,451	10.94
2019	1,399	10.55
2020	1,439	10.85
2021	1,568	11.83
Total	**13,258**	**100**

Panel B: Industry - Wise sample distribution

Industry	Freq.	Percent
Manufacturing	3,143	23.71
Other	2,210	16.67
Non-Durable Consumer	2,065	15.58
Chemicals	1,193	9.00
Shops	1,035	7.81
Telecom	789	5.95
Health	758	5.72
Money Finance	705	5.32
Business Equipment	599	4.52
Durable Consumer	475	3.58
Utilities	166	1.25
Energy	120	0.91
Total	**13,258**	**100**

Note: Our sample consists of 13,258 firm year observations for 2,474 unique firms. In Panel A of this table, we present year-wise distribution of the sample. In Panel B we present industry-wise distribution of the sample. Industry classification is based on Fama French 12 industry classification.

Table 3: Descriptive Statistics

Panel A: Summary statistics

VARIABLES	N	Mean	p50	SD	p25	p75
MKT_CAP (INR Billion)	13258	45.791	1.560	296.807	0.347	9.591
TOTAL ASSETS (INR Billion)	13258	41.897	4.878	120.908	1.439	20.362
SIZE	13258	7.618	7.352	2.365	5.849	9.169
MOMENT	13258	0.015	-0.061	0.448	-0.224	0.153
BTM	13258	0.698	0.156	2.219	0.042	0.520
ROA	13258	0.021	0.022	0.116	-0.006	0.060
△ROA	13258	-0.005	-0.001	0.113	-0.023	0.017
CFO	13258	0.064	0.065	0.111	0.012	0.117
ACCRUAL	13258	-0.043	-0.042	0.134	-0.091	0.005
LEVERAGE	13258	0.160	0.096	0.282	0.028	0.221
△LEVERAGE	13258	-0.003	-0.004	0.114	-0.030	0.014
LIQUID	13258	1.991	1.329	5.439	1.014	1.858
△LIQUID	13258	0.055	0.001	5.351	-0.135	0.158
△MARGIN	13258	-0.877	-0.002	48.847	-0.034	0.023
TURNOVER	13258	0.983	0.860	0.886	0.443	1.315
△TURNOVER	13258	-0.057	-0.019	0.449	-0.149	0.065
F_SCORE	13258	5.066	5.000	1.736	4.000	6.000
INST	13247	0.149	0.000	0.356	0.000	0.000
INST_PCT	13247	0.176	0.034	0.245	0.000	0.293
FOREIGN	13258	0.027	0.000	0.162	0.000	0.000
BHR-12 Month (RAW)	13258	0.262	0.034	0.827	-0.248	0.513
BHR-12 Month (MARKET ADJUSTED)	13258	0.109	-0.037	0.641	-0.280	0.320
BHR-24 Month (RAW)	13258	0.582	0.173	1.514	-0.300	0.910
BHR-24 Month (MARKET ADJUSTED)	13258	0.200	-0.093	1.073	-0.422	0.442

Panel B: Correlation Matrix

	VARIABLE	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	BHR-12 Month (RAW)	1													
2	BHR-12 Month (MARKET ADJUSTED)	0.949*	1												
3	BHR-24 Month (RAW)	0.613*	0.650*	1											
4	BHR-24 Month (MARKET ADJUSTED)	0.631*	0.678*	0.973*	1										
5	ROA	0.031*	0.035*	0.128*	0.137*	1									
6	△ROA	0.019*	0.031*	0.116*	0.121*	0.550*	1								
7	CFO	0.058*	0.055*	0.117*	0.120*	0.296*	0.119*	1							
8	ACCRUAL	-0.021*	-0.015	0.014	0.020*	0.617*	0.376*	-0.569*	1						
9	△LEVERAGE	0.013	0.009	0.005	-0.000	-0.108*	-0.052*	-0.083*	-0.025*	1					
10	△LIQUID	-0.008	-0.005	0.010	0.009	0.024*	-0.017*	0.007	0.014	0.012	1				
11	EQ_OFFER	-0.006	-0.007	-0.004	-0.004	0.014	0.007	0.012	0.001	0.049*	-0.000	1			
12	△MARGIN	0.006	0.006	0.004	0.004	0.004	-0.002	0.020*	-0.013	0.002	0.002	-0.002	1		
13	△TURNOVER	0.006	0.027*	0.098*	0.112*	0.107*	0.201*	0.047*	0.053*	0.028*	-0.003	0.030*	-0.001	1	
14	F-SCORE	0.050*	0.069*	0.202*	0.216*	0.318*	0.284*	0.410*	-0.064*	-0.141*	0.037*	-0.035*	0.033*	0.235*	1

Note: In Panel A of this table, we report the descriptive statistics at of various firm characteristics at consolidated level: mean, median, standard deviation, 25th percentile and 75th Percentile. It comprises of 13,258 firm-year observations for 2,474 unique firms. In Panel B we report correlation between 1 and 2 year BHR return , 9 fundamental signals and composite F-SCORE.

Table 4: Buy Hold returns for portfolios formed based on fundamental analysis.

			12 Month BHR Raw		12 Month BHR (Market Adjusted)	
F_SCORE	Count	Percentage	Mean	Median	Mean	Median
Low (0 -2)	914	6.89%	0.191	-0.0217	0.034	-0.114
Medium (3-6)	9,394	70.86%	0.274	0.0515	0.096	-0.057
High (7 -9)	2,950	22.25%	0.337	0.0993	0.176	0.006
High - low			0.146	0.121	0.142	0.120
t-stat			4.451	5.859	5.482	7.470

Note: This table presents buy-and-hold returns to a fundamental investment strategy based on purchasing firms with strong fundamental signals. F_SCORE is equal to the sum of nine individual binary signals where each binary signal equals one (zero) if the underlying realization is a good (bad) signal about future firm performance. F_SCORE equal to zero (nine) means the firm possesses the least (most) favorable set of financial signals. The Low F_SCORE portfolio consists of firms with an aggregate score of 0 - 2; the High F_SCORE portfolio consists of firms with a score of 7,8 or 9. Medium F_SCORE portfolio consists of firm with scores 3, 4, 5 or 6. High – Low represents hedge portfolio returns earned by taking long position for High F_SCORE firms and short position for low F_SCORE firms.

Table 5: Descriptive Statistics for the Portfolios of High and Low F_SCORE Firms

	Overall		Low F-Score		High F-Score		Difference	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
SIZE	7.618	7.352	6.773	6.577	7.907	7.749	1.134***	1.172***
ACCRUAL	-0.043	-0.042	-0.021	0.005	-0.056	-0.051	-0.035***	-0.056***
BTM	0.698	0.156	1.237	0.388	0.377	0.101	-0.861***	-0.287***
LEVERAGE	0.160	0.096	0.231	0.126	0.131	0.083	-0.099***	-0.044***

Note: In this table, we report the descriptive statistics – mean and median of specific firm characteristics. High and low F_SCORE firms are as defined in table 4. Differences in mean (median) realizations between the high F_SCORE firms and low F_SCORE firms are measured. SIZE is natural log of market value of equity. Accruals is difference between net income and cash flow from operating activities. BTM is book to market ratio. LEVERAGE is ratio of long-term borrowing on total assets.

Table 6: Effect of F-SCORE on Stock performance measure

	(1)	(2)	(3)	(4)
	One-year		Two-year	
	Raw	Market Adjusted	Raw	Market Adjusted
VARIABLES	BHR	BHR	BHR	BHR
F-SCORE	0.044***	0.037***	0.175***	0.132***
	(5.428)	(5.100)	(6.000)	(6.434)
SIZE	-0.033**	-0.028*	-0.075*	-0.054
	(-2.888)	(-2.462)	(-2.458)	(-2.132)
ln (BM)	-0.000	-0.000	-0.068	-0.055
	(-0.003)	(-0.013)	(-1.521)	(-1.670)
BETA	0.020	0.017	0.057	0.075
	(0.805)	(0.875)	(1.150)	(1.886)
Observations	13,258	13,258	13,258	13,258
Adjusted R-squared	0.042	0.042	0.072	0.076

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: In this table we present the results on the association between F-SCORE and buy hold returns (BHR); In column 1 we regress 12-month raw Buy hold return BHR on F-SCORE. In column 2 we regress 12-month BHR market on F-SCORE. In column 3 we regress 24-month raw Buy hold return BHR on F-SCORE. In column 4 we regress 24-month BHR market on F-SCORE. In column 3 we regress 12-month BHR on both parent and consolidated earnings change scaled by end of the year consolidated total assets. We control for *SIZE* natural log of market value of equity; log of *BM* is book to market ratio and *BETA* is 3-year market beta. We estimate regressions using the Fama-MacBeth [1973] method, with the Newey-West [1987] correction. The t-statistics is reported in parentheses. ***, **, and *, correspond to p<0.01, p<0.05, p<0.1, respectively.

Table 7: Impact of information frictions on association between F_SCORE and Buy-Hold return (BHR)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	BHR	BHR	BHR	BHR	BHR	BHR
	RAW	Market Adjusted	RAW	Market Adjusted	RAW	Market Adjusted
F_SCORE	0.044***	0.037***	0.041***	0.034***	0.009	0.007
	(10.462)	(10.298)	(10.405)	(10.204)	(1.145)	(1.034)
INST	0.180***	0.153***				
	(2.850)	(2.849)				
INST*F-SCORE	-0.030***	-0.026***				
	(-2.665)	(-2.714)				
FOREIGN			0.307***	0.256**		
			(2.624)	(2.573)		
FOREIGN*F_SCORE			-0.050**	-0.040**		
			(-2.213)	(-2.113)		
SMALL					-0.346***	-0.281***
					(-4.400)	(-4.240)
SMALL*F_SCORE					0.044***	0.039***
					(4.160)	(4.350)
SIZE	-0.032***	-0.026***	-0.028***	-0.024***	-0.042***	-0.032***
	(-6.281)	(-6.104)	(-6.521)	(-6.386)	(-4.648)	(-4.249)
ln (BM)	0.012**	0.010**	0.014**	0.012**	0.018**	0.015**
	(2.177)	(2.221)	(2.500)	(2.540)	(2.522)	(2.497)
BETA	-0.000	0.000	-0.002	-0.001	-0.011	-0.006
	(-0.037)	(0.047)	(-0.217)	(-0.122)	(-0.853)	(-0.564)
Observations	13,247	13,247	13,258	13,258	6,627	6,627
Adjusted R-squared	0.281	0.115	0.281	0.115	0.250	0.093
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: In this table, we examine impact of institutional ownership (INST), multi-national status (FOREIGN) and Small firms (SMALL) on association between F-SCORE and Buy-Hold return (BHR). In column (1) We regress 1-year BHR (raw) on interaction between indicator variable for institutional ownership greater than 50% among non-promoter holdings (INST) and F-SCORE. In column (2) We regress 1-year BHR (market adjusted) on interaction between indicator variable for institutional ownership greater than 50% among non-promoter holdings (INST) and F-SCORE. In column (3) We regress 1-year BHR (raw) on

interaction between indicator variable for multinational firms (FOREIGN) and F-SCORE. In column (4) We regress 1-year BHR (market adjusted) on interaction between indicator variable for multinational firms (FOREIGN) and F-SCORE. In column (5) We regress 1-year BHR (raw) on interaction between indicator variable for small firm (SMALL) and F-SCORE. SMALL takes value 1 if firm belongs to lowest size quintile, 0 for the top size quintile. In column (2)) We regress 1-year BHR (market adjusted) on interaction between indicator variable for small firm (SMALL) and F-SCORE. We control for *SIZE* natural log of market value of equity; log of *BM* is book to market ratio and *BETA* is 3-year market beta. The t-statistics are reported in parentheses. ***, **, and *, correspond to $p<0.01$, $p<0.05$, $p<0.1$, respectively.