July 22nd 2014
Preliminary and Incomplete
Do not cite without permission

Fundamental Analysis: A comparison of Financial Statement Analysis Driven and Intrinsic Value Driven Approaches

Kevin Li
kevin.li@rotman.utoronto.ca

Partha Mohanram
partha.mohanram@rotman.utoronto.ca

Rotman School of Management
University of Toronto

Abstract: Using cross-sectional forecasts, we are able to compare fundamental analysis strategies based on ratio analysis such as FSCORE from Piotroski (2000) and GSCORE from Mohanram (2005) with strategies based on intrinsic value such as the V/P ratio from Frankel and Lee (1998). We find all three strategies generate significant hedge returns. Combining the V/P ratio with FSCORE or GSCORE leads to a significant increase in hedge returns that hold for a variety of partitions, persist over time and remain after controlling for risk factors. The results suggest a new and powerful method to conduct fundamental analysis and have important implications for academic research in fundamental analysis as well as for practitioners in their elusive quest for alpha generating strategies.

1. Introduction

Fundamental analysis maintains that markets may misprice a security in the short run but that the "correct" price will eventually be reached. Profits are made by purchasing the mispriced security and then waiting for the market to recognize its "mistake" and reprice the security. Fundamental analysis focuses on identifying potential winners and losers in terms of future returns from the cross-section of firms.

Prior research in accounting and finance has taken two distinct approaches towards fundamental analysis. The first approach calculates the “intrinsic value” of a firm by using analysts’ earnings forecasts in conjunction with an accounting-based valuation model. The second approach involves the analysis of multiple pieces of information from firms’ financial statements, a technique referred to as financial statement analysis.

Frankel and Lee (1998) show that the intrinsic value approach can be very successful in picking future winners and losers by identifying firms whose stock price has deviated significantly from the intrinsic value. The financial statement analysis driven approach was tested in Ou and Penman (1989) who show that financial statement ratios can predict future earnings changes. Lev and Thiagarajan (1993) identify specific financial signals that financial analysts typically use and show that these signals are correlated with contemporaneous returns. Abarbanell and Bushee (1998) document that these fundamental signals can be used to create trading strategies that yield significant abnormal returns. Piotroski (2000) and Mohanram (2005) demonstrate that financial statement analysis can separate winners from losers among value stocks and growth stocks, respectively.

Each of these alternative approaches has strengths and weaknesses. The intrinsic value approach is based on the application of rigorous valuation methods, such as the residual income valuation model. Frankel and Lee (1998) make the economically defensible arguments that firms' abnormal performance will decay with time and that firms' stock prices will eventually converge towards their intrinsic value. However, this approach is limited to firms where forecasts of future earnings are available. Further, the intrinsic value model focuses only on summary metrics such as earnings or book values, and ignores the richness of disaggregated financial statement information.

In contrast, the financial statement analysis driven approach can be applied to a wider cross-section of firms and utilizes the richness of financial statement information. For instance, Piotroski (2000) develops signals based on the commonly used Dupont profitability decomposition to identify firms with an improving trend in performance. However, the financial statement analysis driven approach ignores the possibility that the market might already have incorporated the insight from the financial statements in its valuation.

Prior research has neither tried to evaluate nor tried to combine these two alternative approaches towards stock picking. The primary reason for this is the difference in data requirements owing from the need for analysts forecasts to calculate intrinsic value. For instance, Piotroski (2000) considers the intrinsic value approach in the subset of high book-to-market or "value" firms that he focuses on, but concludes that "a forecast-based approach, such as Frankel and Lee (1998), has limited application for differentiating value stocks".

However, recent research has examined the efficacy of cross-sectional earnings forecasts. Hou, van Dijk and Zhang (2012) develop a cross-sectional model that generates forecasts of future earnings without the need for a lengthy time series of data. Li and Mohanram (2014) refine these models by grounding them in accounting theory and generate superior cross-sectional forecasts, especially for the crucial subset of firms without analysts' forecasts. These cross-sectional models allow researchers to estimate future earnings for a wide cross-section of stocks.

The availability of cross-sectional model forecasts for essentially the entire population of firms implies that one can finally answer the following important and interesting questions related to the efficacy of the alternate approaches towards fundamental analysis. Which approach is more effective in picking winners and losers – the intrinsic value approach or the financial statement analysis approach? Are these two approaches correlated – i.e., do they identify broadly similar stocks as potentially undervalued or over-valued? Is there any benefit to combining these two approaches?

We focus on three approaches towards fundamental analysis. The first is the ratio analysis driven value investing approach (FSCORE) in Piotroski (2000). The second is the ratio analysis driven growth investing strategy (GSCORE) from Mohanram (2005). The third is the intrinsic value driven approach (V/P) from Frankel and Lee (1998), using a sample of cross-sectional forecasts from the model provided in Li and Mohanram (2014).[1] For each approach, we implement a hedge strategy by taking a long position in firms in top quintile and a short position in firms in the bottom quintile of the appropriate measure in a given year.[2]

Our sample consists of all firms from 1972 to 2011 for which we have adequate information to compute FSCORE, GSCORE, V/P and one-year-ahead returns (RET_1). The sample consists of 189,719 observations, or an average of 4,743 observations per year. This

[1] The details of the cross-sectional forecasts are provided in the Appendix.

[2] For the two ratio analysis based approaches, we modify the score based approach, and create continuous variables to allow for more efficient portfolio construction, easier tractability of combined strategies, and a more direct approach towards testing incremental hedge returns.

represents nearly the entire population of stocks because of the parsimonious data requirements for the analysis variables.

We first examine the correlations between the three strategies. As expected, FSCORE is positively correlated with GSCORE. Interestingly, both FSCORE and GSCORE show significant negative correlation with V/P. This suggests that the ratio analysis driven approaches to fundamental analysis are inherently different from the intrinsic value approaches, and further, there may even be a trade-off between the two approaches. All three variables show significant positive correlations with future returns.

We next examine the efficacy of these three strategies in generating hedge returns. Consistent with prior research, we find that all three strategies generate economically meaningful and statistically significant abnormal returns. The FSCORE strategy generates average annual hedge returns of 8.39%. The GSCORE strategy performs slightly poorer, generating average hedge returns of 6.85%. The V/P approach generates hedge returns of 8.67%. While all three approaches generate significant hedge returns, the FSCORE and V/P strategies generate significantly greater hedge returns than the GSCORE strategy.

We then move to our primary research question – whether combining the intrinsic value approach (V/P) with the ratio analysis driven approach (FSCORE and GSCORE) help generate superior excess returns. Our results strongly support this conjecture. Combining FSCORE with V/P increases hedge returns from 8.39% for FSCORE alone to 11.67%. Similarly, combining GSCORE with V/P increases hedge returns from 6.85% for GSCORE alone to 10.78%. Further, the improvement works both ways – returns to the V/P strategy also increase significantly when V/P strategy is combined with either the FSCORE or the GSCORE approach.

To ensure that our results are not driven by a non-representative subset of stocks, we partition our sample based on analyst following, exchange listing and size. We find significant improvements in almost all subgroups – followed firms as well as non-followed firms, NYSE/AMEX firms as well as NASDAQ and other firms, and firms in all size groups. This suggests that the combined strategy outlined in this paper is likely to be implementable.

To ensure that our results are not driven by specific time periods, we examine the trends in the performance of the strategies over time. We find that the combined strategy generates significantly higher returns across most years, and more importantly, reduces the incidence of negative hedge returns. Out of the 40 years analyzed, the FSCORE, GSCORE and V/P strategies generate negative hedge returns in 4, 10 and 9 years, respectively. In contrast, the combined FSCORE & V/P strategy and GSCORE & V/P strategy generate negative hedge returns in only 2 and 3 years, respectively.

The low incidence of loss making years suggests that our results are unlikely to be driven by risk. However, to ensure that a risk based explanation is not driving our results, we run Fama and French (1993) factor regressions, using monthly returns for the first year after portfolio formation. We run both the three-factor model that controls for the market ($R_m – R_f$), size (SMB) and book-to-market (HML), as well as the four-factor Carhart (1997) model that also includes momentum (UMD). We find that all the strategies generate significant alphas (excess returns), and that the alphas of the combined strategies are generally significantly greater.

The rest of the paper is organized as follows. Section 2 describes the ratio driven and intrinsic value driven approaches towards fundamental analysis studied in this paper. Section 3 presents the research design and descriptive statistics about the sample. Section 4 presents main empirical results. Section 5 concludes with suggestions for future research.

2. Prior Research

Our paper builds on research from three streams – ratio driven fundamental analysis, intrinsic value driven fundamental analysis, and cross-sectional forecasting. We briefly describe the relevant research in these areas, focusing on four papers, Piotroski (2000), Mohanram (2005), Frankel and Lee (1998), and Li and Mohanram (2014).

2.1 Ratio Driven Fundamental Analysis

A large body of research has focused on the usefulness of financial statement ratios in predicting future realizations of both earnings and returns. Ou and Penman (1989) show that certain financial ratios can help predict future changes in earnings. Lev and Thiagarajan (1993) analyze 12 financials signals purportedly used by financial analysts and show that these signals are correlated with contemporaneous returns. Abarbanell and Bushee (1998) develop an investment strategy based on these signals, which earns significant abnormal returns.

Piotroski (2000) uses financial statement analysis to develop an investment strategy for high book-to-market or value firms. He argues that value firms are ideal candidates for the application of financial statement analysis as financial analysts generally neglect such firms. Piotroski (2000) adopts nine binary signals based on traditional ratio analysis and combines these signals into a single index called FSCORE. He shows that a strategy of taking a long position in high FSCORE firms and a short position in low FSCORE firms generates significant excess returns that are persistent over time, rarely negative and not driven by risk. In a related paper, Piotroski and So (2012) show that the FSCORE strategy is successful across a broad cross-section of stocks, and not just in low book-to-market or value stocks.

Mohanram (2005) follows a similar approach as Piotroski (2000), but focuses on low book-to-market or growth stocks. He tailors the ratios to better suit growth stocks. Mohanram (2005) adopts eight binary signals and converts them into a single index called GSCORE. Similar to Piotroski (2000), he shows that the GSCORE strategy is successful in separating winners from losers among low book-to-market firms.

2.2 Intrinsic Value Based Fundamental Analysis

There is a vast literature in accounting and finance that has tried to correlate stock prices and returns with financial statement metrics such as earnings (Basu, 1977), cash flows (Chan et al., 1991; Lakonishok et al., 1994) and dividends (Litzenberger and Ramaswamy, 1979). Much of the early research was primarily concerned with whether these metrics represented risk factors, and less with the prediction of intrinsic value.

The advent of the residual income valuation (RIV) models from Ohlson (1995) and Feltham and Ohlson (1995) among others allows researchers to link accounting numbers directly to value, without the need to either convert earnings to cash flows or forecast dividends. The clean surplus assumption in these models allows researchers to convert analysts' earnings forecasts into forecasts of future book values and residual income. Frankel and Lee (1998) were among the first papers to use the RIV model to estimate intrinsic value. They rely on the notion of competitive equilibrium to assume that residual income diminishes over time, which allows them to compute a finite terminal value for the estimation of intrinsic value. They operationalize a V/P measure, which is the ratio of the intrinsic value of a firm from the RIV model to the prevailing stock price. They hypothesize that firms with high V/P ratios are undervalued and earn strong returns in the years ahead. Conversely, firms with low V/P ratios are overvalued and earn poor returns in the years ahead. Their empirical results strongly support these conjectures, suggesting that the RIV model is a powerful method to estimate intrinsic value.

Bradshaw (2004) uses the V/P ratio to test whether analysts' forecasts and recommendations are correlated with measures of intrinsic value. He finds scant evidence supporting this and instead finds that analysts are more likely to use heuristic methods like the PEG (Price/Earnings to Growth) ratio. His finding that analysts ignore intrinsic value from formal models such as RIV may explain why these models work in predicting future returns.

2.2 Comparing Ratio Driven and Intrinsic Value Based Fundamental Analysis

The ratio analysis driven and intrinsic value based approaches to fundamental analysis have many differences. Ratio analysis driven approaches rely on the richness of financial statement data and allow one to analyze details of firm performance – e.g., analysis of profitability, margins, efficiency and risk. Intrinsic value approaches focus on a few key metrics – e.g., earnings and book values in the case of the RIV based models. These two approaches might yield similar results. After all, detailed ratio analysis of profitability and risk should also have implications for summary metrics such as earnings, cash flows and book values. On the other hand, it is also possible that these summary metrics might ignore some insights provided by detailed ratio analysis.

Prior research has not been able to compare or combine these two approaches towards fundamental analysis for one simple reason – different data requirements. Ratio analysis can be conducted on virtually any firm that has historical financial data. The computation of intrinsic value metrics such as the V/P in Frankel and Lee (1998), on the other hand, requires forecasts. Historically, only half or less of all U.S. firms have analyst following. Further, as Piotroski

(2000) and others show, the incidence of mispricing is probably the strongest in the subset of firms without analyst following. For such firms, an intrinsic value approach is infeasible.

2.3 Cross-Sectional Forecasting

The prior research has tried to develop alternatives to analyst forecasts for firms without analyst coverage. The typical approach was to generate time series forecasts using firm specific estimation models. However, time series models require a lengthy time series of data, inducing significant survivorship bias. This is especially problematic for firms without analyst following because they are typically young firms that lack such data.

Recent developments in the area of cross-sectional forecasting address these data limitations. Hou, van Dijk and Zhang (2012) use the cross-sectional method to generate forecasts for up to five years into the future. A major advantage of the cross-sectional approach is that it uses the large cross-section of individual firms to compute earnings forecasts. Because the cross-sectional approach does not require the firm whose earnings are being forecasted to be in the estimation sample, there are minimal survivorship requirements. Li and Mohanram (2014) refine the cross-sectional approach by developing models motivated by the residual income model. They show that their models generate more accurate forecasts that better represent market expectations.

2.3 Putting it all together: Our Research Questions

The availability of cross-sectional forecasts allows one to use an intrinsic value approach towards fundamental analysis in the broad cross-section of firms. This allows us to compare, contrast and combine the two different approaches towards fundamental analysis in a common sample that reflects the complete cross-section of firms. Therefore, we are able to ask the following research questions.

First, we can compare the ratio analysis driven approaches to the intrinsic value approaches to see if one dominates the other. As these approaches have not been compared before, we do not have any priors as to which of these methods will show greater efficacy.

RQ1: Which approach towards fundamental analysis generates higher excess returns?

Second, we can combine the two approaches towards fundamental analysis to see if one can do a superior job of generating excess returns. For instance, focusing on high V/P stocks and avoiding low V/P stocks among high FSCORE or GSCORE stocks might provide better long opportunities. Conversely, focusing on low V/P stocks and avoiding high V/P stocks among low FSCORE or GSCORE stocks might provide better short opportunities. Success along this front potentially depends on the correlations between the two styles of fundamental analysis. If the two approaches are strongly positively correlated, then combining them might not generate significant improvements. Essentially, each approach would merely be a transformation of the other. On the other hand, if the two approaches are uncorrelated or even negatively correlated, combining them might accrue significant improvement. Again, we do not have any priors as to whether a combined approach will generate higher excess returns.

RQ2: Does combining ratio analysis based approaches with intrinsic value based approaches to fundamental analysis help generate stronger hedge returns than the individual strategies?

3. Research Design

We need to make a number of assumptions to implement the Piotroski (2000), Mohanram (2005) and Frankel and Lee (1998) approaches towards fundamental analysis. In some cases, we modify the strategies in order to allow for easier comparison and combination of the relevant strategies. In this section, we describe the critical elements of our research design.

3.1 Implementation of Ratio Based Fundamental Analysis (FSCORE and GSCORE)

To identify financially strong firms with high book-to-market ratio, Piotroski (2000) develops a scoring system based on nine fundamental signals: return on assets (ROA), cash flow from operations (CFO), change in ROA (ΔROA), accrual, change in leverage (ΔLEVER), change in liquidity (ΔLIQUID), equity offering (EQ_OFFER), change in gross margin (ΔMARGIN), and change in asset turnover ratio (ΔTURN).[3] Among the nine fundamental signals, ROA, CFO, ΔROA, ΔLIQUID, ΔMARGIN, and ΔTURN are positive signals receiving a score of 1 if positive and 0 otherwise. Accruals and ΔLEVER are considered as negative signals, receiving a score of 1 if negative and 0 otherwise. Equity issuance is also considered a negative signal, receiving a score of 0 with equity issuance and 1 if there is no equity issuance. FSCORE is the sum of the nine individual scores.

To identify financially strong firms with low book-to-market ratio, Mohanram (2005) develops a scoring system based on eight fundamental signals: ROA, CFO, accrual, earnings volatility (VARROA), sale growth volatility (VARSGR), R&D intensity (RDINT), capital

[3] Using COMPUSTAT data items, ROA is measured as ib/at; accrual is (Δact-Δlct-Δche+Δdlc-dp)/at; CFO is oancf/at for years after 1988 or ROA-accrual for years before 1988; LEVER is dltt/at; LIQUID is act/lct; EQ_OFFER is identified using sstk; MARGIN is (sale-cogs)/sale; and TURN is sale/at.

expenditure intensity (CAPINT), and advertising intensity (ADINT).[4] Unlike Piotroski (2000), this approach relies on comparison to industry peers. The positive signals are ROA, CFO, RDINT, CAPINT, and ADINT, receiving a score of 1 if the variable is greater than the contemporaneous industry median, and 0 otherwise. The negative signals are VARROA, VARSGR and accruals, receiving a score of 1 if the variable is less than the contemporaneous industry median, and 0 otherwise. GSCORE is the sum of the eight fundamental signals.

One of the issues with both the FSCORE and GSCORE methodologies is that the knife-edge 0/1 criteria result in a very discrete distribution of scores, with a very few number of firms in the extreme groups and most firms clustered around the middle.[5] This makes the comparison across strategies and the creation of long-short portfolios problematic. For instance, Piotroski (2000) is forced to arbitrarily classify the lower scores (0, 1) into a "low" group and higher scores (8,9) into a "high" group. This means that the groups are often of different sizes and do not correspond neatly to groupings like quintiles or deciles which are often used to analyze hedge returns. To deal with this, we create continuous versions of both FSCORE and GSCORE. We normalize each of the variables underlying the signals to lie between 0 and 1. For FSCORE, each variable is compared to the contemporaneous distribution across all firms. For instance, the firm with the highest ROA will get a score of 1, while the firm with the lowest ROA will get a score of 0, with every other firm getting a score in between based on ranks. FSCORE is defined as the sum of the nine continuous underlying signals. For GSCORE, each variable is normalized to lie between 0 and 1 based on the contemporaneous distribution across firms in the same

[4] Using COMPUSTAT data items, VARROA is the standard deviation of quarterly ROA (ibq/atq) over the past two years; VARSGR is the standard deviation of quarterly sales growth rate ($saleq_t/saleq_{t-1}$-1) over the past two years; RDINT is xrd/at; CAPINT is capx/at; and ADINT is xad/at.

[5] To illustrate, of the 14,043 observations from Piotroski (2000), the distribution by FSCORE was as follows: 0 (57), 1 (339), 2 (859), 3 (1618), 4 (2462), 5 (2787), 6 (2579), 7 (1894), 8 (1115) and 9 (333).

industry (defined using the 48 industry classifications in Fama and French, 1997). GSCORE is similarly defined as the sum of the eight continuous underlying signals.

3.2 Implementation of the Intrinsic Value Approach to Fundamental Analysis (V/P)

We follow the research methodology in Frankel and Lee (1998) and Gebhardt et al. (2001) to implement the intrinsic value approach. Specifically, we estimate the intrinsic value of a firm using the residual income valuation model:

$$V_t^* = B_t + \sum_{i=1}^{\infty} \frac{\mathrm{E}_t[NI_{t+i} - (r_e B_{t+i-1})]}{(1+r_e)^i}$$
$$= B_t + \sum_{i=1}^{\infty} \frac{\mathrm{E}_t[(ROE_{t+i} - r_e) B_{t+i-1}]}{(1+r_e)^i},$$

where B_t is the book value of equity per share (ceq/csho) at time t; Et[.] is expectation based on information available at time t; NI_{t+i} is earnings before special and extraordinary items per share ((ib-spi)/csho) for period t+i; r_e is the cost of equity capital, and ROE_{t+i} is the after-tax return on book equity for period t+i.

To implement the model, we estimate the firm's future earnings per share from t+1 to t+5 using the methodology discussed in the Appendix. We compute book value of equity and return on equity in each period assuming clean surplus accounting: $B_{t+i}=B_{t+i-1}+(1-k)*NI_{t+i}$ and $ROE_{t+i}=NI_{t+i}/B_{t+i-1}$, where the payout ratio (k) is set to dividend divided by net income (dvc/(ib-spi)) in year t for firms with positive earnings, or dividend in t divided by 6% of total assets (dvc/(6%*at)) for firms with negative earnings. If k is greater (less) than one (zero), we set it to one (zero). For periods beyond the forecast horizon (t+5), we assume the firm's return on equity to decay to the industry median by t+12 using linear interpolation. After t+12, the firm earns industry median ROE in perpetuity. Industry median ROE is computed annually using observations from all profitable firms within that industry (defined using the 48 industry classifications in Fama and French, 1997) over the past five years. Finally, consistent with Frankel and Lee (1998), the cost of equity capital (r_e) is estimated using Fama and French (1993) three-factor model within each industry. We use the ratio of the intrinsic value to the prevailing stock price (V/P) to form the trading portfolios. As V/P is a continuous variable, we do not need to standardize this variable when it is used as a standalone strategy.

3.3 Combining Different Approaches to Fundamental Analysis

One way to combine alternative approaches towards fundamental analysis is to form portfolios based on one measure (e.g., FSCORE or GSCORE) and partition each portfolio further based on the other measure (e.g., V/P). Such an approach has the following problems. First, it is not possible to compare the performance across an equal sized sample (i.e., long-short across quintiles). Second, it is also possible that any superior performance that a combined strategy shows might arise from a finer partition along one dimension – i.e., instead of looking at high V/P firms among the high FSCORE quintile, one could just as easily look at high FSCORE decile instead.

In order to combine alternative strategies and retain the portfolio size, we standardize the underlying variables (FSCORE, GSCORE and V/P) each year by subtracting the cross-sectional minimum from the value and dividing the resulting number by the difference between the cross-sectional maximum and minimum. We then add the standardized values to obtain the combined values. For example, to combine FSCORE with V/P, we first standardize both FSCORE and V/P to lie between 0 and 1. We then add the standardized values of FSCORE and V/P, and form quintile portfolios based on the composite variable.

3.4 Return Computation

We analyze the performance of our strategies using a one-year horizon starting on July 1st, ensuring that all financial data are available with at least a three-month lag. What this means is that for firms with fiscal years ending from July to March, we compound returns from the July following the end of the fiscal year end. For firms with fiscal years ending in April, May or June, the return compounding period starts a year later. While this may mean that the data can be stale for a small subset of firms, it ensures that there is no look-ahead bias in return computation. Our basic unit of analysis for returns, RET_1, is the one year buy-and-hold returns over this twelve-month period. Returns are adjusted for delisting if twelve months of returns are not available, consistent with Shumway (1997).

3.5 Sample Selection and Correlations

Table 1 presents a summary of our sample selection procedure. We begin with the universe of 261,291 firm-years of U.S. firms with required financial data on COMPUSTAT to compute FSCORE in the forty-year period from 1972 to 2011. The computation of GSCORE requires additional data to calculate the earnings and sales growth variability, which requires two years of quarterly data. This reduces the sample to 239,882 firm-year observations. Finally, we need the availability of cross-sectional forecasts to estimate the V/P measure. This reduces the sample size to 189,719 observations, which corresponds to 13,986 unique firms.

Panel B presents the correlations between FSCORE, GSCORE and V/P. In addition, we also include future returns (RET_1), size (log of market capitalization LMCAP), and the book-to-market ratio (BM). As all our tests are run annually, we present the average of annual correlations. FSCORE and GSCORE are very strongly correlated. This is not surprising, given that both of them are based on financial statement ratios and many of their signals are similar. Interestingly, both FSCORE and GSCORE are negatively correlated with the V/P ratio, suggesting a potential trade-off between these two strategies. All three strategies show positive correlation with future returns, with the correlation being the strongest for FSCORE and the weakest for V/P. Both FSCORE and GSCORE are positively correlated with size, suggesting that larger firms are likely to have stronger economic fundamentals. FSCORE and GSCORE are also negatively correlated with BM, consistent with firms in financial distress (high BM firms) having weaker fundamentals. V/P shows a slightly negative correlation with size, but a strikingly strong positive correlation with BM. This is consistent with value firms (high BM) being undervalued (high V/P) and growth firms (low BM) being overvalued (low V/P). Given the strong correlations of the three strategies with size and book-to-market, we also run Fama-French factor regressions that control for these factors.

4. Results

4.1 Comparison of the Three Strategies

We begin by examining if the three strategies are effective in separating winners from losers in terms of future stock returns. In each year, we sort the sample of firms into quintiles based on each underlying variable. We then examine the average returns for each quintile, as well as the hedge return for a strategy long in the top quintile and short in the bottom quintile.

The results are presented in Table 2. In addition to the hedge returns, we also present the average values of FSCORE, GSCORE and V/P for each quintile.

Panel A presents the results for quintiles based on FSCORE. The results show that mean RET_1 increases monotonically from 8.86% for the bottom quintile to 17.25% for the top quintile. The average hedge return of 8.39% is highly significant, strongly corroborating the success of the FSCORE strategy in Piotroski (2000). As FSCORE and GSCORE have strong positive correlation, GSCORE also increases monotonically across quintiles of FSCORE. Conversely, as FSCORE and V/P are negatively correlated, V/P declines monotonically across quintiles of FSCORE.

Panel B presents the results for quintiles based on GSCORE. The results show that mean RET_1 increases monotonically from 9.75% for the bottom quintile to 16.60% for the top quintile. The average hedge return of 6.85%, while lower than that for FSCORE, is also highly significant. FSCORE increases monotonically across quintiles of GSCORE, while V/P declines across quintiles of GSCORE.

Panel C presents the results for quintiles based on V/P. Once again, mean RET_1 increases monotonically from 8.93% for the bottom quintile to 17.60% for the top quintile. The average hedge return of 8.67% is the highest among the three strategies. Intriguingly, despite the negative correlation, FSCORE shows a weak increase across quintiles of V/P, while GSCORE declines across quintiles of V/P.

Panel D presents the three pair-wise comparisons of the hedge returns among the three strategies. To summarize, both FSCORE and V/P generate hedge returns that are significantly greater than the hedge returns for GSCORE. While V/P generates the highest hedge returns, they are not statistically different from the hedge returns for FSCORE.

4.2 Combining Ratio Analysis Driven Approaches with Intrinsic Value Driven Approaches

In this section, we examine whether combining the ratio analysis driven FSCORE and GSCORE approaches with the intrinsic value driven V/P approach provides stronger hedge returns than the individual strategies. As described in Section 3, we create composite variables by adding the normalized value of FSCORE or GSCORE to a normalized value of the V/P ratio. We then form quintiles based on the composite variables and analyze the hedge returns. The results are presented in Table 3.

Panel A presents the results for the FSCORE & V/P combined strategy. Given the combined emphasis, both FSCORE and V/P (as well as GSCORE) increase monotonically across quintiles of the composite measure, though the across quintile spreads is lower than the individual strategies reported in Table 2. Thus, this is a hybrid strategy, combining elements of FSCORE and V/P. The last column presents the spread in returns. As the results indicate, the return spread in quintiles increase to 11.67% from the 8.39% for FSCORE alone and 8.67% for V/P alone.

Panel B presents the results for the GSCORE and V/P combined strategy. Once again, both GSCORE and V/P (as well as FSCORE) increase monotonically across quintiles of the composite measure, though the across quintile spreads is lower than the individual strategies reported in Table 2. Thus, this is also a hybrid strategy, combining elements of GSCORE and V/P. Finally, the return spread in quintiles increase to 10.78% from the 6.85% for GSCORE alone and 8.67% for V/P alone.

Panel C tests whether the intrinsic value approach adds to the ratio analysis approach by testing the significance of the difference in hedge returns. Adding V/P increases hedge returns in FSCORE quintiles by 3.29% (t-stat 4.85) and hedge returns in GSCORE quintiles by 3.93%

(t-stat 6.11). Hence, the results suggest that ratio analysis driven approaches to fundamental analysis can be significantly augmented by also considering intrinsic value. Panel D tests the reverse, i.e., whether ratio analysis driven approaches augment intrinsic value approaches. Adding FSCORE increases hedge returns in V/P quintiles by 3.00% (t-stat 4.35). For GSCORE, the increase is more modest at 2.11%, but still significant (t-stat 3.08).

To summarize, the results from Table 3 suggest that fundamental strategies that combine elements of ratio analysis and intrinsic value outperform individual strategies both economically and statistically. In the remainder of the paper, we test whether these improvements hold in a variety of partitions, across time and whether they persist after controlling for risk factors.

4.3 Partition Analysis

We partition our sample along a number of dimensions to see if the results are robust in different relevant subsets of the population. We consider three partitions – analyst following, listing exchange, and size. All three partitions are related to the information environment as well as the implementability of the hedge strategies. The results are presented in Table 4. For brevity, we only present the results in the extreme quintiles and hedge returns.

Panel A partitions the sample based on analyst following. The first three sets of columns present the returns for the three basic strategies. Not surprisingly, for all three basic strategies, the hedge returns are much stronger in the subsample of firms without analyst following. For instance the FSCORE strategy generates hedge returns of 11.01% in firms without analyst following as opposed to 6.43% in firms with analyst following. This is consistent with similar partition results in Piotroski (2000). Similar differences in hedge returns are also seen in for the GSCORE and V/P strategies. The strong performance of the V/P strategy in the subset of firms without analyst following (11.52% hedge returns) also validates the use of cross-sectional forecasts to generate measures of intrinsic value.

The next sets columns present the results for the two combined strategies and examine whether they improve significantly over the individual strategies. For firms without following, we see a statistically and economically significant increase in hedge returns. For instance, the FSCORE & V/P strategy outperforms the FSCORE strategy by 5.86% (t-stat 4.63) and outperforms the V/P strategy by 5.34% (t-stat 4.54) for firms without analyst following. Similar improvements are also seen for the combination of GSCORE & V/P. When we consider firms with analyst following, we also see significant improvements for both the combined strategies, but the magnitude is slightly smaller (in the order of 2-3%). However, given the smaller hedge returns for followed firms, the relative improvement is still impressive.

Panel B partitions the sample based on listing exchange, separating the more liquid NYSE/AMEX firms from stocks listed on the NASDAQ and other exchanges. Interestingly, the FSCORE and V/P strategies appear to generate similar hedge returns in both partitions, while the GSCORE strategy is much less effective in NYSE/AMEX firms. When we consider the combined strategies, we find that the FSCORE and V/P strategies provide a significant improvement to each individual strategy in both partitions. The combined GSCORE and V/P strategy outperforms the GSCORE strategy in both partitions, but only outperforms the V/P strategy among the NASDAQ/Other group.

Panel C partitions the sample into quintiles each year based on market capitalization. The strategies are then run in the subsample of small (bottom quintile), medium (middle three quintiles) and large firms (top quintiles). The results largely mirror the results from the other partitions. All strategies generate the highest hedge returns in small firms and the lowest hedge returns in large firms. In all comparisons other than one (GSCORE & V/P vs V/P in small firms), the combined strategies generate significantly greater hedge returns than the individual strategies. The improvement is particularly striking for the GSCORE strategy. For small firms, the GSCORE strategy's hedge return improves by 5.11% (t-stat 3.51) when paired with the V/P strategy. Even for large firms, the GSCORE strategy's hedge returns improve by an astounding 4.65% (t-stat 4.95) from 3.60% to 8.25%.

To summarize, the improvements generated by combining the ratio analysis driven strategies (FSCORE, GSCORE) with the intrinsic value strategy (V/P) is generally robust across a variety of partitions. This increases our confidence that these hedge returns would not be dissipated by transaction costs and other implementation issues.

4.4 Hedge Returns across Time

While the tables thus far present hedge returns for annual portfolios, the results are pooled across time. To ensure that the results are persistent across time, we analyze the performance of the FSCORE, GSCORE, V/P, and the two combined strategies across time. The results are presented in Table 5.

Panel A presents the results across time, while Panel B summarizes them. As Panel B suggests, the combined strategies generally outperform the individual strategies. The combined FSCORE & V/P strategy earns average annual hedge returns of 12.9%, as opposed to 9.0% for FSCORE and 9.0% for V/P. Further, the Sharpe ratio for the combined strategy, at 1.21, is higher than the Sharpe ratio for FSCORE (1.14) and considerably higher than the Sharpe ratio for V/P (0.76). The combined GSCORE & V/P strategy earns average annual hedge returns of 11.1% (Sharpe ratio = 1.16), as opposed to 6.7% for GSCORE (Sharpe ratio = 0.89) and 9.0% for V/P

(Sharpe ratio = 0.76). The increase in both hedge returns as well as Sharpe ratios suggests that the combined strategy is not merely generating additional hedge returns by incurring additional risk.

Most telling is the fact that the combined strategies reduce years with negative hedge returns. While the FSCORE, GSCORE and V/P strategies earn negative returns in 4, 10 and 9 years respectively out of 40 years, the FSCORE & V/P and GSCORE & V/P strategies earn negative returns in just 2 and 3 years, respectively. Consistent with the interpretation in prior research looking at trading rules (Bernard and Thomas 1989; Sloan 1996; Piotroski 2000, Mohanram 2005), the low incidence of negative hedge returns suggests that the return patterns shown here are unlikely to be driven by risk.

Panel C formally tests the improvement from combining the strategies. Consistent with the results shown earlier in the paper, the combined strategies generate significant incremental hedge returns over the individual strategies. Also, in a majority of the years, the combined strategies generate improved hedge returns. In particular, the addition of the V/P approach improves returns to a GSCORE strategy in 30 out of 40 years. In the following section, we attempt to formally rule out risk based explanations for this superior performance.

4.5 Controlling for Risk

To formally rule out risk based explanations, we run multi factor portfolio models based on the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. We first create hedge portfolios based on the relevant strategy (e.g. Long in top quintile and short in bottom quintile of the relevant metric). Calendar time portfolio regressions are run using monthly returns for the 12 months after portfolio formation. The intercept or alpha of the regression represents the monthly hedge return for each strategy. The results are presented in Table 6.

Panel A presents the results for the three-factor model for each of the five strategies. Among the three standalone strategies, FSCORE has the highest alpha at 0.745 (9.31% annualized). GSCORE has the second highest alpha at 0.626 (7.77% annualized). The alpha for the V/P is the lowest at 0.531 (6.56% annualized). The decline in the performance of V/P can be attributed to the strong loading on the book-to-market factor (HML). When we combine the strategies, the alphas increase. The FSCORE&V/P strategy has an alpha of 0.919 (11.6% annualized), while the GSCORE&V/P strategy has an alpha of 0.847 (10.64% annualized). Panel B tests the significance of the differences in the alphas and shows that combining the strategies increases the alpha significantly in all four comparisons.

Panel C presents the results for the four-factor model. The momentum factor (UMD) loads significantly for all the strategies. Consequently, we observe a slight decline in alphas across all strategies, though the alphas remain economically and statistically significant. Panel D compares the alphas between the combined strategies and standalone strategies and confirms that in all cases, the increase in alpha is statistically and economically significant. To summarize, the results in Table 6 confirm that the increased returns from combining ratio analysis based and intrinsic value based approaches are robust to controlling for risk.

5. Conclusions

In this paper, we take advantage of recent developments in cross-sectional forecasting to generate measure of intrinsic value without the need for analyst forecasts. This allows us to calculate the V/P measure in Frankel and Lee (1998) for a broad cross-section of firms, which enables us to compare and combine the V/P approach with the ratio analysis driven FSCORE and GSCORE approaches from Piotroski (2000) and Mohanram (2005).

We find that while all three metrics are positively correlated with future returns, the V/P metric is negatively correlated with both FSCORE and GSCORE. This suggests that these two approaches towards fundamental analysis are picking up different aspects related to future stock returns and that combining these two approaches might be fruitful. Confirming this, we find that a hybrid strategy that combines ratio analysis (FSCORE or GSCORE) with measures of intrinsic value (V/P) generates excess returns that significantly exceed the excess returns generated by these strategies alone. This superior performance is evident in a wide variety of partitions, persistent across time, and robust to controls for risk factors. Thus, combining these two approaches provides a power tool for fundamental analysis.

The results of this paper have important implications for research in accounting and finance in the area of fundamental analysis. They suggest that the two approaches towards fundamental analysis – a ratio analysis driven approach and an intrinsic value driven approach – are different. Further, combining them is advantageous, as one can generate consistently higher hedge returns that are less likely to be negative.

This paper also has implications for the research on cross-sectional forecasting. Research in accounting has thus far shown that cross-sectional forecasts are useful in the computation of implied cost of capital. Our results show that the cross-sectional forecasts can be used to generate estimates of intrinsic value, which enables researchers to calculate the V/P ratio for the entire population of stocks. This allows the combined strategies to be implemented without reducing the sample of firms.

The results have obvious implications for practitioners in their elusive quest for “alpha”. We present an easy to implement strategy that uses only public information, does not impose lengthy time series data requirements and is driven by economically defensible approaches to fundamental analysis. Many of the traditional trading rules have got arbitraged away, potentially because of greater interest from institutional investors, as Green et al. (2011) show with the accrual anomaly. Our approach of combining ratio based fundamental analysis with intrinsic value based strategies offers much promise.

We also need to mention a couple of caveats regarding the empirical execution of the paper. First, in creating the hybrid strategies, we weight the ratio analysis factor (FSCORE or GSCORE) and the intrinsic value factor (V/P) equally. We make no effort to determine what an optimal weight on these two factors might be. While this makes our method more parsimonious, it may also understate the potential of the strategies. Second, we focus on the entire population of firms. In reality, investors may have a sectorial focus, with sectors determined by factors such as industry, investing style, and size. While we do carry out some partition analyses in the paper, it is unclear that such an approach will work in every subset of stocks that investors may wish to focus on. Finally, in our tests, we control for risk factors using multi-factor asset pricing models, and further, the pattern of hedge returns across time is consistently positive. However, we cannot rule out the possibility that our results may arise from other unobserved risk factors.

References

Abarbanell, J. and B. Bushee. 1998. Abnormal returns to a fundamental analysis strategy. The Accounting Review 73(1), 19-45.

Basu, S. 1977. Investment performance of common stocks in relation to their price earnings ratios: a test of the efficient market hypothesis. Journal of Finance 32, 663-682.

Bernard, V. and J. Thomas. 1989. Post-earnings announcement drift: Delayed price response or risk premium. Journal of Accounting Research 27, 1–36.

Bradshaw, M. 2004. How do analysts use their earnings forecasts in generating stock recommendations? The Accounting Review 79(1), 25-50.

Carhart, M. 1997. On persistence in mutual fund performance. Journal of Finance 52, 57-82.

Chan, L., Y. Hamao, and J. Lakonishok. 1991. Fundamentals and stock returns in Japan. Journal of Finance 46, 1739-1764.

Fama, E. and K. French. 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

_________ and ________. 1997. Industry costs of equity. Journal of Financial Economics 43: 153-193.

Feltham, G. and J. Ohlson. 1995. Valuation and clean surplus accounting for operating and financial activities. Contemporary Accounting Research 11, 689–732.

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

Gebhardt, W., C. Lee, and B. Swaminathan. 2001. Toward an implied cost of capital. Journal of Accounting Research, 39, 135-176.

Green, J., J. Hand, and M. Soliman. 2011. Going, going, gone? The death of the US accruals anomaly. Management Science 57, 797-816.

Hou, K., M. van Dijk, and Y. Zhang. 2012. The implied cost of equity: A new approach. Journal of Accounting and Economics 53, 504-526.

Lakonishok, J., A. Shleifer, and R. Vishny. 1994. Contrarian investment, extrapolation and risk. Journal of Finance 44, 1541-1578.

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

Li, K. and P. Mohanram. 2014. Evaluating cross-sectional forecasting models for implied cost of capital. Review of Accounting Studies, forthcoming.

Litzenberger, R. and K. Ramaswamy. 1979. The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence. Journal of Financial Economics 7, 163-196.

Mohanram, P. 2005. Separating winners from losers among low book-to-market stocks using financial statement analysis. Review of Accounting Studies 10, 133-170.

Ohlson, J. 1995. Earnings, book values, and dividends in equity valuation. Contemporary Accounting Research 11, 661-687.

Ou, J. and S. Penman. 1989. Accounting measures, price-earnings ratio and the information content of security prices. Journal of Accounting Research 27, 111-143.

Piotroski, J. 2000. Value investing: The use of historical financial statement information to separate winners from losers. Journal of Accounting Research 38, 1-41.

Piotroski, J. and E. So. 2012. Identifying expectation errors in value/glamour strategies: A fundamental analysis approach. Review of Financial Studies 25(9): 2841-2875.

Richardson, S, R. Sloan, M. Soliman, and I. Tuna. 2005. Accrual reliability, earnings persistence and stock prices. Journal of Accounting and Economics 39: 437-485.

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

Shumway, T. 1997. The delisting return bias in CRSP data. Journal of Finance 52, 327-340.

Appendix: Generating Cross-sectional Earnings Forecasts

Following Li and Mohanram (2014), we forecast future earnings using the following model:

$$E_{t+\tau} = \chi_0 + \chi_1 * NegE_t + \chi_2 * E_t + \chi_3 * NegE_t * E_t + \chi_4 * B_t + \chi_5 * TACC_t + \varepsilon$$

where τ = 1 to 5; E_t is earnings per share before special and extraordinary items ((ib-spi)/csho); $NegE_t$ is an indicator variable for loss firms; B_t is book value of equity per share (ceq/csho); $TACC_t$ is total accrual per share calculated following Richardson et al. (2005), i.e., (ΔWC+ ΔNCO+ΔFIN)/csho, where WC is (act-che)-(lct-dlc); NCO is (at-act-ivao)-(lt-lct-dltt); and FIN is (ivst+ivao)-(dltt+dlc+pstk).

We estimate this cross-sectional model using all available observations over the past ten years. For example, if 2000 is the year t, we use data from 1990 to 1999 to estimate the coefficients that will be used to compute the earnings of 2001 (year t+1). Similarly, we use data from 1989 to 1998 to estimate the coefficients that will be used to compute the earnings of 2002 (year t+2). This ensures that the earnings forecasts are strictly out of sample. We estimate the model as of June 30 of each year. To further reduce look-ahead bias, we assume that financial information for firms with fiscal year ending (FYE) in April to June is not available on June 30. In other words, only the financials of firms with FYE from April of year t-1 to March of year t are used for estimation of year t. For each firm and each year t in our sample, we compute earnings forecasts for year t+1 to year t+5 by multiplying the independent variables in year t with the pooled regression coefficients estimated using the previous ten years of data. This method only requires a firm have non-missing independent variables in year t to estimate its future earnings. As a result, the survivorship bias is kept to a minimum

Table 1: Sample Selection and Correlation Statistics

Sample consists of 189,719 observations from 1972 to 2011. FSCORE and GSCORE are financial statement ratio based metrics from Piotroski (2000) and Mohanram (2005). V/P is an intrinsic value based metric from Frankel and Lee (1998). See section 3.1 for details. RET_1 is one-year-ahead buy-and-hold returns. See section 3.4 for details. LMCAP is log of market capitalization and BM is the book-to-market ratio. Panel B presents average annual correlations between the above metrics. Figures above/below diagonal represent Pearson/Spearman correlations. Significance levels are represented by *** (1%), ** (5%) and * (10%).

Panel A: Sample Selection Criteria

Criterion	Firm-Years	Unique firms
Observations with COMPUSTAT data for FSCORE and returns on CRSP	261,291	18,048
Availability of data to compute GSCORE	239,882	16,743
Availability of cross-sectional forecasts to calculate V/P	189,719	13,986

Panel B: Correlation Matrix

	FSCORE	GSCORE	V/P	RET_1	LMCAP	BM
FSCORE		0.393***	-0.080***	0.069***	0.112***	-0.186***
GSCORE	0.401***		-0.146***	0.053***	0.304***	-0.239***
V/P	-0.075***	-0.169***		0.032***	-0.134***	0.436***
RET_1	0.090***	0.078***	0.065***		-0.009	0.062***
LMCAP	0.118***	0.293***	-0.195***	0.024*		-0.209***
BM	-0.211***	-0.251***	0.679***	0.071***	-0.225***	

Table 2: Performance of FSCORE, GSCORE and V/P Strategies

Sample consists of 189,719 observations from 1972 to 2011. FSCORE and GSCORE are financial statement ratio based metrics from Piotroski (2000) and Mohanram (2005). V/P is an intrinsic value based metric from Frankel and Lee (1998). See section 3.1 for details. RET_1 is one-year-ahead buy-and-hold returns. See section 3.4 for details. Firms are split into quintiles each year based on the relevant variable. Figures in italics are t-statistics for difference of means computed using a pooled estimate of standard error.

Panel A: Hedge Returns for FSCORE Strategy					
Quintile	N	FSCORE	GSCORE	V/P	RET_1
0	37932	3.17	2.97	0.84	8.86%
1	37948	4.54	3.57	0.82	12.51%
2	37951	5.34	4.05	0.75	15.29%
3	37957	6.10	4.52	0.68	15.44%
4	37931	7.14	4.85	0.64	17.25%
5-1		3.97	1.88	-0.20	8.39%
t-stat		*512.81*	*168.97*	*-16.96*	*17.18*
Panel B: Hedge Returns for GSCORE Strategy					
Quintile	N	FSCORE	GSCORE	V/P	RET_1
0	37928	4.43	1.70	0.93	9.75%
1	37950	5.00	3.08	0.83	13.47%
2	37960	5.32	4.09	0.73	14.07%
3	37953	5.61	4.93	0.67	15.45%
4	37928	5.92	6.17	0.56	16.60%
5-1		1.49	4.47	-0.37	6.85%
t-stat		*128.59*	*696.46*	*-25.05*	*15.44*
Panel C: Hedge Returns for V/P Strategy					
Quintile	N	FSCORE	GSCORE	V/P	RET_1
0	37925	5.03	4.02	0.24	8.93%
1	38006	5.38	4.37	0.43	13.34%
2	37958	5.36	4.18	0.59	14.46%
3	37914	5.31	3.89	0.80	15.02%
4	37916	5.21	3.51	1.68	17.60%
5-1		0.18	-0.52	1.44	8.67%
t-stat		*14.36*	*-41.15*	*69.04*	*17.24*
Panel D: Comparison of Return Spreads across Strategies					
FSCORE vs GSCORE					1.53%
					2.33
FSCORE vs V/P					-0.29%
					-0.41
GSCORE vs V/P					-1.82%
					-2.71

Table 3: Combining Ratio Analysis Driven Approaches with Intrinsic Value Approaches

Sample consists of 189,719 observations from 1972 to 2011. FSCORE and GSCORE are financial statement ratio based metrics from Piotroski (2000) and Mohanram (2005). V/P is an intrinsic value based metric from Frankel and Lee (1998). See section 3.1 for details. FSCORE and GSCORE are combined with V/P to create combined strategies. See section 3.3 for details. RET_1 is one-year-ahead buy-and-hold returns. See section 3.4 for details. Firms are split into quintiles each year based on the relevant variable. Figures in italics are t-statistics for difference of means computed using a pooled estimate of standard error.

Panel A: Hedge Returns for FSCORE & V/P Combined Strategy					
Quintile	N	FSCORE	GSCORE	V/P	RET_1
0	37930	3.65	3.32	0.36	7.67%
1	37946	4.74	3.90	0.60	11.58%
2	37962	5.37	4.18	0.68	14.56%
3	37950	5.88	4.27	0.91	16.20%
4	37931	6.64	4.30	1.17	19.34%
5-1		2.99	0.99	0.81	11.67%
t-stat		*324.30*	*83.56*	*60.70*	*24.81*
Panel B: Hedge Returns for GSCORE & V/P Combined Strategy					
Quintile	N	FSCORE	GSCORE	V/P	RET_1
0	37925	4.51	2.35	0.37	7.86%
1	37954	5.04	3.23	0.68	12.46%
2	37949	5.37	4.06	0.77	14.61%
3	37951	5.59	4.84	0.86	15.76%
4	37940	5.76	5.48	1.05	18.65%
5-1		1.25	3.13	0.68	10.78%
t-stat		*104.09*	*359.19*	*78.76*	*23.18*
Panel C: Impact of V/P on FSCORE, GSCORE					
FSCORE alone (from Table 2)					8.39%
FSCORE and V/P					11.67%
Improvement					3.29%
t-stat					*4.85*
GSCORE alone (from Table 2)					6.85%
GSCORE and V/P					10.78%
Improvement					3.93%
t-stat					*6.11*
Panel D: Impact of FSCORE, GSCORE on V/P					
V/P alone (from Table 2)					8.67%
FSCORE and V/P					11.67%
Improvement					3.00%
t-stat					*4.35*
V/P alone (from Table 2)					8.67%
GSCORE and V/P					10.78%
Improvement					2.11%
t-stat					*3.08*

Table 4: Future Returns by Partitions Based on Size, Analyst Following and Exchange Listing

Sample consists of 189,719 observations from 1972 to 2011. FSCORE and GSCORE are financial statement ratio based metrics from Piotroski (2000) and Mohanram (2005). V/P is an intrinsic value based metric from Frankel and Lee (1998). See section 3.1 for details. FSCORE and GSCORE are combined with V/P after normalization to create combined strategies. See section 3.3 for details. RET_1 is one-year-ahead buy-and-hold returns. See section 3.4 for details. Firms are split into quintiles each year based on the relevant variable. In Panel A, the analysis is run by partitions based on analyst following. In Panel B, the analysis is run by partitions based on exchange listing. In Panel C, the analysis is run by partitions based on size (market capitalization) – firms in the top/bottom quintile in a given year are in the large/small group, while firms in all other quintiles are in the medium group. Figures in italics are t-statistics for difference of means computed using a pooled estimate of standard error.

Panel A: Sample Partitioned on Analyst Following

		FSCORE (1)		GSCORE (2)		V/P (3)		FSCORE & V/P (4)		GSCORE & V/P (5)		(4)–(1)	(4)–(3)	(5)-(2)	(5)–(3)
	Quintile	N	RET_1	N	RET_1	N	RET_1	N	RET_1	N	RET_1				
Firms without Following	1	14250	8.00%	14277	8.58%	14251	6.09%	14242	4.61%	14243	5.25%				
	5	14253	19.01%	14228	17.69%	14247	17.62%	14255	21.47%	14254	20.28%				
	5-1		11.01%		9.11%		11.52%		16.86%		15.04%	5.86%	5.34%	5.92%	3.51%
	t-stat		*11.92*		*10.63*		*14.44*		*19.49*		*18.11*	*4.63*	*4.54*	*4.97*	*3.05*
Firms with Following	1	23665	9.83%	23663	10.79%	23672	10.44%	23668	9.38%	23664	9.28%				
	5	23668	16.26%	23675	16.00%	23676	17.07%	23672	17.92%	23675	17.72%				
	5-1		6.43%		5.22%		6.63%		8.54%		8.45%	2.11%	1.91%	3.23%	1.82%
	t-stat		*11.67*		*10.17*		*11.60*		*15.89*		*15.45*	*2.74*	*2.43*	*4.31*	*2.30*

Panel B: Sample Partitioned on Exchange Listing

		FSCORE (1)		GSCORE (2)		V/P (3)		FSCORE & V/P (4)		GSCORE & V/P (5)		(4)–(1)	(4)–(3)	(5)-(2)	(5)–(3)
	Quintile	N	RET_1	N	RET_1	N	RET_1	N	RET_1	N	RET_1				
NYSE/ AMEX	1	20156	11.95%	20156	14.36%	20160	11.56%	20155	10.65%	20153	11.68%				
	5	20158	19.53%	20147	17.43%	20163	20.06%	20163	21.43%	20161	20.13%				
	5-1		7.58%		3.07%		8.50%		10.79%		8.44%	3.21%	2.28%	5.37%	-0.06%
	t-stat		*12.09*		*5.54*		*13.65*		*17.84*		*14.85*	*3.68*	*2.63*	*6.76*	*-0.07*
NASDAQ/ Other	1	17762	5.83%	17721	5.19%	17757	6.28%	17759	4.71%	17757	3.82%				
	5	17759	14.63%	17753	15.55%	17759	14.73%	17765	16.98%	17763	16.56%				
	5-1		8.81%		10.36%		8.45%		12.27%		12.74%	3.47%	3.82%	2.38%	4.28%
	t-stat		*11.80*		*14.55*		*10.81*		*16.91*		*17.39*	*3.33*	*3.58*	*2.33*	*4.00*

Panel C: Sample Partitioned on Size

		FSCORE (1)		GSCORE (2)		V/P (3)		FSCORE & V/P (4)		GSCORE & V/P (5)		(4)–(1)	(4)–(3)	(5)-(2)	(5)–(3)
	Quintile	N	RET_1	N	RET_1	N	RET_1	N	RET_1	N	RET_1				
Small Firms	1	7468	6.36%	7474	7.81%	7468	5.32%	7468	4.58%	7469	5.46%				
	5	7474	18.45%	7486	15.79%	7475	18.04%	7476	20.97%	7475	18.55%				
	5-1		12.09%		7.99%		12.72%		16.40%		13.09%	4.30%	3.68%	5.11%	0.37%
	t-stat		*10.06*		*7.78*		*10.13*		*13.95*		*12.69*	*2.56*	*2.14*	*3.51*	*0.23*
Medium Firms	1	22858	9.44%	22854	9.96%	22861	10.30%	22862	9.18%	22860	8.65%				
	5	22863	17.62%	22886	17.41%	22864	17.36%	22865	19.40%	22863	18.72%				
	5-1		8.19%		7.45%		7.06%		10.22%		10.07%	2.04%	3.17%	2.62%	3.01%
	t-stat		*12.40*		*12.66*		*10.81*		*16.36*		*15.53*	*2.24*	*3.51*	*2.99*	*3.27*
Large Firms	1	7573	9.82%	7565	11.18%	7574	9.43%	7573	8.55%	7575	8.58%				
	5	7578	15.48%	7573	14.79%	7578	15.14%	7581	16.05%	7578	16.83%				
	5-1		5.66%		3.60%		5.70%		7.51%		8.25%	1.85%	1.81%	4.65%	2.55%
	t-stat		*8.08*		*5.56*		*7.95*		*10.97*		*12.14*	*1.89*	*1.82*	*4.95*	*2.58*

Table 5: Performance of Hedge Strategies across Time

Sample consists of 189,719 observations from 1972 to 2011. FSCORE and GSCORE are financial statement ratio based metrics from Piotroski (2000) and Mohanram (2005). V/P is an intrinsic value based metric from Frankel and Lee (1998). See section 3.1 for details. FSCORE and GSCORE are combined with V/P after normalization to create combined strategies. See section 3.3 for details. RET_1 is one-year-ahead buy-and-hold returns. See section 3.4 for details. Firms are split into quintiles each year based on the relevant variable.

Panel A: Average Annual Hedge Returns

YEAR	FSCORE	GSCORE	V/P	FSCORE & V/P	GSCORE & V/P
1972	23.3%	19.3%	-0.1%	25.0%	16.0%
1973	13.3%	3.4%	11.3%	19.5%	8.3%
1974	4.8%	7.7%	18.6%	16.7%	18.9%
1975	6.8%	-5.7%	27.2%	21.3%	13.0%
1976	6.1%	3.8%	18.7%	17.5%	13.9%
1977	9.5%	-2.6%	-5.8%	4.9%	-6.1%
1978	15.0%	2.2%	-9.4%	4.9%	-2.7%
1979	3.3%	5.3%	-0.4%	0.3%	6.8%
1980	4.6%	0.5%	22.6%	22.4%	13.8%
1981	3.6%	3.9%	0.2%	6.5%	5.2%
1982	15.9%	0.8%	18.2%	24.3%	14.5%
1983	20.8%	8.5%	14.5%	26.9%	17.7%
1984	14.3%	9.1%	1.5%	13.1%	9.1%
1985	12.6%	17.0%	0.1%	12.3%	13.7%
1986	18.4%	14.4%	1.9%	14.0%	13.4%
1987	15.1%	10.5%	8.5%	17.4%	12.0%
1988	19.4%	18.0%	3.6%	14.5%	15.2%
1989	16.1%	16.1%	6.6%	16.8%	18.8%
1990	3.8%	7.1%	15.4%	12.1%	17.2%
1991	3.0%	-2.0%	12.2%	12.4%	10.3%
1992	3.0%	7.3%	15.6%	14.2%	15.3%
1993	2.4%	20.8%	3.1%	7.2%	14.5%
1994	6.7%	-0.7%	10.2%	6.6%	1.3%
1995	20.8%	14.5%	16.6%	22.9%	22.7%
1996	10.5%	6.8%	20.0%	24.1%	17.8%
1997	8.1%	15.0%	0.0%	3.4%	8.9%
1998	9.5%	15.7%	-6.2%	-7.3%	0.2%
1999	20.9%	16.5%	42.1%	42.5%	44.1%
2000	14.5%	8.5%	36.8%	39.3%	34.4%
2001	-6.6%	-0.1%	10.8%	5.9%	10.8%
2002	-4.6%	-2.5%	22.7%	13.0%	14.7%
2003	4.4%	-3.2%	12.8%	12.7%	4.0%
2004	9.1%	-0.1%	-0.7%	6.4%	0.0%
2005	9.9%	5.1%	2.0%	7.9%	4.5%
2006	18.7%	13.6%	-1.6%	11.4%	9.4%
2007	7.3%	10.0%	-1.3%	5.6%	5.3%
2008	0.4%	-4.3%	5.9%	2.8%	1.8%
2009	7.6%	9.7%	-13.1%	-8.0%	-3.1%
2010	-2.9%	2.9%	4.7%	0.4%	5.3%
2011	-9.0%	-5.5%	14.0%	1.6%	3.0%

Panel B: Summary Statistics across the Strategies

	FSCORE	GSCORE	V/P	FSCORE & V/P	GSCORE & V/P
Mean Hedge Returns	9.0%	6.7%	9.0%	12.9%	11.1%
Std. Dev. of Hedge Returns	7.9%	7.5%	11.8%	10.7%	9.5%
Sharpe Ratio	1.14	0.89	0.76	1.21	1.16
Min Hedge Returns	-9.0%	-5.7%	-13.1%	-8.0%	-6.1%
Max Hedge Returns	23.3%	20.8%	42.1%	42.5%	44.1%
# Years with Negative Hedge Returns	4/40	10/40	9/40	2/40	3/40

Panel C: Comparison of Annual Hedge Returns across the Strategies

Comparison			Improvement	t-stat	# Years with improved hedge returns
FSCORE & V/P	vs.	FSCORE	3.9%	*2.63*	25/40
FSCORE & V/P	vs.	V/P	3.9%	*3.31*	26/40
GSCORE & V/P	vs.	GSCORE	4.0%	*2.52*	30/40
GSCORE & V/P	vs.	V/P	2.1%	*1.79*	24/40

Table 6: Fama-French Regressions for Hedge Portfolios Based on FSCORE, V/P and Combination

Sample consists of 189,719 observations from 1972 to 2011. FSCORE and GSCORE are financial statement ratio based metrics from Piotroski (2000) and Mohanram (2005). V/P is an intrinsic value based metric from Frankel and Lee (1998). See section 3.1 for details. FSCORE and GSCORE are combined with V/P after normalization to create combined strategies. See section 3.3 for details. Long-short hedge portfolios are formed for the 12 months starting July 1st after the fiscal year end based on the relevant variables. Hedge returns are regressed on the market, size, book-to-market and momentum factors. The regression has 480 monthly observations from July1973 to June 2013. See section 4.5 for details. Figures in italics are t-statistics. For Panels B and D, t-statistics are obtained from incremental hedge portfolios (e.g., to compare FSCORE & V/P vs. FSCORE, a hedge portfolio long in the FSCORE & V/P hedge portfolio and short in the FSCORE hedge portfolio is created).

Panel A: Fama-French Three-factor Model Regressions

Strategy	Alpha	R_m-R_f	SMB	HML	Adj. R^2
FSCORE	0.745	-0.052	-0.296	-0.098	11.4%
	5.97	*-1.83*	*-7.24*	*-2.27*	
GSCORE	0.626	-0.016	-0.335	-0.231	19.5%
	5.92	*-0.69*	*-9.66*	*-6.33*	
V/P	0.531	-0.211	0.246	0.759	56.8%
	4.88	*-8.58*	*6.89*	*20.26*	
FSCORE & V/P	0.919	-0.205	-0.052	0.445	48.5%
	9.82	*-9.66*	*-1.68*	*13.82*	
GSCORE & V/P	0.847	-0.185	-0.086	0.387	47.2%
	9.72	*-9.37*	*-3.01*	*12.91*	

Panel B: Comparison of Three-factor Alphas across the Strategies

Comparison	Alpha difference	*t-stat*
FSCORE & V/P vs. FSCORE	0.175	*1.80*
FSCORE & V/P vs. V/P	0.379	*3.80*
GSCORE & V/P vs. GSCORE	0.221	*2.26*
GSCORE & V/P vs. V/P	0.316	*3.53*

Panel C: Carhart Four-factor Model Regressions

Strategy	Alpha	R_m-R_f	SMB	HML	UMD	Adj. R^2
FSCORE	0.559	-0.010	-0.299	-0.029	0.212	22.0%
	4.69	*-0.36*	*-7.77*	*-0.71*	*8.11*	
GSCORE	0.550	0.001	-0.336	-0.203	0.087	21.6%
	5.17	*0.03*	*-9.81*	*-5.52*	*3.72*	
V/P	0.453	-0.194	0.245	0.788	0.089	57.9%
	4.14	*-7.83*	*6.95*	*20.85*	*3.71*	
FSCORE & V/P	0.754	-0.167	-0.054	0.507	0.189	57.3%
	8.68	*-8.51*	*-1.91*	*16.89*	*9.95*	
GSCORE & V/P	0.733	-0.159	-0.087	0.429	0.129	52.1%
	8.66	*-8.31*	*-3.21*	*14.69*	*7.00*	

Panel D: Comparison of Four-factor Alphas across the Strategies

Comparison	Alpha difference	*t-stat*
FSCORE & V/P vs. FSCORE	0.195	*1.97*
FSCORE & V/P vs. V/P	0.301	*2.94*
GSCORE & V/P vs. GSCORE	0.183	*1.84*
GSCORE & V/P vs. V/P	0.280	*3.09*