Fundamental Analysis: Combining the Search for Quality with the Search for Value.

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Abstract: Using cross-sectional forecasts, we compare fundamental analysis strategies based on quality, such as FSCORE from Piotroski (2000) and GSCORE from Mohanram (2005), with strategies based on value, such as the V/P ratio from Frankel and Lee (1998) and the PEG ratio. We find that all four strategies generate significant hedge returns. Combining quality-driven (FSCORE or GSCORE) with value-driven approaches (V/P or PEG) leads to a significant increase in hedge returns that holds for a variety of partitions, persists over time, and is robust after controlling for risk factors and portfolio size. The results suggest a powerful method to conduct fundamental analysis that combines quality-driven and value-driven approaches, and have important implications for academic research on 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 the correct price will eventually be reached. Profits are made by purchasing the mispriced security and then waiting for the market to correct the misvaluation. Prior research has primarily taken two distinct approaches towards fundamental analysis. One approach searches for value – i.e., firms that appear to have stock prices less than estimates of intrinsic value. Frankel and Lee (1998) show that the deviation of firms' stock prices from their intrinsic values predicts future stock returns. The second approach searches for quality – i.e., firms whose accounting fundamentals portend well for future performance. The efficacy of the quality approach is shown in Ou and Penman (1989), Lev and Thiagarajan (1993), and Abarbanell and Bushee (1998), who collectively document the ability of financial statement signals to predict future earnings changes and stock returns. Piotroski (2000) and Mohanram (2005) tailor specific strategies to identify high and low quality firms among value stocks and growth stocks, respectively.

Each of these alternative approaches has strengths and weaknesses. The value-driven approach is often 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.[1] Further, the value-driven approach typically focuses only on summary metrics such as earnings or book values, and ignores the richness of disaggregated financial statement information. In contrast, the quality-driven approach can be applied to a wider

[1] Lee (2014) argues that "the essential task in valuation is forecasting. The technical differences in alternative valuation models are trivial when compared to the importance of making a better forecast of future payoffs."

cross-section of firms as it relies on historical financial information and utilizes the richness of financial statement information. However, the quality-driven approach ignores the possibility that the market might 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 screening. One reason for this is the difference in data requirements owing from the need for analyst forecasts to calculate intrinsic value. For instance, Piotroski (2000) considers the value-driven approach in the subset of high book-to-market or value firms, but concludes that "a forecast-based approach, such as Frankel and Lee (1998), has limited application for differentiating value stocks". However, an emerging stream of research develops cross-sectional models that can generate earnings forecasts for nearly the entire universe of firms. (see Hou, van Dijk and Zhang (2012) and Li and Mohanram (2014)).

The availability of cross-sectional model forecasts for essentially the entire population of firms implies that one can finally answer the following questions related to the efficacy of the two alternative approaches towards fundamental analysis. Which approach is more effective in picking winners and losers? Are these two approaches correlated – i.e., whether the search for value and the search for quality identify the same stocks as potentially undervalued or overvalued? Is there any benefit to combine these two approaches?

We focus on four distinct strategies. The first two strategies are based on measures of quality – the FSCORE value investing strategy from Piotroski (2000), and the GSCORE growth investing strategy from Mohanram (2005). The next two strategies are value-driven approaches using cross-sectional forecasts - the V/P strategy from Frankel and Lee (1998) based on the residual income valuation model, and the PEG strategy based on the price-earnings to growth ratio that is often used as a heuristic measure of overvaluation. We multiple the PEG ratio with minus one (labeled as NEGPEG) to make it positively correlated with stock returns. For each strategy, we construct a hedge portfolio by taking a long position in firms in the top quintile and a short position in firms in the bottom quintile of the respective measure in a given year.

Our sample consists of all firms from 1973 to 2012 for which we have adequate information to compute FSCORE, GSCORE, V/P, NEGPEG, and one-year-ahead returns. The sample consists of 98,766 observations, or an average of 2,469 observations per year. We first examine the efficacy of these strategies in generating hedge returns. Consistent with prior research, all strategies generate economically meaningful and statistically significant annual hedge returns (7.44% for FSCORE, 6.06% for GSCORE, 6.55% for V/P, 5.68% for NEGPEG). We then examine the correlations among the four strategies. As expected, the two quality-driven approaches, FSCORE and GSCORE, are strongly positively correlated. Similarly, the two value-driven approaches, V/P and NEGPEG, also show a strong positive correlation. Interestingly, both FSCORE and GSCORE show significant negative correlations with V/P and NEGPEG. This suggests that the quality-driven approaches to fundamental analysis are inherently different from the value-driven approaches – i.e., quality is not cheap, and that combining these two approaches in the quest for "affordable quality" may be fruitful.

To combine the value-driven approach (V/P or NEGPEG) with the quality-driven approach (FSCORE or GSCORE), we go long in the firms in the top quintiles of both approaches and go short in the firms in the bottom quintiles of both approaches. Our results show that the combined strategies generate significantly higher excess returns than the standalone strategies. Combining FSCORE with V/P increases hedge returns from 7.44% for FSCORE alone to 17.94%. Similarly, combining GSCORE with V/P increases hedge returns from 6.06% for GSCORE alone to 21.45%. Similar improvements are observed when we combine FSCORE or GSCORE with NEGPEG.

Further, the improvement works both ways – returns to the V/P and NEGPEG strategies also increase significantly when they are combined with either FSCORE or GSCORE. These improvements are not driven by smaller portfolio size, as we fail to see similar improvements in finer partitions of the four individual strategies.

To ensure that our results are not driven by a non-representative subset of stocks, we partition our sample based on the book-to-market ratio (BM), analyst following, exchange listing, size, and institutional ownership. We find significant improvements in almost all subgroups – value firms (high BM) as well as growth firms (low BM), followed firms as well as non-followed firms, NYSE/AMEX firms as well as NASDAQ firms, firms in all size groups, and firms with different levels of institutional ownership. 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 performance of the strategies over time. We find that the combined strategies generate significantly higher returns in most years, increase Sharpe ratios, and reduce the incidence of negative hedge returns. The low incidence of loss making years suggests that our results are unlikely to be driven by risk. However, to confirm that additional risk is not driving our results, we run Fama and French factor regressions, using monthly returns in the first year after portfolio formation. We run the Fama and French (1993) three-factor model that controls for market (R_m – R_f), size (SMB) and book-to-market (HML), the Carhart (1997) four-factor model that includes momentum (UMD), and the Fama and French (2015) five-factor model that includes profitability (RMW) and investment (CMA). We find that while the individual strategies generate significant alphas (excess returns), the alphas of the combined strategies are significantly greater.

Finally, we compare the results of our combined approach to approaches used by practitioners that combines elements of value with quality, focusing on the well-established Graham and Dodd (1934) approach. We find that while the Graham-Dodd approach does generate excess returns, our combined approach generates significantly greater excess returns and can be applied to a much broader set of firms.

The rest of the paper is organized as follows. Section 2 describes the quality and intrinsic value approaches towards fundamental analysis studied in this paper. Section 3 presents the research design and descriptive statistics of 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 –fundamental analysis focused on quality, fundamental analysis focused on value, 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 Quality-driven Fundamental Analysis

A large body of research has focused on the usefulness of financial statement ratios in identifying firms that will perform strongly in terms of future 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 financial 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. Novy-Marx (2013) finds that profitable firms outperform unprofitable firms.

Piotroski (2000) uses financial statement analysis to develop an investment strategy for high BM or value firms. He combines nine signals based on traditional ratio analysis into a single index called FSCORE. He then 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 value stocks. Mohanram (2005) follows a similar approach as Piotroski (2000), but focuses on low BM or growth stocks. He tailors the ratios to better suit growth stocks. He combines eight signals into a single index called GSCORE, and shows that the GSCORE strategy is successful in separating winners from losers among growth stocks.

2.2 Value-driven 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 represent 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 convert earnings to cash flows. 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 use 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 future returns. Conversely, firms with low V/P ratios are overvalued and earn poor future returns. Their empirical results strongly support these conjectures, confirming the efficacy of the RIV model to estimate intrinsic value.

Bradshaw (2004) tests whether analysts' forecasts and recommendations are correlated with measures of intrinsic value. He finds that while analysts' forecasts and recommendations are only weakly correlated with intrinsic value measures from formal models, such as the V/P ratio from the RIV model, they are strongly correlated with heuristic methods like the PEG ratio.

2.3 Comparing Quality Driven and Value Driven Fundamental Analysis

The quality-driven and value-driven approaches to fundamental analysis have many differences. The quality-driven approaches rely on the richness of financial statement data and allow one to analyze the finer details of firm performance, such as profitability, margins, efficiency and risk. In contrast, the value-driven approaches focus on whether the prevailing stock price justifies the valuation determined by a few key metrics – e.g., earnings and book values in the case of the RIV based models. It is possible that these two approaches might yield similar results as detailed analysis of profitability and risk should also have implications for summary metrics like earnings, cash flows, and book values. On the other hand, these summary metrics might ignore some insights provided by the detailed financial statement analysis. Alternatively, it is also possible that the insights from the detailed analysis have been impounded into the stock price (e.g., Asness et al. 2013).

Prior research has been unable to compare these two approaches towards fundamental analysis primarily because of different data requirements. Measures of quality can be created for virtually any firm that has historical financial data. On the other hand, the computation of intrinsic value metrics, such as the V/P in Frankel and Lee (1998) or the PEG ratio, requires earnings forecasts. Historically, only half of all U.S. firms have analyst following. Further, as Piotroski (2000) and others show, the incidence of mispricing is often the strongest in the subset of firms without analyst following. For such firms, an intrinsic value approach has, till recently, been infeasible.

2.4 Cross-Sectional Forecasting

The typical approach used in prior research to generate forecasts for firms without analyst coverage is to generate time series forecasts using firm specific estimation models. However, such models require a lengthy time series of data, which is especially problematic, as firms without analyst following are typically young firms that lack such data.

Recent developments in 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.

The models developed in these studies allow researchers to generate forecasts for a large sample of firms where analyst forecasts are unavailable and time series models are infeasible. However, one potential drawback could be the lower forecast accuracy. The results in Hou, van Dijk and Zhang (2012) indicate that cross-sectional forecasts have higher absolute forecast error than analyst forecasts for the subsample where analyst forecasts are available. As the prior research on intrinsic value approach has used analyst forecasts, it is an open question as to whether such approach will be effective using noisier cross-sectional forecasts.

2.5 Putting it All Together: Our Research Questions

The availability of cross-sectional forecasts allows one to use the value-driven 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 quality-driven approaches with the value-driven 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 examine whether combining the two approaches towards fundamental analysis generates superior excess returns. Specially, we focus on the set of firms for which both approaches yield consistent conclusions. For example, when both the quality-driven approach (FSCORE or GSCORE) and the value-driven approach (V/P or NEGPEG) give a low rank to a stock, the combined evidence suggests that the stock has weak fundamentals, which are not reflected in the current stock price. In other words, the stock is clearly overvalued. On the other hand, when both approaches give a high rank to a stock, it suggests that the firm has strong fundamentals yet to be reflected by the stock price. In other words, the stock is clearly undervalued. Hence, our combined strategies will take a long position in firms with better quality (high FSCORE or GSCORE) that also appear underpriced (high V/P or NEGPEG) and take a short position in firms with weaker quality (low FSCORE or GSCORE) that also appear overpriced (low V/P or NEGPEG).

The success of the combined strategies 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, and most of the firms will be placed into similar buckets based on the two approaches. On the other hand, if the two approaches are uncorrelated or even negatively correlated, combining them might generate significant improvements. We do not have any priors as to whether a combined approach will generate higher excess returns.

> RQ2: Does combining quality-driven approaches with value-driven approaches to fundamental analysis help generate higher hedge returns than the individual strategies?

3. Research Design

In this section, we describe the critical elements of our research design. In particular, we present the details of our implementation of 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.

3.1 Implementation of Quality-driven Fundamental Analysis (FSCORE and GSCORE)

To identify financially strong value firms, 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).[2] Among the nine fundamental signals, ROA, CFO, ΔROA, ΔLIQUID, ΔMARGIN, and ΔTURN are positive signals, receiving a score of one if positive and zero otherwise. Accruals and ΔLEVER are negative signals, receiving a score of one if negative and zero otherwise. Equity issuance is also a negative signal, receiving a score of zero with equity issuance and one if there is no equity issuance. FSCORE is the sum of the nine individual scores.

To identify financially strong growth firms, 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 expenditure intensity (CAPINT), and advertising intensity (ADINT).[3] 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 one if the variable is greater than the contemporaneous industry median, and zero otherwise. The negative signals are VARROA, VARSGR and accruals, receiving a score of one if the variable is less than the contemporaneous industry median, and zero otherwise. GSCORE is the sum of the eight fundamental signals.

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[2] 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.

[3] 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.

One problem with both the FSCORE and GSCORE is that the 0/1 criteria result in a distribution of scores, with few firms in the extreme groups and most firms clustered around the middle.[4] This makes the comparison across strategies and the creation of long-short portfolios problematic, as the groups are often of different sizes and do not correspond neatly to groupings like quintiles or deciles used to analyze hedge returns. To deal with this, we create continuous versions of FSCORE and GSCORE. We normalize each of the variables underlying the signals to lie between zero and one. 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 one, while the firm with the lowest ROA will get a score of zero, 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 signal is normalized to lie between zero and one based on the contemporaneous distribution across firms in the same 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 Value-driven Approach to Fundamental Analysis (V/P and PEG)

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

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

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

where B_t is the book value of equity per share (ceq/csho) at time t; $E_t[.]$ 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 Appendix I. 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 k is the estimated payout ratio.[5] We assume that abnormal earnings stay constant after the forecast horizon to estimate terminal value. We use the risk-free rate (yield on the ten-year U.S. treasury) plus 5% as the cost of equity capital (r_e), which is cross-sectionally constant but varies across time.[6]

To implement the PEG strategy, we first compute the forward P/E ratio (i.e., the prevailing stock price divided by t+1 earnings forecast from the cross-sectional model), and then divide the P/E ratio by annual earnings growth rate, implied by earnings forecasts for t+1 and t+5. We require earnings forecast for t+1 and earnings growth rate to be positive (i.e., forecast for t+5 is greater

[5] 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).

[6] Results are similar if we use a constant cost of equity (10%), industry specific cost of equity, or firm specific cost of equity using either a CAPM based model or a Fama-French three- or four-factor model. This is consistent with finding in Frankel and Lee (1998) that varying the discount rate has little effect on the results.

than forecast for t+1). Finally, we multiply the PEG ratio with minus one (labeled as NEGPEG) to make it a measure of cheapness (i.e., higher NEGPEG indicates attractive pricing).

3.3 Combining Different Approaches to Fundamental Analysis

To implement the standalone strategies, we sort firms into quintiles every year based on FSCORE, GSCORE, V/P and NEGPEG, respectively. To combine the quality-driven and value-driven approaches towards fundamental analysis, we take a long position in firms in the highest quintiles of both approaches and a short position in firms in the lowest quintiles of both approaches. For example, to combine FSCORE with V/P, we go long in the firms in quintile 5 of both FSCORE and V/P, and short the firms in quintile 1 of both FSCORE and V/P.

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. Specifically, for firms with fiscal years ending from July to March, we compound returns from July 1st following the end of the fiscal year. For firms with fiscal years ending in April, May, or June, the return compounding period starts on July 1st a year later. Although the data can be stale for a small subset of firms, it ensures that there is no look-ahead bias in return computation. We compute the buy-hold size-adjusted returns over this twelve-month period (RET_1) by measuring the buy-hold return in excess of the buy-hold return on the CRSP size-matched decile portfolio. We also adjust for delisting return 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 159,294 firm-year observations of U.S. companies listed on NYSE/AMEX, and NASDAQ (share code 10 or 11) with required CRSP returns, stock prices greater than $1, and financial data on COMPUSTAT to compute FSCORE in the forty-year period from 1973 to 2012. The computation of the earnings and sales growth variability in GSCORE requires two years of quarterly data. This reduces the sample to 141,162 firm-year observations. In addition, we need the cross-sectional forecasts to estimate the V/P measure. This reduces the sample size to 119,215 observations. Finally, the requirement of positive EPS_1 forecast and earnings growth rate to calculate the NEGPEG ratio further reduces the sample to 98,766 firm-year observations, which corresponds to 12,102 unique firms.

4. Results

4.1 Comparison of the Four Standalone Strategies

We begin by examining if the four standalone strategies are effective in separating winners from losers in terms of future stock returns. In each year, we sort the 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 going long in the top quintile and going short in the bottom quintile. The results are presented in Table 2.

The first column presents the results for the quintiles based on FSCORE. The mean RET_1 increases monotonically from -2.14% for the bottom quintile to 5.30% for the top quintile. The average hedge return of 7.44% is the highest among the four strategies, strongly corroborating the success of the FSCORE strategy in Piotroski (2000). The second column presents the results for the quintiles based on GSCORE. The mean RET_1 increases monotonically from -1.76% for the bottom quintile to 4.31% for the top quintile. The average hedge return of 6.06%, while lower than that for FSCORE, is also highly significant. The third column presents the results for the quintiles based on V/P. The mean RET_1 increases monotonically from -1.43% for the bottom quintile to 5.11% for the top quintile. The average hedge return of 6.55% is also highly significant. The last column presents the results for the quintiles based on NEGPEG. Once again, the mean RET_1 increases monotonically from -0.72% for the bottom quintile to 4.96% for the top quintile. The average hedge return of 5.68% is the lowest among the four strategies, but still highly significant. In sum, all four standalone strategies generate economically and statistically significant hedge returns, confirming the effectiveness of quality and cheapness investments.

Table 3 Panel A presents the correlations between FSCORE, GSCORE, V/P, and NEGPEG. As all of our tests are run annually, we present the average of annual correlations. FSCORE and GSCORE are strongly correlated. This is not surprising, as both 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 and NEGPEG ratio, suggesting a potential trade-off between these two approaches. The negative correlation between the two quality-driven approaches (FSCORE and GSCORE) and the two value-driven approaches (V/P and NEGPEG) also shows that firms with high quality are also more expensive relative to their intrinsic value – i.e., quality does not usually come cheap.

Panel B reports mean FSCORE, GSCORE, V/P, and NEGPEG in quintiles formed on respective strategy. The first set reports the results for quintiles based on FSCORE. As GSCORE positively correlates with FSCORE, it also increases monotonically across the quintiles of FSCORE. Conversely, as V/P and NEGPEG negatively correlate with FSCORE, they decline monotonically across the quintiles of FSCORE. Similar patterns are observed in the rest of Panel B. This confirms the negative correlation observed earlier between the quality-driven and the value-driven approaches – i.e., the quest for quality works against the quest for value. In other words, the standalone quality-driven approaches (FSCORE and GSCORE) potentially ignore the likelihood that the quality may have already been impounded into stock prices in terms of higher valuations. On the other hand, the standalone value-driven approaches (V/P and NEGPEG) potentially ignore the possibility that a cheap valuation may be caused by weak fundamentals. These results suggest that our strategy, to focus on the subset of firms where both approaches are concordant rather than discordant, may prove to be fruitful.

4.2 Combining Quality-driven and Value-driven approaches to Fundamental Analysis

We now examine whether combining the quality-driven approach (FSCORE or GSCORE) with the value-driven approach (V/P or NEGPEG) provides stronger hedge returns than the individual strategies. As described in Section 3.3, the combined strategy takes a long position of the firms in the highest quintiles of both approaches and a short position of the firms in the lowest quintiles of both approaches.

Table 4 Panel A presents the results for combining V/P and NEGPEG with FSCORE. The information is presented by FSCORE quintiles, and then by V/P (NEGPEG) quintiles within each FSCORE quintile. For brevity, we condense the results of the middle quintiles (Q2 to Q4). Within each FSCORE quintile, the mean RET_1 increases with V/P (NEGPEG) and the return spread between the highest and lowest V/P (NEGPEG) quintiles are all significantly positive. Focusing on the two extreme groups, the mean RET_1 is -6.36% (-6.32%) for firms in the quintile 1 of both FSCORE and V/P (NEGPEG), and 11.58% (10.44%) for firms in the quintile 5 of both FSCORE and V/P (NEGPEG). The combined strategy yields highly positive mean hedge return of 17.94% (16.76%), which is significantly higher than the hedge return of the standalone strategy: 7.44% for FSCORE, 6.55% for V/P, and 5.68% for NEGPEG.

Table 4 Panel B presents the results for combining V/P and NEGPEG with GSCORE. Once again, we observe that the mean RET_1 increases monotonically with V/P (NEGPEG) in all GSCORE quintiles. The return spread between the highest and lowest V/P (NEGPEG) quintiles are all significantly positive. Finally, the combined strategy yields a hedge return of 21.45% (20.67%), which is significantly higher than the hedge return of the standalone strategy: 6.06% for GSCORE, 6.55% for V/P, and 5.68% for NEGPEG.

To summarize, the results in Table 4 suggest that the strategies that combine elements of quality and value outperform the individual strategies both economically and statistically. In the remaining tests, we examine whether these improvements hold in a variety of partitions, across time, and after controlling for risk factors and portfolio size.

4.3 Controlling for Portfolio Size

A potential concern with our approach is that the superior performance might be due to a finer partition of the sample. As Table 3 shows, the long and short positions of the standalone strategies each include about 19,700 observations over 40 years (around 490 observations per year). In contrast, the number of observations included in the long or short positions of the combined strategies varies between 1,700 and 3,400 (about 43-85 observations per year), as shown in Tables 4. To examine whether a finer partition of the sample can generate the superior hedge returns achieved by the combined strategies, we sort firms into 25 and 50 equal-sized groups based on the standalone strategies, and compare the return spreads of the extreme groups with the return spreads of the combined strategies in Table 5.

Panel A of Table 5 reports the results of the 25 equal-sized groups, where the long and short positions each include about 3,900 observations, similar to the maximum portfolio size of the combined strategies. As the results in the first column show, the finer partitions indeed increase the hedge returns of the standalone strategies. In particular, the hedge returns are 11.41% for FSCORE, 9.48% for GSCORE, 10.15% for V/P, and 10.77% for NEGPEG, which are higher than the hedge returns based on quintiles reported in Table 2: 7.44%, 6.06%, 6.55%, and 5.68%, respectively. The second and third columns compare the hedge returns based on the finer partitions with the hedge returns of the combined strategies (reported in Table 4). The results show that the combined strategies still significantly outperform the standalone strategies based on 25 equal-sized groups. For example, the FSCORE & V/P and FSCORE & NEGPEG strategies generate 17.94% and 16.76% hedge returns respectively, both of which are higher than the 11.41% of the FSCORE strategy. The improvements are both economically and statistically significant. The results are similar for the remaining comparisons.

Panel B of Table 5 reports the results of the 50 equal-sized groups. The long and short positions each include about 1,950 observations, similar to the minimum portfolio size of the combined strategies. This further refinement of the partitions only slightly increases the hedge returns of the FSCORE, V/P, and NEGPEG strategies. For example, the hedge return of the FSCORE strategy increases by only 0.52%, from 11.41% to 11.93%. Interestingly, the finer partition actually reduces the hedge return of the GSCORE strategy, from 9.48% to 9.33%. This suggests that finer partitions of the sample do not always improve hedge returns. More importantly, even with smaller portfolio size, the standalone strategies still underperform the combined strategies. For example, the hedge return for FSCORE based on the 50 equal-sized groups is 11.93%, still significantly lower than the 17.94% of the FSCORE & V/P strategy.

To summarize, the results in Table 5 provide reassurance that the superior returns generated by our combined strategies are not an artefact of smaller sample size, as the combined strategies significantly outperform the standalone strategies with similar portfolio size.

4.4 Contextual Fundamental Analysis

Mohanram (2005) shows that the FSCORE strategy works best in value (high BM) stocks, while the GSCORE strategy works best in growth (low BM) stocks. Prior studies provide strong evidence that the BM ratio explains cross-sectional stock returns (e.g., Fama and French, 1992; Rosenberg et al., 1985; Stattman, 1980). Further, Piotroski and So (2012) show that returns to the FSCORE strategy are amplified when conditioning on the BM ratio. In this section, we analyze the efficacy of the individual and combined strategies across subsets based on the value-growth partition.

Table 6 reports results in the subsamples of growth stocks (lowest tercile of BM), medium BM stocks, and value stocks (highest tercile of BM). Given that FSCORE was originally designed for value stocks in Piotroski (2000), it is not surprising to see that it performs the best in this subsample. Specifically, FSCORE generates 8.01%, 7.83%, and 9.97% hedge returns in growth, medium BM, and value stocks, respectively. Consistent with Mohanram (2005), GSCORE performs the best in growth stocks, generating 10.92%, 6.63%, and 4.80% hedge returns in growth, medium BM, and value stocks, respectively. Finally, both V/P and NEGPEG perform the best in value stocks. Specifically, V/P generates 4.55%, 3.21%, and 7.30%, while NEGPEG yields 1.99%, 2.31%, and 8.55% hedge returns in growth, medium, and value stocks, respectively. Among the four standalone strategies, FSCORE generates the highest hedge returns in both value and medium stocks, while GSCORE generates the highest hedge returns in growth stocks.

The FSCORE & V/P (FSCORE & NEGPEG) strategy performs the best in value stocks, generating 13.97%, 12.87%, and 19.42% (14.00%, 11.31%, and 19.90%) hedge returns for growth, medium, and value stocks, respectively. In contrast, the GSCORE & V/P (GSCORE & NEGPEG) strategy performs the best in growth stocks, yielding 18.57%, 10.99%, and 8.99% (20.07%, 9.57%, and 11.26%) hedge returns for the three groups. Among the four combined strategies, the GSCORE & NEGPEG strategy generates the highest hedge return in growth stocks; the FSCORE & V/P strategy generates the highest hedge return in medium stocks; while the FSCORE & NEGPEG strategy generates the highest hedge return in value stocks.

Finally, Table 6 reports the improvements in hedge returns of the combined strategies over the standalone strategies. The differences in hedge returns between the combined strategies and the standalone strategies are all positive in the three subsamples. For growth stocks, the improvements in hedge returns range from 5.96% to 18.08%, and they are all economically and statistically significant. For medium BM stocks, the improvements are all statistically significant, except for the difference between the GSCORE & NEGPEG strategy and the GSCORE alone. Finally, for value stocks, the improvements are statistically significant for the FSCORE based combinations, but not necessarily for the GSCORE based strategies.

To summarize, Table 6 shows that the combined strategies generally outperform the standalone strategies in all of the three groups partitioned by BM. The improvements are more pronounced when the quality-driven strategies are implemented in the appropriate context (i.e., FSCORE for high BM stocks and GSCORE for low BM stocks). The strong improvements in all groups across the value-glamour spectrum suggest that the increased returns are not an artefact of trading on the BM effect (i.e., going long on high BM stocks and shorting low BM stocks).

4.5 Partition Analysis

In this section, we partition the sample along a number of dimensions to see if the results are robust in different subsets of the population. We consider four partitions – analyst following, firm size, listing exchange, and institutional ownership. All these partitions are related to the information environment as well as the implementability of the hedge strategies. The results are presented in Table 7. For brevity, we only present the hedge return of each strategy, as well as the comparison of the hedge returns between the combined and the standalone strategies.

The first set of columns presents the returns by partitions of analyst following. Each of the four standalone strategies generates positive and statistically significant hedge returns in both partitions. In particular, the strong performance of the V/P and NEGPEG strategies in the subsample without analyst following validates the use of cross-sectional forecasts to generate measures of intrinsic value. Furthermore, the combined strategies generate economically and statistically significant improvements in hedge returns in both partitions, ranging from 8.84% to 12.62%.

The next set of columns partitions the sample on firm size (market capitalization). As expected, the level of hedge returns declines as firm size increases. For instance, the FSCORE strategy generates 10.19%, 8.02%, and 4.43% in small, medium, and large firms, respectively. However, across all three size groupings and for all the combinations analyzed, we see economically and statistically significant improvements. For instance, combining FSCORE with V/P improves hedge returns for large firms by 7.49% to 11.92%. The strong performance of the combined strategies in the subset of large firms is especially important, as it suggests that such a strategy is likely to be implementable.

The third set of columns partitions the sample by exchange listing status. This partition is also related to the implementability of the strategies, as shorting NYSE/AMEX stocks is easier than shorting NASDAQ stocks. Consistent with Piotroski (2000) and Mohanram (2005), the quality-driven FSCORE and GSCORE strategies generate higher hedge returns in NASDAQ listed firms. Interestingly, the value-driven V/P and NEGPEG strategies appear to generate similar hedge returns in both partitions. When we analyze the combined strategies, we find significant improvements for both subsamples, including the more liquid NYSE/AMEX partition.

The last set of columns partitions the sample on institutional ownership. In this partition, we also see significant improvements when we combine the two alternative approaches towards fundamental analysis. For instance, combining FSCORE with V/P improves hedge returns from 4.27% to 17.45% in the subsample with high levels of institutional ownership. The strong performance of the combined strategies in the high institutional ownership subsample should allay implementability concerns, as such firms are more liquid and easier to short.

To summarize, the improvements generated by combining the quality-driven strategies (FSCORE, GSCORE) with the value-driven strategies (V/P, NEGPEG) are robust across a variety of partitions. This increases our confidence that the improvement in hedge returns would not be dissipated by transaction costs and other implementation issues.

4.6 Hedge Returns across Time

While the tables thus far present hedge returns for annual portfolios, the results are pooled over the sample period. To ensure that the results are persistent, we analyze the performance of the four standalone strategies and the four combined strategies across time. Panel A of Figure 1 plots the hedge returns of the four standalone strategies across time. Although all four strategies generate positive hedge returns for the majority of the sample period, the incidence of negative hedge returns is also not uncommon, especially for GSCORE and V/P. In contrast, all four combined strategies generate hedge returns that are higher in magnitude and more consistently positive, as shown in Panel B.

Table 8 summarizes the results of Figure 1. As Panel A shows, the combined strategies significantly outperform the individual strategies. For example, the FSCORE & V/P combined strategy earns average annual hedge returns of 16.88%, as opposed to 7.15% for FSCORE and 7.13% for V/P. Further, the Sharpe ratio for the combined strategy, at 1.22, is marginally higher than the Sharpe ratio for FSCORE (1.19) and considerably higher than the Sharpe ratio for V/P (0.51). The GSCORE & NEGPEG combined strategy earns average annual hedge returns of 18.52% (Sharpe ratio = 1.16), as opposed to 5.47% for GSCORE (Sharpe ratio = 0.56) and 6.21% for NEGPEG (Sharpe ratio = 0.58). Similar results are observed in the remaining two combined strategies. The increase in both hedge returns and Sharpe ratios suggests that the additional hedge returns are not merely the result of incurring additional risk.

Most telling is the fact that the combined strategies reduce years with negative returns. While the FSCORE, GSCORE, V/P, and NEGPEG strategies earn negative returns in 5, 13, 14, and 9 years respectively out of 40, the combined strategies earn negative returns in only 4 or 5 years. Consistent with the interpretation in prior research on anomalies and fundamental analysis (e.g., Bernard and Thomas 1989; Sloan 1996; Piotroski 2000; Mohanram 2005, Li 2011), the rare incidence of negative returns suggests that the returns are unlikely to be driven by risk.

Panel B formally tests the improvements from combining the strategies. Consistent with earlier results, the combined strategies generate significant incremental hedge returns over individual strategies. Further, the combined strategies improve returns in a majority of the years. For example, the addition of FSCORE improves returns to a V/P strategy in 34 out of 40 years. In the following section, we test whether these strong returns are caused by additional risk.

4.7 Controlling for Risk

To confirm that additional risk is not driving the hedge returns, we run multi-factor portfolio models based on the Fama and French (1993) three-factor, Carhart (1997) four-factor and Fama and French (2015) five-factor models. We first create hedge portfolios based on the relevant strategies (e.g., long in top quintile and short in bottom quintile). Calendar time portfolio regressions are run using monthly hedge returns for the 12 months after portfolio formation. The intercept or alpha of the regression represents the monthly excess return for each strategy. The results are presented in Table 9.

Panel A presents the results for the individual strategies. Among the four standalone strategies, FSCORE has the highest alpha. For example, the three-factor adjusted alpha is 0.64 (7.98% annualized) for FSCORE, 0.52 (6.42% annualized) for GSCORE and V/P, and 0.43 (5.25% annualized) for NEGPEG. [7] Panel B shows that the combined strategies generate substantially higher alpha. The FSCORE & V/P, GSCORE & V/P, FSCORE & NEGPEG, and GSCORE & NEGPEG strategies have three-factor adjusted alphas of 1.35 (17.50% annualized), 1.55 (20.27% annualized), 1.22 (15.69% annualized), and 1.41 (18.26% annualized), respectively. The results are similar for the four-factor and five-factor adjusted alphas. Panel C tests the

[7] The decline in the performance of V/P and NEGPEG relative to the portfolio tests in prior tables can be attributed to the strong loading on book-to-market (HML).

significance of the increase in alphas and shows that combining the strategies increases alpha significantly in all comparisons and across all risk models. To summarize, the results in Table 9 confirm that the increased returns from combining quality-driven and value-driven approaches are robust to controlling for risk.

4.8 Comparison with Graham-Dodd Approach of Combining Quality and Value

Graham and Dodd (1934) propose a simple stock selection method, which includes ten characteristics that consider both value and quality (See Appendix II for details). In this section, we examine whether our combined strategies generate superior hedge returns than the Graham-Dodd approach. We use the implementation of the Graham-Dodd screen from Lee (2014).

Table 10 Panel A reports mean RET_1 as well as FSCORE, GSCORE, V/P, and NEGPEG across Graham-Dodd score (GDS), which ranges from zero to ten. We are able to compute GDS for only 47,645 observations, or less than half of our sample. The main reason for the decline in sample size is the lengthy earnings history that this approach requires (five years of lagged data). A closer look shows that Graham-Dodd approach indeed incorporates both quality and value. The two value metrics, V/P and NEGPEG, both increase with GDS. For example, V/P is 0.41 for firms with GDS of zero, and 2.00 for firms with GDS of ten. In addition, the two quality metrics, FSCORE and GSCORE, also generally increase with GDS, although the pattern of GSCORE is less monotonic.

The 0/1 criteria underlying GDS result in a distribution that has few firms in the extreme groups. Therefore, we combine the firms with GDS of zero and one to form the short position and the firms with GDS of nine and ten to form the long position. The return difference between the two groups is 8.75% and is highly significant.

We next compare the performance of the Graham and Dodd approach to our combined strategies, in the same subsample. We find that the combined strategies generate significant hedge returns that appear to be more than double of that from the Graham-Dodd approach: 14.32% for FSCORE&V/P, 16.69% for FSCORE&NEGPEG, 20.42% for GSCORE&V/P, and 20.87% for GSCORE&NEGPEG. Panel B of Table 10 shows that all four combined strategies significantly outperform Graham-Dodd approach. This reinforces the strength of our approach of combining quality-driven and value-driven fundamental analysis. In addition to generating stronger hedge returns, our combined approach can be applied to a much broader sample of stocks.

5. Conclusions

In this paper, we take advantage of recent developments in the literature on cross-sectional forecasting to generate measures of intrinsic value. This allows us to calculate the V/P measure in Frankel and Lee (1998) and the PEG ratio for a broad cross-section of firms, enabling us to combine value-driven approaches with quality-driven approaches from Piotroski (2000) and Mohanram (2005).

We first find that, consistent with prior results, both the quality-driven approaches (FSCORE and GSCORE) as well as the value-driven approaches (V/P and PEG) are individually successful in generating hedge returns. Our key finding is that a strategy that combines quality with value generates excess returns that significantly exceed the excess returns of the standalone strategies. This superior performance is not an artefact of smaller portfolio size, evident in a wide variety of partitions, persistent across time, and robust to controls for risk factors. Thus, combining these two approaches provides a powerful tool for fundamental analysis.

Our findings corroborate the argument in Asness et al. (2013) and Lee (2014) that fundamental analysis should incorporate two key elements: quality and cheapness. Lee argues that successful fundamental investors find quality companies and buy them at reasonable prices. Our combined strategies do precisely this, by going long on firms with strong fundamentals (high FSCORE/GSCORE) and cheap valuation (high V/P or low PEG), and shorting firms with weak fundamentals (low FSCORE/GSCORE) and expensive valuation (low V/P or high PEG).

The results of this paper have important implications for research in the area of fundamental analysis. They suggest that the two approaches towards fundamental analysis – the quality-driven approach and the intrinsic value approach – are different. Further, combining them is advantageous, as one can generate consistently higher hedge returns without taking additional risk. This paper also has implications for the research on cross-sectional forecasting. Research in accounting has thus far shown the utility of cross-sectional forecasts 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 the computation of the V/P ratio or PEG ratio, thereby allowing the combined strategies to be implemented for the entire population of stocks.

The results have obvious implications for practitioners in their elusive quest for "alpha". Our approach is easy to implement, uses only public information, does not impose lengthy time series data requirements (unlike the Graham-Dodd screen), and is driven by economically defensible approaches to fundamental analysis. Many traditional trading rules have been arbitraged away, potentially because of greater interest from institutional investors, as Green et al. (2011) show with the accrual anomaly. Our approach of combining quality-driven and value-driven strategies offers much promise.

We also need to mention some caveats regarding our results. First, our hybrid strategies focus on the simple intersection between the quality-driven (FSCORE or GSCORE) and value-driven (V/P or PEG) strategies, with no effort to determine the optimal weight on these two approaches. 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 wish to focus on sectors based on industry, investing style, and size. While we do show the robustness of this approach in a variety of partitions, it is unclear that this approach will work in every subset of stocks. Finally, while we control for risk factors using multi-factor asset pricing models, and the pattern of hedge returns across time is consistently positive, we cannot rule out the possibility that our results may arise from other unobserved risk factors.

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Appendix I: 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

Appendix II: Replicating the Graham-Dodd Approach

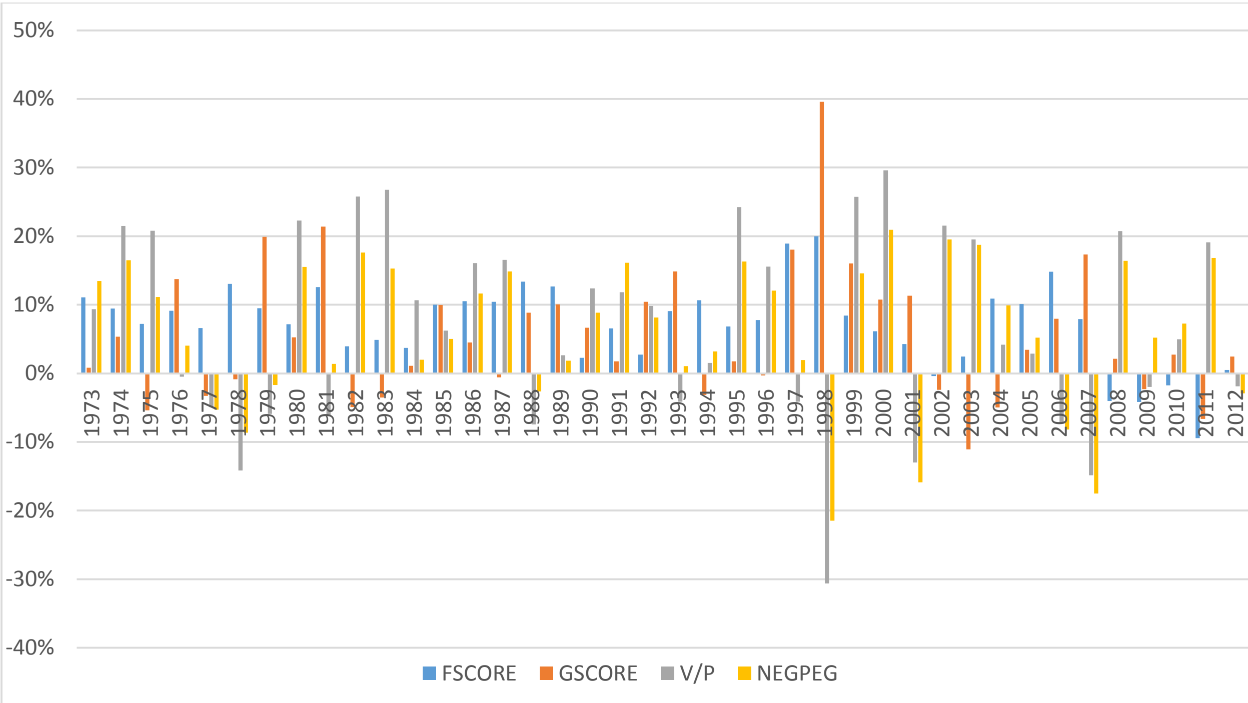
Graham and Dodd (1934) approach ranks stocks based on ten characteristics. We use the modified screen in Lee (2014). We modify the cutoffs related to earnings and dividend yield, as very few firms satisfy the original screen.

> (1) Earnings to price ratio that is double the AAA bond yield. Earnings to price ratio is computed from Compustat (epspx/prcc_f). Data on the AAA yield is obtained from the St. Louis Fed. We use the average yield for the previous fiscal year.
>
> (2) PE (price-to-earnings ratio) of the stock is less than 70% of the average PE for all stocks over the last 5 years. PE is computed only for firm with positive earnings from Compustat (prcc_f/epspx)
>
> (3) Dividend yield > two-thirds of the AAA Corporate Bond Yield. As in Lee (2014), we replace dividend yield with free cash flow yield calculated as (ibc + xidoc +dpc + txdc +esubc +sppiv +fopo) divided by market capitalization (prcc_f*csho)
>
> (4) Price < tangible book value (defined as book value of equity minus intangible assets, or ceq - intan)
>
> (5) Price < net current asset value (NCAV), where NCAV is defined as current assets minus current liabilities or (act – lct)
>
> (6) D/E ratio < 1 where D/E is computed as (dlc+dltt)/ceq
>
> (7) Current ratio > 2, where current ratio is computed as (act/lct)
>
> (8) Debt < twice net current assets, i.e., (dltt+dlc) < 2* (act)
>
> (9) Historical growth in EPS (over the last 5 years) > 7%
>
> (10) No more than one year of declining earnings over the previous 5 years.

A score of one is given to each condition that is satisfied. Hence, the score ranges from zero to ten, with higher scores indicating better investment.

Figure 1: Time-series Performance

Panel A: Annual Hedge Returns for Standalone Strategies (1973-2012)



Panel B: Annual Hedge Returns for Combined Strategies (1973-2012)

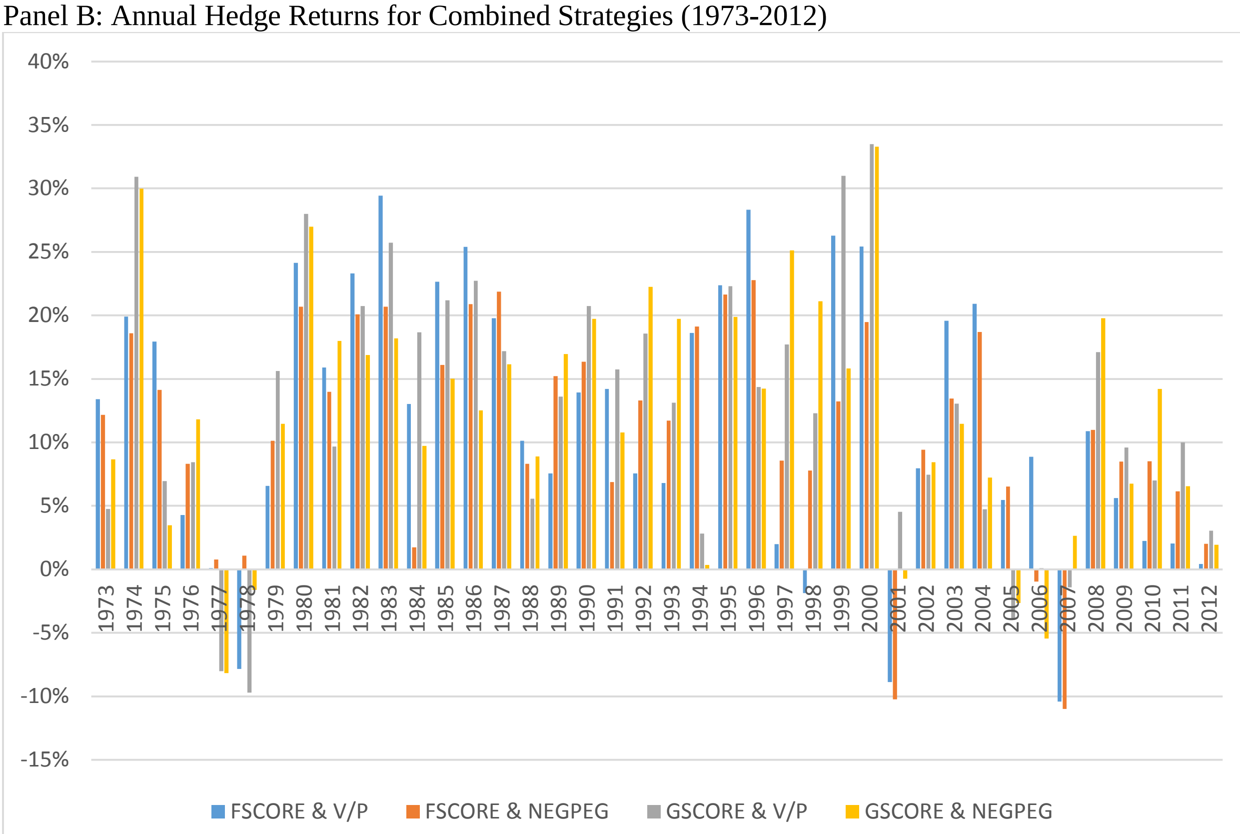


Table 1: Sample Selection and Correlation Statistics

Sample consists of 98,766 observations from 1973 to 2012. FSCORE and GSCORE are quality-driven metrics from Piotroski (2000) and Mohanram (2005). See section 3.1 for details. V/P is an intrinsic value driven metric from Frankel and Lee (1998). NEGPEG is an intrinsic value driven metric calculated using price to earnings ratio and earnings growth. See section 3.2 for details.

Criterion	Firm-Years	Unique firms
Observations between 1973-2012 with CRSP returns, Stock Price >= $1, and COMPUSTAT data to compute FSCORE	159,294	16,889
Availability of data to compute GSCORE	141,162	15,272
Availability of cross-sectional forecasts to calculate V/P	119,215	13,775
Positive EPS_1 forecast and growth rate to calculate NEGPEG	98,766	12,102

Table 2: Returns to Quality and Value

Sample consists of 98,766 observations from 1973 to 2012. Firms are split into quintiles each year based on FSCORE, GSCORE, V/P, and NEGPEG, respectively. RET_1 is one-year-ahead buy-hold size-adjusted returns. See section 3 for the definitions of the variables. The table reports pooled mean RET_1 for each quantile partitioned on respective strategy. Figures in italics are t-statistics for difference of means computed using a pooled estimate of standard error.

	Quality		**Value**	
Quintile	FSCORE	GSCORE	V/P	NEGPEG
1	-2.14%	-1.76%	-1.43%	-0.72%
2	0.57%	0.98%	1.24%	0.31%
3	2.01%	1.99%	1.37%	1.59%
4	2.90%	3.13%	2.36%	2.52%
5	5.30%	4.31%	5.11%	4.96%
5-1	**7.44%**	**6.06%**	**6.55%**	**5.68%**
t-stat	***(12.76)***	***(10.97)***	***(10.64)***	***(9.55)***

Table 3: Quality is Expensive

Sample consists of 98,766 observations from 1973 to 2012. Firms are split into quintiles each year based on FSCORE, GSCORE, V/P, and NEGPEG, respectively. See section 3 for the definitions of the variables. Panel A reports Pearson (above diagonal) and Spearman (below diagonal) correlations. ***, ** and * denote significance at 0.01, 0.05 and 0.10 level using two-tailed test, respectively. Panel B reports pooled mean FSCORE, GSCORE, V/P and NEGPEG for each quantile partitioned on respective strategy. Figures in italics are t-statistics for difference of means computed using a pooled estimate of standard error.

Panel A: Correlation Matrix

	FSCORE	GSCORE	V/P	NEGPEG
FSCORE		0.392***	-0.084***	-0.142***
GSCORE	0.395***		-0.245***	-0.244***
V/P	-0.114***	-0.262***		0.560***
NEGPEG	-0.162***	-0.307***	0.852***	

Panel B: Comparison of Quality and Value across Quintiles

Quintiles based on FSCORE

Quintile	N	FSCORE	GSCORE	V/P	NEGPEG
1	19,739	3.54	3.24	0.98	-1.34
2	19,757	4.32	3.62	0.96	-1.42
3	19,767	4.83	3.90	0.91	-1.61
4	19,758	5.35	4.18	0.85	-1.78
5	19,745	6.15	4.38	0.84	-1.94
5-1		**2.61**	**1.14**	**-0.15**	**-0.60**
t-stat		***(424.84)***	***(120.87)***	***(-21.51)***	***(-33.46)***

Quintiles based on GSCORE

Quintile	N	FSCORE	GSCORE	V/P	NEGPEG
1	19,739	4.29	2.39	1.10	-1.26
2	19,759	4.63	3.30	0.98	-1.42
3	19,766	4.87	3.88	0.92	-1.54
4	19,758	5.08	4.44	0.83	-1.71
5	19,744	5.33	5.31	0.71	-2.16
5-1		**1.03**	**2.92**	**-0.39**	**-0.89**
t-stat		***(108.67)***	***(618.43)***	***(-55.67)***	***(-49.00)***

Quintiles based on V/P

Quintile	N	FSCORE	GSCORE	V/P	NEGPEG
1	19,739	4.99	4.16	0.36	-3.26
2	19,759	4.91	4.10	0.60	-1.88
3	19,765	4.82	3.92	0.80	-1.35
4	19,759	4.74	3.70	1.04	-0.98
5	19,744	4.73	3.44	1.74	-0.61
5-1		**-0.26**	**-0.72**	**1.37**	**2.65**
t-stat		***(-24.35)***	***(-69.63)***	***(199.56)***	***(136.74)***

Quintiles based on NEGPEG

Quintile	N	FSCORE	GSCORE	V/P	NEGPEG
1	19,744	5.10	4.32	0.44	-3.75
2	19,759	4.93	4.07	0.64	-1.76
3	19,765	4.78	3.83	0.81	-1.22
4	19,759	4.70	3.66	1.01	-0.86
5	19,739	4.70	3.43	1.65	-0.50
5-1		**-0.40**	**-0.89**	**1.21**	**3.25**
t-stat		***(-37.54)***	***(-86.57)***	***(168.27)***	***(162.23)***

Table 4: Returns to the Combination of Quality and Value

Sample consists of 98,766 observations from 1973 to 2012. Firms are split into quintiles each year based on FSCORE, GSCORE, V/P and NEGPEG, respectively. RET_1 is one-year-ahead buy-hold size-adjusted returns. See section 3 for the definitions of the variables. This table reports the pooled mean RET_1 for various combinations of quality-driven and value-driven strategies. Figures in italics are t-statistics for difference of means computed using a pooled estimate of standard error.

Panel A: Hedge Returns for Combining Quality (FSCORE) with Value (V/P or NEGPEG)

FSCORE Quintile	V/P Quintile	N	RET_1	NEGPEG Quintile	N	RET_1
1	1	3,243	-6.36%	1	2,580	-6.32%
	2,3,4	11,786	-2.18%	2,3,4	12,078	-2.49%
	5	4,710	0.88%	5	5,081	0.82%
2,3,4	1	11,371	-1.80%	1	11,464	-0.86%
	2,3,4	36,252	1.96%	2,3,4	36,566	1.65%
	5	11,659	4.95%	5	11,252	5.17%
5	1	5,125	2.51%	1	5,700	2.10%
	2,3,4	11,245	4.69%	2,3,4	10,639	5.37%
	5	3,375	11.58%	5	3,406	10.44%
	(5&5-1&1)		**17.94%**	**(5&5-1&1)**		**16.76%**
	t-stat		***(10.70)***	***t-stat***		***(9.97)***
	Standalone FSCORE strategy[+]		**7.44%**	***Standalone FSCORE strategy***[+]		**7.44%**
	t-stat		***(12.76)***	***t-stat***		***(12.76)***
	Combined - Standalone		**10.50%**	***Combined - Standalone***		***9.32%***
	t-stat		***(5.91)***	***t-stat***		***(5.24)***
	(5&5-1&1)		**17.94%**	**(5&5-1&1)**		**16.76%**
	t-stat		***(10.70)***	***t-stat***		***(9.97)***
	Standalone V/P strategy[+]		**6.55%**	***Standalone NEGPEG strategy***[+]		***5.68%***
	t-stat		**(10.64)**	***t-stat***		***(9.53)***
	Combined - Standalone		**11.39%**	***Combined - Standalone***		***11.08%***
	t-stat		**(6.38)**	***t-stat***		***(6.21)***

[+] *From Table 2*

Table 4: Continued.

Panel B: Hedge Returns for Combining Quality (GSCORE) with Value (V/P or NEGPEG)

GSCORE Quintile	V/P Quintile	N	RET_1	NEGPEG Quintile	N	RET_1
1	1	2,793	-9.87%	1	2,146	-8.61%
	2,3,4	10,728	-2.19%	2,3,4	11,276	-2.61%
	5	6,218	2.64%	5	6,317	2.11%
2,3,4	1	10,964	-1.27%	1	10,529	-0.93%
	2,3,4	36,472	1.90%	2,3,4	37,033	1.79%
	5	11,847	5.49%	5	11,721	5.47%
5	1	5,982	2.21%	1	7,069	1.98%
	2,3,4	12,083	4.34%	2,3,4	10,974	4.60%
	5	1,679	11.58%	5	1,701	12.06%
	(5&5-1&1)		**21.45%**	**(5&5-1&1)**		**20.67%**
	t-stat		***(9.58)***	***t-stat***		***(9.04)***
	Standalone GSCORE strategy[+]		**6.06%**	***Standalone GSCORE strategy***[+]		**6.06%**
	t-stat		***(10.97)***	***t-stat***		***(10.97)***
	Combined - Standalone		**15.39%**	***Combined - Standalone***		**14.61%**
	t-stat		***(6.68)***	***t-stat***		***(6.21)***
	(5&5-1&1)		**21.45%**	**(5&5-1&1)**		**20.67%**
	t-stat		***(9.58)***	***t-stat***		***(9.04)***
	Standalone V/P strategy[+]		**6.55%**	***Standalone NEGPEG strategy***[+]		**5.68%**
	t-stat		**(10.64)**	***t-stat***		**(9.55)**
	Combined - Standalone		**14.90%**	***Combined - Standalone***		**14.99%**
	t-stat		**(6.42)**	***t-stat***		**(6.34)**

[+] *From Table 2*

Table 5: Controlling for Portfolio Size

Sample consists of 98,766 observations from 1973 to 2012. This table compares hedge returns of the combined strategies with standalone strategies formed in 25 equal-sized groups (Panel A) and 50 equal-sized groups (Panel B). See section 3 for the definitions of the variables. Figures in italics are t-statistics for difference of means computed using a pooled estimate of standard error.

Panel A: Comparison of Standalone Strategies in 25 Equal-sized Groups with Combined Strategies

	25 FSCORE Groups (1)	FSCORE & V/P (2)	(2) – (1)	FSCORE & NEGPEG (3)	(3) – (1)
Hedge	11.41%	17.94%	6.53%	16.76%	5.35%
t-stat	*(7.48)*	*(10.70)*	*(2.88)*	*(9.97)*	*(2.25)*
	25 GSCORE Groups (1)	GSCORE & V/P (2)	(2) – (1)	GSCORE & NEGPEG (3)	(3) – (1)
Hedge	9.48%	21.45%	11.97%	20.67%	11.19%
t-stat	*(8.10)*	*(9.58)*	*(4.74)*	*(9.04)*	*(3.50)*
	25 V/P Groups (1)	FSCORE & V/P (2)	(2) – (1)	GSCORE & V/P (3)	(3) – (1)
Hedge	10.15%	17.94%	7.79%	21.45%	11.30%
t-stat	*(6.36)*	*(10.70)*	*(3.36)*	*(9.58)*	*(4.04)*
	25 NEGPEG Groups (1)	FSCORE & NEGPEG (2)	(2) – (1)	GSCORE & NEGPEG (3)	(3) – (1)
Hedge	10.77%	16.76%	5.99%	20.67%	9.89%
t-stat	*(6.94)*	*(9.97)*	*(2.62)*	*(9.04)*	*(3.49)*

Panel B: Comparison of Standalone Strategies in 50 Equal-sized Groups with Combined Strategies

	50 FSCORE Groups (1)	FSCORE & V/P (2)	(2) – (1)	FSCORE & NEGPEG (3)	(3) – (1)
Hedge	11.93%	17.94%	6.01%	16.76%	4.83%
t-stat	*(5.28)*	*(10.70)*	*(2.14)*	*(9.97)*	*(2.03)*
	50 GSCORE Groups (1)	GSCORE & V/P (2)	(2) – (1)	GSCORE & NEGPEG (3)	(3) – (1)
Hedge	9.33%	21.45%	12.12%	20.67%	11.34%
t-stat	*(5.79)*	*(9.58)*	*(4.40)*	*(9.04)*	*(3.54)*
	50 V/P Groups (1)	FSCORE & V/P (2)	(2) – (1)	GSCORE & V/P (3)	(3) – (1)
Hedge	11.73%	17.94%	6.21%	21.45%	9.72%
t-stat	*(5.14)*	*(10.70)*	*(2.19)*	*(9.58)*	*(3.47)*
	50 NEGPEG Groups (1)	FSCORE & NEGPEG (2)	(2) – (1)	GSCORE & NEGPEG (3)	(3) – (1)
Hedge	12.10%	16.76%	4.66%	20.67%	8.57%
t-stat	*(5.50)*	*(9.97)*	*(1.68)*	*(9.04)*	*(3.02)*

Table 6: Performance of the Combined Strategies in Value and Growth Stocks

Sample consists of 98,766 observations from 1973 to 2012. Firms are split into quintiles each year based on FSCORE, GSCORE, V/P and NEGPEG, respectively. In addition, firms are sorted into terciles each year based on book-to-market ratio: growth (the lowest BM), medium, and value (the highest BM). This table reports mean hedge returns of standalone FSCORE, GSCORE, V/P and NEGPEG strategies, the combined FSCORE & V/P, GSCORE & V/P, FSCORE & NEGPEG, and GSCORE & NEGPEG strategies, and the pairwise comparisons between standalone and combined strategies. Figures in italics are t-statistics computed using a pooled estimate of standard error.

Strategies	**Growth (low B/M)**	**Medium B/M**	**Value (high B/M)**
FSCORE	8.01%	7.83%	9.97%
	(6.23)	*(10.94)*	*(6.46)*
GSCORE	10.92%	6.63%	4.80%
	(8.91)	*(10.00)*	*(3.26)*
V/P	4.55%	3.21%	7.30%
	(3.43)	*(4.47)*	*(5.03)*
NEGPEG	1.99%	2.31%	8.55%
	(1.51)	*(3.24)*	*(5.81)*
FSCORE & V/P	13.97%	12.87%	19.42%
	(5.06)	*(7.43)*	*(6.86)*
GSCORE & V/P	18.57%	10.99%	8.99%
	(6.26)	*(6.14)*	*(2.73)*
FSCORE & NEGPEG	14.00%	11.31%	19.90%
	(4.60)	*(6.45)*	*(6.49)*
GSCORE & NEGPEG	20.07%	9.57%	11.26%
	(5.63)	*(5.20)*	*(3.31)*
Improvement:			
FSCORE & V/P vs. FSCORE	5.96%	5.04%	9.45%
	(1.96)	*(2.69)*	*(2.93)*
FSCORE & V/P vs. V/P	9.42%	9.66%	12.11%
	(3.08)	*(5.15)*	*(3.81)*
GSCORE & V/P vs. GSCORE	7.65%	4.36%	4.19%
	(2.38)	*(2.28)*	*(1.16)*
GSCORE & V/P vs. V/P	14.02%	7.78%	1.68%
	(4.31)	*(4.03)*	*(0.47)*
FSCORE & NEGPEG vs. FSCORE	5.99%	3.48%	9.93%
	(1.81)	*(1.84)*	*(2.89)*
FSCORE & NEGPEG vs. NEGPEG	12.01%	9.00%	11.35%
	(3.62)	*(4.75)*	*(3.34)*
GSCORE & NEGPEG vs. GSCORE	9.15%	2.94%	6.47%
	(2.43)	*(1.51)*	*(1.75)*
GSCORE & NEGPEG vs. NEGPEG	18.08%	7.26%	2.71%
	(4.76)	*(3.68)*	*(0.73)*

Table 7: Hedge Returns by Partitions on Analyst Following, Size, Listing Exchange, and Institutional Ownership

Sample consists of 98,766 observations from 1973 to 2012. Firms are split into quintiles each year based on FSCORE, GSCORE, V/P and NEGPEG, respectively. This table reports mean hedge returns of standalone FSCORE, GSCORE, V/P and NEGPEG strategies, the combined FSCORE & V/P, GSCORE & V/P, FSCORE & NEGPEG, and GSCORE & NEGPEG strategies, and the pairwise comparisons between standalone and combined strategies. The results are presented in partitions by analyst following, firm size (market capitalization), exchange listing, and institutional ownership. Figures in italics are t-statistics computed using a pooled estimate of standard error.

	Analyst		Size			Listing Exchange		Institutional Ownership		
Strategies	**Yes**	**No**	**Small**	**Med.**	**Large**	**NYSE/ AMEX**	**NASDAQ**	**Low**	**Med.**	**High**
FSCORE	6.11%	9.14%	10.19%	8.02%	4.43%	6.14%	8.14%	9.13%	8.60%	4.27%
	(8.42)	*(9.80)*	*(8.00)*	*(8.73)*	*(6.31)*	*(8.03)*	*(9.53)*	*(8.79)*	*(7.77)*	*(4.95)*
GSCORE	4.99%	6.07%	8.88%	8.07%	4.19%	2.96%	8.63%	6.06%	7.46%	4.52%
	(7.34)	*(6.95)*	*(7.42)*	*(8.60)*	*(6.66)*	*(4.22)*	*(10.40)*	*(6.11)*	*(7.14)*	*(5.49)*
V/P	5.42%	8.43%	7.41%	7.22%	3.72%	6.33%	6.36%	5.49%	7.01%	7.80%
	(7.27)	*(8.75)*	*(5.73)*	*(7.58)*	*(5.01)*	*(7.97)*	*(7.11)*	*(4.80)*	*(6.17)*	*(9.20)*
NEGPEG	5.52%	7.47%	9.47%	4.60%	2.66%	6.25%	6.39%	4.02%	7.25%	7.19%
	(7.66)	*(7.74)*	*(7.41)*	*(4.76)*	*(3.81)*	*(7.99)*	*(7.23)*	*(3.62)*	*(6.57)*	*(8.68)*
FSCORE & V/P	17.13%	21.05%	17.61%	18.83%	11.92%	16.49%	18.59%	18.48%	20.44%	17.45%
	(8.36)	*(8.53)*	*(6.38)*	*(7.96)*	*(5.74)*	*(6.76)*	*(8.11)*	*(6.65)*	*(7.26)*	*(5.78)*
GSCORE & V/P	16.73%	17.28%	16.83%	17.48%	10.79%	19.45%	19.05%	14.69%	22.28%	18.55%
	(6.76)	*(5.53)*	*(5.35)*	*(7.71)*	*(4.68)*	*(5.05)*	*(7.15)*	*(4.03)*	*(6.78)*	*(4.82)*
FSCORE & NEGPEG	16.75%	19.41%	19.51%	15.66%	11.32%	16.31%	20.47%	16.82%	20.78%	17.95%
	(7.83)	*(7.59)*	*(7.05)*	*(6.21)*	*(4.79)*	*(6.37)*	*(8.89)*	*(5.90)*	*(7.56)*	*(5.39)*
GSCORE & NEGPEG	16.64%	16.31%	20.10%	15.44%	11.77%	15.39%	23.29%	15.62%	21.81%	17.46%
	(6.48)	*(4.92)*	*(6.32)*	*(6.47)*	*(4.78)*	*(3.86)*	*(8.14)*	*(4.06)*	*(6.36)*	*(4.22)*
Improvement:										
FSCORE & V/P vs. FSCORE	11.02%	11.91%	7.42%	10.81%	7.49%	10.35%	10.45%	9.35%	11.84%	13.17%
	(5.07)	*(4.52)*	*(2.44)*	*(4.26)*	*(3.42)*	*(4.05)*	*(4.28)*	*(3.15)*	*(3.91)*	*(4.19)*
FSCORE & V/P vs. V/P	11.71%	12.62%	10.20%	11.61%	8.20%	10.16%	12.23%	12.99%	13.43%	9.65%
	(5.37)	*(4.77)*	*(3.35)*	*(4.55)*	*(3.72)*	*(3.96)*	*(4.97)*	*(4.32)*	*(4.42)*	*(3.08)*
GSCORE & V/P vs. GSCORE	11.74%	11.21%	7.95%	9.41%	6.60%	16.49%	10.42%	8.63%	14.82%	14.02%
	(4.57)	*(3.46)*	*(2.36)*	*(3.84)*	*(2.76)*	*(4.21)*	*(3.74)*	*(2.29)*	*(4.30)*	*(3.56)*
GSCORE & V/P vs. V/P	11.31%	8.85%	9.42%	10.26%	7.07%	13.12%	12.69%	9.20%	15.27%	10.75%
	(4.37)	*(2.71)*	*(2.77)*	*(4.17)*	*(2.92)*	*(3.34)*	*(4.51)*	*(2.41)*	*(4.40)*	*(2.73)*
FSCORE & NEGPEG vs. FSCORE	10.64%	10.27%	9.32%	7.64%	6.89%	10.17%	12.33%	7.69%	12.18%	13.68%
	(4.71)	*(3.77)*	*(3.06)*	*(2.85)*	*(2.79)*	*(3.81)*	*(5.02)*	*(2.53)*	*(4.11)*	*(3.97)*
FSCORE & NEGPEG vs. NEGPEG	11.23%	11.94%	10.04%	11.06%	8.66%	10.06%	14.08%	12.80%	13.53%	10.76%
	(4.98)	*(4.37)*	*(3.29)*	*(4.09)*	*(3.52)*	*(3.76)*	*(5.71)*	*(4.18)*	*(4.57)*	*(3.14)*
GSCORE & NEGPEG vs. GSCORE	11.65%	10.24%	11.22%	7.37%	7.59%	12.43%	14.66%	9.56%	14.35%	12.94%
	(4.39)	*(2.99)*	*(3.30)*	*(2.88)*	*(2.98)*	*(3.07)*	*(4.92)*	*(2.41)*	*(4.00)*	*(3.07)*
GSCORE & NEGPEG vs. NEGPEG	11.12%	8.84%	10.63%	10.84%	9.11%	9.14%	16.90%	11.60%	14.56%	10.27%
	(4.17)	*(2.56)*	*(3.10)*	*(4.21)*	*(3.56)*	*(2.25)*	*(5.64)*	*(2.90)*	*(4.04)*	*(2.43)*

Table 8: Performance of Hedge Strategies across Time

Sample consists of 98,766 observations from 1973 to 2012. This table reports annual mean hedge returns of standalone FSCORE, GSCORE, V/P and NEGPEG strategies, and the combined FSCORE & V/P, GSCORE & V/P, FSCORE & NEGPEG, and GSCORE & NEGPEG strategies. See section 3 for the definitions of the variables. Sharpe Ratio is the ratio of the time series mean to the time series standard deviation of hedge returns.

Panel A: Summary Statistics of Annual Hedge Returns across the Strategies

	FSCORE	GSCORE	V/P	NEGPEG	FSCORE & V/P	GSCORE & V/P	FSCORE & NEGPEG	GSCORE & NEGPEG
Mean	7.15%	5.47%	7.13%	6.21%	16.88%	19.14%	15.47%	18.52%
Std. Dev	6.01%	9.68%	14.09%	10.63%	13.87%	18.17%	12.52%	15.92%
Min	-9.45%	-11.06%	-30.62%	-21.48%	-13.82%	-28.94%	-18.26%	-14.94%
Max	20.01%	39.59%	29.62%	20.94%	49.56%	61.67%	42.17%	53.40%
Sharpe Ratio	1.19	0.56	0.51	0.58	1.22	1.05	1.24	1.16
Negative Years	5/40	13/40	14/40	9/40	4/40	5/40	4/40	5/40

Panel B: Comparison of Annual Hedge Returns across the Strategies

	Improvement	*t-stat*	# Years with improved hedge returns
FSCORE & V/P vs. FSCORE	9.74%	*4.07*	29/40
FSCORE & V/P vs. V/P	9.75%	*3.12*	34/40
GSCORE & V/P vs. GSCORE	13.67%	*4.20*	31/40
GSCORE & V/P vs. V/P	12.01%	*3.30*	34/40
FSCORE & NEGPEG vs. FSCORE	8.37%	*3.82*	31/40
FSCORE & NEGPEG vs. NEGPEG	9.31%	*3.59*	33/40
GSCORE & NEGPEG vs. GSCORE	13.02%	*4.41*	32/40
GSCORE & NEGPEG vs. NEGPEG	12.27%	*4.05*	34/40

Table 9: Fama-French Regressions for Hedge Portfolios

Sample consists of 98,766 observations from 1973 to 2012. 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, profitability and investment factors. The regression has 480 monthly observations from July 1973 to June 2013. See section 4.6 for details. Figures in italics are t-statistics.

Panel A: Fama-French Regressions for Individual Strategies

	Alpha	R_m-R_f	SMB	HML	UMD	RMW	CMA	Adj. R^2
FSCORE	0.64	-0.01	-0.07	-0.21				11.20%
	(8.01)	*(-0.76)*	*(-2.65)*	*(-7.71)*				
	0.54	0.01	-0.08	-0.18	0.11			18.20%
	(6.94)	*(0.43)*	*(-3.10)*	*(-6.50)*	*(6.40)*			
	0.58	-0.01	-0.03	-0.21		0.14	-0.01	13.30%
	(7.12)	*(-0.40)*	*(-0.92)*	*(-5.84)*		*(3.53)*	*(-0.22)*	
GSCORE	0.52	0.00	-0.28	-0.28				24.30%
	(5.97)	*(0.13)*	*(-9.60)*	*(-9.34)*				
	0.47	0.01	-0.28	-0.26	0.05			25.40%
	(5.36)	*(0.65)*	*(-9.80)*	*(-8.61)*	*(2.76)*			
	0.35	0.03	-0.19	-0.37		0.29	0.17	31.40%
	(4.12)	*(1.69)*	*(-6.34)*	*(-9.57)*		*(7.06)*	*(2.85)*	
V/P	0.52	-0.16	0.45	0.86				60.20%
	(4.74)	*(-6.33)*	*(12.32)*	*(22.66)*				
	0.46	-0.14	0.45	0.88	0.07			60.80%
	(4.13)	*(-5.72)*	*(12.25)*	*(22.92)*	*(2.88)*			
	0.50	-0.15	0.44	0.80		-0.01	0.14	60.20%
	(4.40)	*(-5.60)*	*(10.91)*	*(15.66)*		*(-0.24)*	*(1.77)*	
NEGPEG	0.43	-0.12	0.70	0.67				52.00%
	(3.55)	*(-4.25)*	*(17.48)*	*(16.08)*				
	0.38	-0.11	0.70	0.69	0.06			52.30%
	(3.10)	*(-3.80)*	*(17.41)*	*(16.19)*	*(2.01)*			
	0.42	-0.10	0.67	0.59		-0.07	0.20	52.40%
	(3.35)	*(-3.63)*	*(15.27)*	*(10.57)*		*(-1.16)*	*(2.23)*	

Table 9: Continued.

Panel B: Fama-French Regressions for Strategies combining Quality and Value

	Alpha	R_m-R_f	SMB	HML	UMD	RMW	CMA	Adj. R^2
FSCORE & V/P	1.35	-0.24	0.39	0.60				36.50%
	(9.19)	*(-7.32)*	*(7.97)*	*(11.86)*				
	1.17	-0.20	0.38	0.67	0.21			41.90%
	(8.13)	*(-6.25)*	*(7.96)*	*(13.54)*	*(6.71)*			
	1.27	-0.22	0.41	0.52		0.10	0.19	36.60%
	(8.34)	*(-6.32)*	*(7.62)*	*(7.58)*		*(1.33)*	*(1.76)*	
GSCORE & V/P	1.55	-0.31	0.19	0.61				34.30%
	(9.21)	*(-8.26)*	*(3.40)*	*(10.57)*				
	1.38	-0.28	0.18	0.68	0.19			37.70%
	(8.28)	*(-7.36)*	*(3.21)*	*(11.71)*	*(5.17)*			
	1.32	-0.26	0.25	0.39		0.27	0.49	36.90%
	(7.72)	*(-6.52)*	*(4.16)*	*(5.12)*		*(3.27)*	*(4.09)*	
FSCORE & NEGPEG	1.22	-0.14	0.57	0.40				26.70%
	(7.99)	*(-4.11)*	*(11.12)*	*(7.63)*				
	1.05	-0.10	0.55	0.47	0.20			31.60%
	(6.97)	*(-3.06)*	*(11.18)*	*(8.97)*	*(5.90)*			
	1.10	-0.10	0.56	0.23		0.05	0.40	28.40%
	(7.07)	*(-2.91)*	*(10.2)*	*(3.31)*		*(0.64)*	*(3.61)*	
GSCORE & NEGPEG	1.41	-0.19	0.54	0.47				22.60%
	(7.67)	*(-4.60)*	*(8.85)*	*(7.41)*				
	1.21	-0.15	0.52	0.54	0.22			27.10%
	(6.69)	*(-3.62)*	*(8.81)*	*(8.62)*	*(5.47)*			
	1.13	-0.12	0.59	0.16		0.26	0.70	27.20%
	(6.14)	*(-2.75)*	*(9.12)*	*(1.94)*		*(2.92)*	*(5.35)*	

Panel C: Increase in Alpha by combining Quality and Value

	3-factor model		*4-factor model*		*5-factor model*	
	Increase	*(t-stat)*	Increase	*(t-stat)*	Increase	*(t-stat)*
FSCORE & V/P vs. FSCORE	0.71	*(5.03)*	0.62	*(4.36)*	0.68	*(4.71)*
FSCORE & V/P vs. V/P	0.83	*(6.42)*	0.71	*(5.49)*	0.77	*(5.74)*
GSCORE & V/P vs. GSCORE	1.03	*(6.04)*	0.91	*(5.30)*	0.97	*(5.48)*
GSCORE & V/P vs. V/P	1.03	*(6.86)*	0.92	*(6.11)*	0.82	*(5.36)*
FSCORE & NEGPEG vs. FSCORE	0.58	*(3.63)*	0.50	*(3.12)*	0.52	*(3.21)*
FSCORE & NEGPEG vs. NEGPEG	0.79	*(6.33)*	0.67	*(5.37)*	0.69	*(5.34)*
GSCORE & NEGPEG vs. GSCORE	0.89	*(4.65)*	0.75	*(3.88)*	0.78	*(4.00)*
GSCORE & NEGPEG vs. NEGPEG	0.98	*(6.12)*	0.83	*(5.23)*	0.72	*(4.45)*

Table 10: Comparison with Graham-Dodd Approach of Combining Quality and Value

Sample consists of 47,645 observations from 1973 to 2012 for which data is available to compute the Graham-Dodd score (see Appendix II for details). Firms with a score of 0 or 1 (9 or 10) are classified as low (high) and hedge returns are computed between high and low groups. For the combined strategies discussed earlier, hedge returns are formed between the firms in the highest quintiles of both quality (FSCORE or GSCORE) and value (V/P or NEGPEG). RET_1 is one-year-ahead buy-hold size-adjusted returns. See section 3 for the definitions of the variables. Pane A reports the pooled mean RET_1 as well as FSCORE, GSCORE, V/P, and NEGPEG for various combinations of quality and value strategies. Figures in italics are t-statistics for difference of means computed using a pooled estimate of standard error. Panel B compares the hedge returns between the Graham-Dodd strategy and the four combined strategies from earlier tables.

Panel A: Performance of Graham-Dodd Strategy and Our Combined Strategies

Graham-Dodd Score	N	FSCORE	GSCORE	V/P	NEGPEG	RET1
0	114	4.61	3.52	0.41	-2.26	-11.61%
1	1,555	4.76	3.56	0.68	-1.84	-1.91%
2	4,099	4.85	3.85	0.66	-1.97	1.50%
3	9,213	4.97	4.08	0.67	-1.81	1.09%
4	10,344	5.01	4.15	0.74	-1.71	3.11%
5	8,469	5.07	4.15	0.86	-1.59	4.22%
6	6,375	5.07	4.11	1.04	-1.33	5.32%
7	4,202	5.15	4.01	1.25	-1.12	5.02%
8	2,106	5.17	3.88	1.52	-0.81	5.20%
9	868	5.28	3.80	1.83	-0.59	6.36%
10	300	5.37	3.88	2.00	-0.50	5.67%
Low (0,1)	1,669	4.75	3.56	0.67	-1.87	-2.57%
High (9,10)	1,168	5.30	3.82	1.87	-0.57	6.18%
High - Low		0.55	0.26	1.21	1.30	8.75%
		(15.34)	(7.35)	(42.85)	(30.11)	(5.34)
FSCORE&V/P						
Low (1,1)	1,082	3.60	3.60	0.42	-2.49	-3.16%
High (5,5)	1,522	6.26	3.98	1.73	-0.62	11.16%
High - Low		2.66	0.38	1.31	1.87	14.32%
		(111.85)	(10.45)	(57.27)	(28.07)	(5.93)
FSCORE&NEGPEG						
Low (1,1)	945	3.66	3.70	0.46	-3.08	-4.72%
High (5,5)	1,479	6.29	4.00	1.60	-0.46	11.97%
High - Low		2.63	0.30	1.14	2.63	16.69%
		(105.67)	(7.85)	(46.39)	(34.65)	(6.71)
GSCORE&V/P						
Low (1,1)	742	4.48	2.43	0.38	-2.55	-6.01%
High (5,5)	813	5.43	5.19	1.58	-0.61	14.41%
High - Low		0.95	2.76	1.20	1.94	20.42%
		(18.87)	(122.93)	(43.04)	(23.30)	(5.62)
GSCORE&NEGPEG						
Low (1,1)	631	4.58	2.44	0.47	-3.19	-4.32%
High (5,5)	788	5.48	5.19	1.49	-0.49	16.55%
High - Low		0.90	2.75	1.02	2.70	20.87%
		(17.22)	(122.69)	(32.80)	(25.62)	(5.52)

Table 10: Continued.

Panel B: Comparison of Annual Hedge Returns

	Difference	*t-stat*
Graham-Dodd vs. FSCORE & V/P	-5.57%	*-1.91*
Graham-Dodd vs. FSCORE & NEGPEG	-7.94%	*-2.67*
Graham-Dodd vs. GSCORE & V/P	-11.67%	*-2.93*
Graham-Dodd vs. GSCORE & NEGPEG	-12.12%	*-2.94*