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

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ABSTRACT

Using cross-sectional forecasts, we combine fundamental analysis strategies based on quality, such as the *FSCORE* from Piotroski (2000) and the *GSCORE* from Mohanram (2005), with strategies based on value, such as the *V/P* ratio from Frankel and Lee (1998) and the *PEG* ratio. While all four strategies generate significant hedge returns, combining quality-driven and value-driven approaches substantially improves the efficacy of fundamental analysis. Our parsimonious two-dimensional approach can be applied to a wide cross section of stocks and outperforms common practitioner approaches that require a lengthy time series of data. The improvements in hedge returns hold for a variety of partitions and are robust to controls for risk factors and other determinants of stock returns. While the efficacy of fundamental analysis has declined in recent years, this can partially be attributed to investors arbitraging away excess returns by investing in fundamental strategies.

Analyse fondamentale : conjuguer recherche de qualité et recherche de valeur

RÉSUMÉ

À l'aide de prévisions transversales, les auteurs associent des stratégies d'analyse fondamentale basées sur la qualité, comme le *FSCORE* de Piotroski (2000) et le *GSCORE* de Mohanram (2005), et des stratégies basées sur la valeur comme le ratio *V/P* de Frankel et Lee (1998) et le ratio *PEG*. Bien que les quatre stratégies produisent toutes des rendements de couverture importants, la conjugaison de méthodes axées sur la qualité et de méthodes axées sur la valeur améliore sensiblement l'efficacité de l'analyse fondamentale. L'approche bidimensionnelle parcimonieuse des auteurs peut être appliquée à un vaste échantillon d'actions et surpasse les approches couramment utilisées dans la pratique qui exigent de longues séries de données chronologiques. Les améliorations des rendements de couverture se maintiennent dans une variété de segments et résistent au contrôle des facteurs de risques et à d'autres déterminants du rendement des actions. Le déclin de l'efficacité de l'analyse fondamentale au cours des années récentes pourrait être attribué dans une certaine proportion au fait que les investisseurs se départissent des rendements excédentaires grâce à l'arbitrage, en investissant dans des stratégies fondamentales.

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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. Traditionally, there are two dimensions in the quest to identify mispriced securities. The first dimension searches for value by identifying stocks whose prices are below their true or intrinsic value. The second dimension searches for quality by identifying firms whose accounting fundamentals may portend well for future performance. Since Graham and Dodd (1934), practitioners have tried to combine value and quality in their stock picking.

The prior academic research on fundamental analysis has focused on each of the two dimensions separately. The efficacy of the value-driven approach is shown by Frankel and Lee (1998), who demonstrate that the deviation of firms' stock price from intrinsic value predicts future stock returns. The efficacy of the quality-driven approach is shown by Piotroski (2000) and Mohanram (2005), who identify underpriced and overpriced securities using accounting-based signals, tailored towards value stocks and growth stocks, respectively. Each of these 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 (RIV) 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 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 already incorporated the insight from the financial statements in its valuation.

Unlike practitioners, prior academic research on fundamental analysis has not tried to combine these alternative approaches towards stock screening. One reason for this is the difference in data requirements stemming from the need for analyst forecasts to calculate intrinsic value. For instance, Piotroski (2000) considers applying 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 (Hou et al. 2012 and Li and Mohanram 2014). The availability of cross-sectional model forecasts implies that one can finally answer the following questions about 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 (that is, do the search for value and the search for quality identify the same stocks as potentially mispriced)? Is there any benefit in combining these two approaches? Finally, how does the efficacy of the combined strategies compare to practitioners' strategies, such as the Graham and Dodd approach?

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 or "cheapness" based approaches using cross-sectional forecasts—the *V/P* strategy from Frankel and Lee (1998) based on the RIV model, and a strategy based on the price-earnings to growth (*PEG*) ratio that is used as a heuristic measure of overvaluation. We multiply the *PEG* ratio by −1 (labeled as *NEGPEG*) to make it positively correlated with stock returns. Our sample consists of all firms

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."

from 1974 to 2015 for which we have adequate information to compute *FSCORE*, *GSCORE*, *V/P*, *NEGPEG*, and one-year-ahead returns. The sample consists of 103,494 observations, or an average of 2,464 observations per year.

We begin by examining the efficacy of a typical Graham and Dodd (1934) stock screen as implemented by Lee (2014), which we label as *GDSCORE.*[2] We find that *GDSCORE* is effective in separating winners from losers, with average annual hedge returns of 9.08 percent. Further, it clearly captures both quality (*FSCORE* and *GSCORE*) as well as value (*V/P* and *NEGPEG*). However, because of data limitations, the screen can only be applied to 49,961 observations, which represent less than half of our sample. *GDSCORE* requires a lengthy time series of data (e.g., historical EPS growth over five years), which excludes a considerable part of the universe of stocks.

We next examine the efficacy of and the correlations between the individual quality and value strategies. Consistent with prior research, all strategies generate economically meaningful and statistically significant annual hedge returns (6.71 percent for *FSCORE*, 5.82 percent for *GSCORE*, 6.41 percent for *V/P*, 5.70 percent for *NEGPEG*). 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—that is, quality is not cheap—and that combining these two approaches in the quest for "affordable quality" may be fruitful. Combining these approaches has the potential to replicate what *GDSCORE* tries to accomplish but without the onerous data requirements.

We combine our quest for quality and value using the following procedure. First, we create quintiles along the dimension of quality (*FSCORE* or *GSCORE*), and within each quintile we create quintiles of value (*V/P* or *NEGPEG*). We identify the long firms as those in the highest value quintile within the highest quality quintile and, conversely, the short firms as those in the lowest value quintile within the lowest quality quintile. Our results show that the combined strategies generate significantly higher excess returns than the stand-alone strategies. Combining *FSCORE* with *V/P* increases hedge returns from 6.71 percent for *FSCORE* alone and 6.41 percent for *V/P* alone to 15.06 percent. Similarly, combining *FSCORE* with *NEGPEG* increases hedge returns to 14.97 percent. Similar improvements are observed when we combine *GSCORE* with *V/P* or *NEGPEG.*

We compare the efficacy of our combined approach with the Graham and Dodd strategy. We find that in the subset of firms for which *GDSCORE* can be estimated, our combined strategies perform better. For instance, combining *FSCORE* and *V/P* generates average hedge returns of 12.51 percent, a significant improvement over the 9.08 percent generated by *GDSCORE.* More importantly, the combined strategy generates a significant hedge return of 15.65 percent in the subsample of firms for which *GDSCORE* cannot be estimated.

Our combined strategy considers the top/bottom 20 percent along the value dimension within the top/bottom 20 percent along the quality dimension, implying that the long and short stocks represent only 4 percent of the sample. Could the return improvement simply stem from the fact that we focus on the extremes of the distribution? To test this, we compare the combined strategies with 25 equal-sized groups partitioned on the individual strategies. The combined strategies still significantly outperform the individual strategies when we control for portfolio size. For instance, while using 25 *FSCORE* groups increases average hedge returns to 9.84 percent, it is significantly less than the 15.06 percent generated by the *FSCORE* and *V/P* combination. This comparison also sheds light on why our combined approach works. When we consider a finer partition of *FSCORE*, we also find that the inverse relationship with value worsens; that is, the

2. Please see Appendix 2 for details of the construction of *GDSCORE.*

high *FSCORE* firms are also more likely to be expensive (lower *V/P*). Looking at the top (bottom) *V/P* quintile within high (low) *FSCORE* firms ensures that we pick attractively priced high-quality firms for the long side, and highly priced low-quality firms for the short side.

To ensure that our results are not driven by a nonrepresentative subset of stocks, we partition our sample based on the book-to-market ratio (*B/M*), analyst following, listing exchange, size, and institutional ownership. We find significant improvements over the stand-alone strategies in almost all subgroups—value firms (high *B/M*) as well as growth firms (low *B/M*), followed firms as well as non-followed firms, NYSE/AMEX firms as well as NASDAQ firms, small and large firms, and firms with different levels of institutional ownership. This suggests that the combined strategy outlined in this article is likely to be implementable.

We next examine the performance of the strategies over time. We find that the combined strategies generate significantly higher returns than the stand-alone strategies 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. We do, however, find that the ability of the strategies to generate hedge returns has declined after 2002, consistent with the findings in Green et al. (2017) and others that the characteristics-based predictability of stock returns has declined in recent years.

To confirm that additional risk does not drive our results, we run factor regressions with monthly returns in the first year after portfolio formation, using a variety of specifications that control for the market ($R_m - R_f$), size (*SMB*), book-to-market (*HML*), momentum (*UMD*), profitability (*RMW*), investment (*CMA*), and the "quality minus junk" factor (*QMJ*) from Asness et al. (2013). We find that the combined strategies generate significantly greater alphas than the stand-alone strategies in all specifications. Finally, our results are robust after controlling for the characteristic equivalents of factors in the prominent benchmark factor models in Carhart (1997), Fama and French (2015), and Hou et al. (2015), as well as the independent determinants of stock returns identified by Green et al. (2017).

The rest of the article is organized as follows. Section 2 describes the quality-based and value-based approaches towards fundamental analysis analyzed in this paper. Section 3 presents the research design and sample descriptive statistics. Section 4 presents the main empirical results. Section 5 considers and controls for alternative explanations for our results. Section 6 concludes.

2. Prior research

Our article 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).

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 *B/M* or value firms. He combines nine signals based on traditional ratio analysis 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. Mohanram (2005) follows a similar approach as Piotroski (2000) but focuses on low *B/M* or 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.

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 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.

Comparing quality-driven and value-driven fundamental analysis

The quality-driven and value-driven approaches to fundamental analysis have many differences. 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, 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. However, it is also possible that these two approaches yield different results. For example, the summary metrics might ignore insights provided by detailed financial statement analysis, or the insights from the detailed analysis might have been impounded into the stock price.

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

Cross-sectional forecasting

The typical approach 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 et al. (2012) use the cross-sectional method to generate forecasts for up to five years into the future. 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 for which analyst forecasts are unavailable and time-series models are infeasible. However, one potential drawback could be the lower forecast accuracy. The results in Hou et al. (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 empirical question as to whether intrinsic value estimates using cross-sectional forecasts will be effective.

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. 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 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), Frankel and Lee (1998), and *PEG* approaches towards fundamental analysis. In some cases, we modify the strategies to allow for easier comparison and combination of the relevant strategies.

*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 ($\Delta LEVER$), change in liquidity ($\Delta LIQUID$), equity offering (*EQ_OFFER*), change in gross margin ($\Delta MARGIN$), and change in asset turnover ratio ($\Delta TURN$).[3] Among the nine fundamental signals, *ROA*, *CFO*, ΔROA, $\Delta LIQUID$, $\Delta MARGIN$, and $\Delta TURN$ are positive signals, with a score of one if positive and zero otherwise. Accruals and $\Delta LEVER$ are negative signals, with a score of one if negative and zero otherwise. Equity offering is also a negative signal, with 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*), sales growth volatility (*VARSGR*), R&D intensity (*RDINT*), capital 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*, with a score of one if greater than the contemporaneous industry median, and zero otherwise. The negative signals are *VARROA*, *VARSGR*, and accruals, with a score of one if less than the contemporaneous industry median, and zero otherwise. *GSCORE* is the sum of the eight signals.

Both *FSCORE* and *GSCORE* use 0/1 criteria, resulting in very few firms with extreme scores and most firms clustered around the middle.[5] 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 variable 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. 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). *FSCORE* and *GSCORE* are defined as the sum of their continuous underlying signals.

*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 RIV model:

3. Using COMPUSTAT data items, *ROA* is measured as *ib/at*; accrual is $(\Delta act - \Delta lct - \Delta che + \Delta dlc - dp)/at$; *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.*

4. Using COMPUSTAT data items, *VARROA* is the SD of quarterly *ROA* (*ibq/atq*) over the past two years; *VARSGR* is the SD 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. 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 (1,618), 4 (2,462), 5 (2,787), 6 (2,579), 7 (1,894), 8 (1,115), and 9 (333).

$$
\begin{aligned}
V_t^* &= B_t + \sum_{i=1}^{\infty} \frac{E_t[NI_{t+i} - (r_e B_{t+i-1})]}{(1+r_e)^i} \\
&= B_t + \sum_{i=1}^{\infty} \frac{E_t[(ROE_{t+i} - r_e) B_{t+i-1}]}{(1+r_e)^i}
\end{aligned}
\tag{1}
$$

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 1. We compute book value of equity and return on equity in each period assuming clean surplus accounting: $B_{t+i} = B_{t+i-1} + (1-k) \times NI_{t+i}$ and $ROE_{t+i} = NI_{t+i} / B_{t+i-1}$, where k is the estimated payout ratio.[6] We assume that abnormal earnings stay constant after the forecast horizon to estimate the terminal value. We use the risk-free rate (yield on the 10-year U.S. treasury) plus 5 percent as the cost of equity capital (r_e), which is cross-sectionally constant but varies across time.[7]

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

Combining different approaches to fundamental analysis

To implement the stand-alone strategies, we form quintiles every year based on *FSCORE*, *GSCORE*, *V/P*, and *NEGPEG*, respectively. To combine the quality-driven and value-driven approaches, we first create quintiles along the dimension of quality (*FSCORE* or *GSCORE*), and within each quintile we create quintiles of value (*V/P* or *NEGPEG*). We identify the long firms as those in the highest value quintile within the highest quality quintile and, conversely, the short firms as those in the lowest value quintile within the lowest quality quintile.[8]

Return computation

We analyze the performance of our strategies using a one-year horizon starting on July 1, 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 1 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 1 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 12-month period (RET_1) by measuring the buy-hold return in excess of

6. 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 percent 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).
7. Results are similar if we use a constant cost of equity (10 percent), 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 the finding in Frankel and Lee (1998) that varying the discount rate has little effect on the results.
8. In a robustness test, we first partition the sample into quintiles based on the value dimension (*V/P* or *NEGPEG*). Within each quintile, we further partition the sample into quintiles based on the quality dimension (*FSCORE* or *GSCORE*). The results are very similar using this alternative method to construct portfolios.

the buy-hold return on the CRSP size-matched decile portfolio. We also adjust for delisting return, consistent with Shumway (1997).

Sample selection and correlations

Table 1 presents a summary of our sample selection procedure. We begin with the universe of 156,240 firm-year observations of the U.S. companies listed on NYSE/AMEX, and NASDAQ (share code 10 or 11) with required CRSP returns, stock prices greater than $1 and less than $1,000, and financial data on COMPUSTAT to compute *FSCORE* in the 42-year period from 1974 to 2015. The computation of the earnings and sales growth volatility in *GSCORE* requires two years of quarterly data. This reduces the sample to 139,820 firm-year observations. In addition, we need the cross-sectional forecasts to estimate the *V/P* measure. This reduces the sample size to 124,015 observations. Finally, the requirement of positive EPS_1 forecast and earnings growth rate to calculate the *NEGPEG* ratio further reduces the sample to 103,494 firm-year observations, which corresponds to 12,269 unique firms.

4. Results

Graham and Dodd approach of combining value and quality

Graham and Dodd (1934) propose a simple stock selection method, which includes ten characteristics that consider both value and quality (see Appendix 2 for details). We begin by examining the efficacy of the Graham-Dodd approach. We use the implementation of the Graham-Dodd screen from Lee (2014).

Table 2 reports mean RET_1 as well as *FSCORE*, *GSCORE*, *V/P*, and *NEGPEG* across Graham-Dodd score (*GDSCORE*), which ranges from zero to 10. We are able to compute *GDSCORE* for only 49,961 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 the Graham-Dodd approach indeed incorporates both quality and value. The two value metrics, *V/P* and *NEGPEG*, both increase with *GDSCORE*. For example, *V/P* is 0.41 for firms with *GDSCORE* of zero, and 2.01 for firms with *GDSCORE* of 10. In addition, the two quality metrics, *FSCORE* and *GSCORE*, also generally increase with *GDSCORE*, although the pattern of *GSCORE* is less monotonic. The 0/1 criteria underlying *GDSCORE* result in very few firms with extreme scores. Therefore, we combine the firms with *GDSCORE* of zero and one for the short position and the firms with *GDSCORE* of 9 and 10 for the long position. The return difference between the two groups is 9.08 percent and is highly

TABLE 1
Sample selection and correlation statistics

Criterion	Firm-years	Unique firms
Observations from 1974 to 2015 with		
CRSP returns		
Stock price >= $1 and Stock price <= $1000		
COMPUSTAT data to compute *FSCORE*	156,240	16,571
Availability of data to compute *GSCORE*	139,820	14,971
Availability of cross-sectional forecasts to calculate *V/P*	124,015	13,897
Positive EPS_1 forecast and growth rate to calculate *NEGPEG*	103,494	12,269
Availability of data to calculate Graham and Dodd score	49,961	6,231

Notes: Sample consists of 103,494 observations from 1974 to 2015. *FSCORE* and *GSCORE* are quality-driven metrics from Piotroski (2000) and Mohanram (2005). *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 for details.

TABLE 2
Combining quality and value using the Graham and Dodd strategy

GDSCORE	*N*	*FSCORE*	*GSCORE*	*V/P*	*NEGPEG*	RET_1
Missing	53,533	4.63	3.69	0.94	−1.67	0.51%
0	116	4.57	3.51	0.41	−2.26	−8.93%
1	1,591	4.75	3.57	0.68	−1.83	−2.06%
2	4,262	4.84	3.86	0.66	−2.00	1.58%
3	9,563	4.96	4.08	0.67	−1.85	1.35%
4	10,860	4.99	4.15	0.75	−1.76	3.18%
5	8,995	5.04	4.16	0.87	−1.68	4.13%
6	6,819	5.04	4.14	1.03	−1.44	4.89%
7	4,418	5.13	4.02	1.24	−1.21	4.04%
8	2,145	5.17	3.88	1.54	−0.79	4.92%
9	890	5.28	3.80	1.86	−0.58	6.62%
10	302	5.35	3.88	2.01	−0.51	6.38%
Low (0, 1)	1,707	4.74	3.57	0.66	−1.86	−2.52%
High (9, 10)	1,192	5.30	3.82	1.90	−0.56	6.56%
High − Low		0.56	0.25	1.23	1.30	9.08%
(*t*-statistic)		(15.48)	(7.08)	(40.33)	(33.55)	(5.46)

Notes: Sample consists of 103,494 observations from 1974 to 2015. Of these, data were unavailable for 53,533 observations to compute the Graham-Dodd score (*GDSCORE*; see Appendix 2 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. *FSCORE* and *GSCORE* are quality-driven metrics from Piotroski (2000) and Mohanram (2005). *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. RET_1 is one-year-ahead buy-hold size-adjusted returns. See section 3 for the definitions of the variables. Figures in parentheses are *t*-statistics for difference of means computed using a pooled estimate of standard error.

significant. These results show that the Graham-Dodd approach is a simple way to combine value and quality. However, because the signals underlying this approach require a lengthy time series of data, this approach is not feasible for more than half of the firms.

Comparison of the four stand-alone strategies

We next examine if the four stand-alone 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, focusing on the hedge return for a strategy going long in the top quintile and short in the bottom quintile.

Panel A of Table 3 reports the results. For *FSCORE*, the mean RET_1 increases monotonically from −1.75 percent for the bottom quintile to 4.96 percent for the top quintile. The average hedge return of 6.71 percent is the highest among the four strategies, corroborating the success of the *FSCORE* strategy in Piotroski (2000). The average hedge return for *GSCORE* is 5.82 percent, lower than *FSCORE* but also highly significant. For the value-based strategies, we find a significant average hedge return of 6.41 percent for *V/P* and 5.70 percent for *NEGPEG.* Panel B of Table 3 presents the pairwise comparisons of the hedge returns across the individual strategies. Although *FSCORE* generates the highest hedge return, none of the return differences are significant. The difference between the highest and the lowest hedge returns (*FSCORE* and *NEGPEG*, respectively) is only 1 percent (*t*-statistic 1.23). In sum, all strategies generate economically and statistically significant returns, confirming the effectiveness of quality- and value-based fundamental analysis.

TABLE 3

Performance of and correlation between quality- and value-based strategies

Panel A: Returns to quality- and value-based strategies

	Quality		Value	
Quintile	*FSCORE*	*GSCORE*	*V/P*	*NEGPEG*
1	−1.75%	−1.84%	−1.35%	−0.79%
2	0.82%	1.35%	1.27%	0.48%
3	2.05%	2.45%	1.50%	1.88%
4	2.80%	2.93%	2.40%	2.40%
5	4.96%	3.98%	5.06%	4.91%
5 − 1	6.71%	5.82%	6.41%	5.70%
(*t*-statistic)	(11.82)	(10.96)	(10.72)	(9.90)

Panel B: Pairwise comparisons of hedge returns

Comparison	Difference in hedge returns(%)	(*t*-statistic)
FSCORE vs. *GSCORE*	0.88	(1.14)
FSCORE vs. *V/P*	0.29	(0.35)
FSCORE vs. *NEGPEG*	1.00	(1.23)
GSCORE vs. *V/P*	−0.59	(−0.74)
GSCORE vs. *NEGPEG*	0.11	(0.15)
V/P vs. *NEGPEG*	0.71	(0.85)

Panel C: Correlation matrix

	FSCORE	*GSCORE*	*V/P*	*NEGPEG*
FSCORE		0.319	−0.123	−0.056
GSCORE	0.316		−0.206	−0.219
V/P	−0.164	−0.222		0.560
NEGPEG	−0.042	−0.277	0.741	

Panel D: Comparison of quality and value across quintiles

Quintile	*N*	*FSCORE*	*GSCORE*	*V/P*	*NEGPEG*
Quintiles based on FSCORE					
1	20,682	3.52	3.24	0.99	−1.38
2	20,704	4.30	3.63	0.97	−1.45
3	20,711	4.80	3.90	0.92	−1.63
4	20,702	5.32	4.19	0.86	−1.82
5	20,695	6.12	4.39	0.85	−1.97
5 − 1		2.60	1.15	−0.14	−0.59
(*t*-statistic)		(431.75)	(124.33)	(−20.20)	(−36.58)

(The table is continued on the next page.)

TABLE 3 (continued)

Panel D: Comparison of quality and value across quintiles

Quintile	*N*	*FSCORE*	*GSCORE*	*V/P*	*NEGPEG*
Quintiles based on *GSCORE*					
1	20,684	4.27	2.40	1.11	−1.29
2	20,701	4.60	3.31	1.00	−1.43
3	20,711	4.85	3.88	0.92	−1.55
4	20,703	5.05	4.44	0.83	−1.76
5	20,695	5.30	5.31	0.71	−2.21
5 − 1		1.03	2.91	−0.40	−0.92
(*t*-statistic)		(111.18)	(632.10)	(−56.71)	(−56.46)
Quintiles based on *V/P*					
1	20,683	4.96	4.18	0.37	−3.31
2	20,702	4.89	4.10	0.61	−1.94
3	20,711	4.79	3.91	0.80	−1.38
4	20,703	4.71	3.70	1.04	−1.00
5	20,695	4.71	3.45	1.75	−0.61
5 − 1		−0.25	−0.73	1.38	2.70
(*t*-statistic)		(−23.62)	(−72.25)	(197.72)	(166.53)
Quintiles based on *NEGPEG*					
1	20,683	5.07	4.33	0.44	−3.77
2	20,702	4.90	4.08	0.64	−1.82
3	20,711	4.75	3.84	0.81	−1.26
4	20,702	4.67	3.67	1.02	−0.88
5	20,696	4.66	3.43	1.67	−0.51
5 − 1		−0.41	−0.90	1.23	3.26
(*t*-statistic)		(−39.32)	(−89.66)	(169.18)	(199.83)

Notes: Sample consists of 103,494 observations from 1974 to 2015. 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. Panel A reports pooled mean RET_1 for each quintile partitioned on respective strategy. Figures in parentheses are *t*-statistics for difference of means computed using a pooled estimate of standard error. Panel B reports pairwise comparisons of hedge returns among the individual strategies. Panel C reports Pearson (above diagonal) and Spearman (below diagonal) correlations. All correlations in panel C are significant at the 0.01 level using a two-tailed test. Panel D reports pooled mean *FSCORE*, *GSCORE*, *V/P*, and *NEGPEG* for each quintile partitioned on respective strategy.

Panel C of Table 3 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. Unsurprisingly, *FSCORE* and *GSCORE* are strongly positively correlated, as both are based on financial statement ratios and many of their underlying signals are similar. Interestingly, both *FSCORE* and *GSCORE* are negatively correlated with *V/P* and *NEGPEG*, suggesting that high-quality firms are also more expensive; that is, quality does not usually come cheap.

Panel D of Table 3 reports mean *FSCORE*, *GSCORE*, *V/P*, and *NEGPEG* in quintiles formed on each respective strategy. We first report means for quintiles based on *FSCORE*. Mean *GSCORE* increases monotonically across *FSCORE* quintiles as they are positively correlated. Conversely, as *V/P* and *NEGPEG* are negatively correlated with *FSCORE*, their means decline monotonically across *FSCORE* quintiles. Similar patterns are observed in the rest of panel D, confirming the negative correlation between quality and value. It shows that the quest for quality works against the quest for value. Stand-alone quality-driven approaches (*FSCORE* and *GSCORE*) potentially ignore the likelihood that high/low quality may have already been impounded into stock prices in terms of higher/lower valuations. Conversely, stand-alone value-driven approaches (*V/P* and *NEGPEG*) ignore the possibility that a cheap/expensive valuation may be caused by weak/strong fundamentals.

Combining quality-driven and value-driven approaches to fundamental analysis

We now examine whether combining the quality-driven approach (*FSCORE* and *GSCORE*) with the value-driven approach (*V/P* and *NEGPEG*) provides stronger hedge returns than the individual strategies. As described in section 3, the combined strategy takes a long position of the firms in the highest value quintile within the highest quality quintile and a short position of the firms in the lowest value quintile within the lowest quality quintile.

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. 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 −5.00 percent (−5.12 percent) for firms in quintile 1 of both *FSCORE* and *V/P* (*NEGPEG*), and 10.06 percent (9.85 percent) for firms in quintile 5 of both *FSCORE* and *V/P* (*NEGPEG*). The combined strategy yields highly positive mean hedge return of 15.06 percent for *FSCORE* and *V/P* (14.97 percent for *FSCORE* and *NEGPEG*), which is significantly higher than the hedge returns of the stand-alone strategies: 6.71 percent for *FSCORE*, 6.41 percent for *V/P*, and 5.70 percent for *NEGPEG*. We observe that most of the hedge returns of the combined strategies using *FSCORE* are contributed by the long side of the hedge portfolios (e.g., 10.06 out of 15.06 percent for the *FSCORE* and *V/P* strategy). In addition, a significant portion of the return improvements over the stand-alone strategies also comes from the long side of the hedge portfolio. For example, among the 8.35 percent difference in hedge return between the *FSCORE* and *V/P* strategy and the *FSCORE* strategy, the long side contributes 5.10 percent and the short side contributes 3.25 percent.

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 using *GSCORE* and *V/P* yields a hedge return of 14.88 percent (13.38 percent for *GSCORE* and *NEGPEG*), which is significantly higher than the hedge returns of the stand-alone strategies: 5.82 percent for *GSCORE*, 6.41 percent for *V/P*, and 5.70 percent for *NEGPEG*. Interestingly, unlike the *FSCORE* based strategies, most of the improvements appear to come from the short side. This is not surprising given the results in Mohanram (2005) that *GSCORE* is most effective on the short side.

Comparison with the Graham-Dodd approach

In Table 5, we compare the combined strategies with the Graham and Dodd approach. We find that the combined strategies generate significant hedge returns in both subsamples partitioned by the availability of Graham-Dodd score (*GDSCORE*). Specifically, in the subsample without *GDSCORE*, the hedge returns are 15.65 percent for *FSCORE* and *V/P*, 13.50 percent for *FSCORE* and *NEGPEG*, 14.98 percent for *GSCORE* and *V/P*, and 13.71 percent for *GSCORE* and *NEGPEG*, respectively. Focusing on the subsample of firms with *GDSCORE*, we observe that the combined strategies generate higher hedge returns than *GDSCORE*, especially *FSCORE* combined with *V/P* or *NEGPEG*. As shown in Table 2, the Graham-Dodd strategy generates average hedge return of 9.08 percent. In contrast, the hedge returns of our combined strategies are 12.51 percent for *FSCORE* and *V/P*, 14.06 percent for *FSCORE* and *NEGPEG*, 11.94 percent for *GSCORE* and *V/P*, and 11.70 percent for *GSCORE* and *NEGPEG*, respectively. This reinforces the strength of our approach of combining

TABLE 4

Returns to the combination of quality and value

Panel A: Hedge returns for combining quality (*FSCORE*) with value (*V/P* or *NEGPEG*)

FSCORE quintile	*V/P* quintile	*N*	RET_1 (%)	(*t*-statistic)	*NEGPEG* quintile	*N*	RET_1 (%)	(*t*-statistic)
1	1	4,115	−5.00		1	4,114	−5.12	
	2, 3, 4	12,437	−1.39		2, 3, 4	12,438	−1.77	
	5	4,130	0.42		5	4,130	1.69	
2, 3, 4	1	12,372	−1.68		1	12,373	−0.80	
	2, 3, 4	37,340	2.02		2, 3, 4	37,339	1.71	
	5	12,405	5.06		5	12,405	5.11	
5	1	4,119	0.34		1	4,119	1.16	
	2, 3, 4	12,442	4.79		2, 3, 4	12,442	4.59	
	5	4,134	10.06		5	4,134	9.85	
	(5 and 5 − 1 and 1)		15.06	(10.27)	(5 and 5 − 1 and 1)		14.97	(10.40)
	Stand-alone *FSCORE* strategy+		6.71	(11.82)	Stand-alone *FSCORE* strategy+		6.71	(11.82)
	Improvement		8.35	(5.32)	Improvement		8.26	(5.34)
	Long side		5.10	(4.05)	Long side		4.89	(3.78)
	Short side		3.25	(3.47)	Short side		3.37	(3.97)
	Stand-alone *V/P* strategy+		6.41	(10.72)	Stand-alone *NEGPEG* strategy+		5.70	(9.90)
	Total improvement		8.65	(5.46)	Total improvement		9.27	(5.97)
	Long side improvement		5.00	(3.91)	Long side improvement		4.94	(3.75)
	Short side improvement		3.65	(3.91)	Short side improvement		4.33	(5.28)

(The table is continued on the next page.)

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 (%)	(*t*-statistic)	*NEGPEG* quintile	*N*	RET_1 (%)	(*t*-statistic)
1	1	4,116	−7.79		1	4,116	−6.13	
	2, 3, 4	12,436	−1.39		2, 3, 4	12,437	−1.91	
	5	4,132	2.75		5	4,131	2.65	
2, 3, 4	1	12,372	−1.01		1	12,372	−1.01	
	2, 3, 4	37,340	2.02		2, 3, 4	37,340	1.91	
	5	12,403	6.14		5	12,403	6.49	
5	1	4,119	1.28		1	4,119	1.25	
	2, 3, 4	12,442	3.85		2, 3, 4	12,442	3.80	
	5	4,134	7.09		5	4,134	7.25	
	(5 and 5 − 1 and 1)		14.88	(11.55)	(5 and 5 − 1 and 1)		13.38	(10.37)
	Stand-alone *GSCORE* strategy+		5.82	(10.96)	Stand-alone *GSCORE* strategy+		5.82	(10.96)
	Improvement		9.06	(6.50)	Improvement		7.56	(5.41)
	Long side		3.10	(3.01)	Long side		3.26	(3.01)
	Short side		5.95	(6.36)	Short side		4.29	(4.89)
	Stand-alone *V/P* strategy+		6.41	(10.72)	Stand-alone *NEGPEG* strategy+		5.70	(9.90)
	Total improvement		8.47	(5.96)	Total improvement		7.68	(5.43)
	Long side improvement		2.03	(1.87)	Long side improvement		2.34	(2.06)
	Short side improvement		6.43	(7.13)	Short side improvement		5.34	(6.34)

Notes: Sample consists of 103,494 observations from 1974 to 2015. Firms are first split into quintiles each year based on *FSCORE* or *GSCORE.* Within each quintile, firms are further split into quintiles based on *V/P* or *NEGPEG*, respectively. RET_1 is one-year-ahead buy-hold size-adjusted returns. See section 3 for the definitions of the variables. Panel A reports the pooled mean RET_1 for combined *FSCORE* and *V/P* and *FSCORE* and *NEGPEG* strategies. Panel B reports the pooled mean RET_1 for the combined *GSCORE* and *V/P* and *GSCORE* and *NEGPEG* strategies. Figures in parentheses are *t*-statistics for difference of means computed using a pooled estimate of standard error. + From Table 3, panel A.

TABLE 5
Comparison with Graham-Dodd approach of combining quality and value

	No Graham and Dodd data		Graham and Dodd data available	
Strategy	*N*	RET_1	*N*	RET_1
FSCORE and *V/P*				
Low (1, 1)	2,120	−6.22%	1,978	−3.24%
High (5, 5)	2,136	9.43%	1,988	9.28%
High − Low		15.65%		12.51%
		(7.52)		(6.37)
Difference from Graham and Dodd		N/A		3.43%
				(1.88)
FSCORE and *NEGPEG*				
Low (1, 1)	2,118	−5.54%	1,978	−3.51%
High (5, 5)	2,136	7.96%	1,988	10.55%
High − Low		13.50%		14.06%
		(6.50)		(7.18)
Difference from Graham and Dodd		N/A		4.97%
				(2.74)
GSCORE and *V/P*				
Low (1, 1)	2,119	−10.51%	1,978	−3.44%
High (5, 5)	2,136	4.48%	1,988	8.50%
High − Low		14.98%		11.94%
		(8.64)		(6.46)
Difference from Graham and Dodd		N/A		2.85%
				(1.62)
GSCORE and *NEGPEG*				
Low (1, 1)	2,119	−9.73%	1,978	−2.70%
High (5, 5)	2,136	3.97%	1,988	9.00%
High − Low		13.71%		11.70%
		(8.05)		(6.50)
Difference from Graham and Dodd		N/A		2.61%
				(1.50)

Notes: Sample consists of 103,494 observations from 1974 to 2015. Data for the Graham-Dodd score were unavailable for 53,533 observations (see Appendix 2). Firms are first split into quintiles each year based on *FSCORE* or *GSCORE.* Each *FSCORE* (*GSCORE*) quintile is further split into quintiles based on *V/P* or *NEGPEG.* RET_1 is one-year-ahead buy-hold size-adjusted returns. See section 3 for the definitions of the variables. This table reports pooled mean RET_1 of long and short portfolios for combinations of quality and value strategies in subsamples based on the availability of the Graham-Dodd score, and the differences in hedge returns between the combined strategies and the Graham-Dodd strategy reported in Table 2. Figures in parentheses are *t*-statistics for difference of means computed using a pooled estimate of standard error.

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.

Why do combined strategies outperform stand-alone quality and value strategies?

The results thus far indicate that strategies combining elements of quality and value outperform strategies based solely on one of these dimensions. A potential concern is that the superior performance might be due to a finer partition of the sample. As panel C of Table 3 shows, the long and short positions of the stand-alone strategies each include about 20,700 observations over 42 years (around 493 observations per year). In contrast, the number of observations included in the long or short positions of the combined strategies is about 4,100 (about 98 observations per year), as shown in Table 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 equal-sized groups based on the stand-alone strategies and compare the return spreads of the extreme groups with the return spreads of the combined strategies in Table 6.

Panel A of Table 6 compares the results of the 25 equal-sized *FSCORE* groups with those of *FSCORE* and *V/P* and *FSCORE* and *NEGPEG* combined strategies. The stand-alone strategy now has around 4,100 observations in both the long and short positions, similar to those of the combined strategies. The finer partitions indeed increase the hedge return of the stand-alone *FSCORE* strategy from 6.71 percent (reported in Table 3) to 9.84 percent. However, the finer partition does not address the issue that the quest for quality works against the quest for value. Although the firms in Group 25 have significantly higher mean *FSCORE* than the firms in Group 1, they are also more expensive than the firms in Group 1, as shown by the significantly lower mean *V/P* and *NEGPEG*. In contrast, our combined strategies are able to incorporate the elements of both quality-driven and value-driven fundamental analysis. Although the combined strategies have slightly lower spread in *FSCORE* between the long and short positions (2.70 for *FSCORE* and *V/P* and 2.63 for *FSCORE* and *NEGPEG* versus 3.93 for 25 *FSCORE* groups), they have appropriate spreads in the value metrics: 1.25 of *V/P* spread for *FSCORE* and *V/P* and 2.59 of *NEGPEG* spread for *FSCORE* and *NEGPEG*, compared to −0.11 of *V/P* spread and −0.53 of *NEGPEG* spread for the stand-alone 25 *FSCORE* groups.

The success of this approach that combines a quest for quality with a quest for value can be seen in the significantly higher hedge return than those of the stand-alone strategies. For example, the hedge returns of *FSCORE* and *V/P* and *FSCORE* and *NEGPEG* at 15.06 percent and 14.97 percent, respectively, are significantly higher than the 9.84 percent using 25 *FSCORE* groups. The remaining panels in Table 6 show similar results when we compare the combined strategies with finer partitions of stand-alone *GSCORE* (panel B), *V/P* (panel C), and *NEGPEG* (panel D) strategies. The results in Table 6 hence suggest that the superior returns generated by our combined strategies are not an artifact of smaller sample size, as the combined strategies significantly outperform stand-alone strategies with similar portfolio size by picking attractively priced high-quality firms for the long side and highly priced low-quality firms for the short side.

Contextual fundamental analysis

Mohanram (2005) shows that the *FSCORE* strategy works best in value (high *B/M*) stocks, while the *GSCORE* strategy works best in growth (low *B/M*) stocks. We next analyze the efficacy of the individual and combined strategies across the value-growth partition.

Table 7 reports results in the subsamples of growth stocks (lowest tercile of *B/M*), medium *B/M* stocks, and value stocks (highest tercile of *B/M*). *FSCORE* performs the best in value stocks, generating 7.14, 7.03, and 9.33 percent hedge returns in growth, medium *B/M*, and value stocks, respectively. *GSCORE* performs the best in growth stocks, generating 9.15, 5.33, and 6.22 percent hedge returns in growth, medium *B/M*, and value stocks, respectively. Finally, both *V/P* and *NEGPEG* perform the best in value stocks. Specifically, *V/P* generates 4.70, 2.74, and 6.17 percent, while *NEGPEG* yields 2.61, 2.15, and 6.82 percent hedge returns in growth, medium *B/M*, and value stocks, respectively.

The *FSCORE* and *V/P* (*FSCORE* and *NEGPEG*) strategy performs the best in value stocks, generating 13.21, 12.18, and 14.42 percent (12.42, 10.50, and 14.20 percent) hedge returns for growth, medium *B/M*, and value stocks, respectively. In contrast, the *GSCORE* and *V/P* (*GSCORE* and *NEGPEG*) strategy performs the best in growth stocks, yielding 14.97, 6.80, and 9.90 percent (14.07, 5.63, and 11.06 percent) hedge returns for the three groups. The differences in hedge returns between the combined strategies and the stand-alone strategies are all positive in the three subsamples. For growth stocks, we see meaningful and statistically significant increases in hedge returns ranging from 4.92 to 11.46 percent. For medium *B/M* stocks, the increases, while

TABLE 6
Controlling for portfolio size

Panel A: Comparison of *FSCORE* & *V/P* and *FSCORE* & *NEGPEG* with 25 groups of *FSCORE*

25 groups of *FSCORE*						Quintiles of *FSCORE* and *V/P*					Quintiles of *FSCORE* and *NEGPEG*				
Group	*N*	*FSCORE*	*V/P*	*NEGPEG*	RET_1	Group	*N*	*FSCORE*	*V/P*	RET_1	Group	*N*	*FSCORE*	*NEGPEG*	RET_1
1	4,113	2.85	1.01	−1.41	−4.57%	LL (1, 1)	4,115	3.47	0.41	−5.00%	LL (1, 1)	4,114	3.52	−3.15	−5.12%
25	4,119	6.78	0.90	−1.94	5.27%	HH (5, 5)	4,134	6.17	1.66	10.06%	HH (5, 5)	4,134	6.15	−0.56	9.85%
25 − 1		3.93	−0.11	−0.53	9.84%	HH − LL		2.70	1.25	15.06%	HH − LL		2.63	2.59	14.97%
		(336.47)	(−6.33)	(−13.75)	(6.77)			(191.75)	(89.55)	(10.27)			(187.1)	(76.66)	(10.4)
						Diff. from 25 groups of *FSCORE*				5.22%	Diff. from 25 groups of *FSCORE*				5.13%
										(2.53)					(2.51)

Panel B: Comparison of *GSCORE* & *V/P* and *GSCORE* & *NEGPEG* with 25 groups of *GSCORE*

25 groups of *GSCORE*						Quintiles of *GSCORE* and *V/P*					Quintiles of *GSCORE* and *NEGPEG*				
Group	*N*	*GSCORE*	*V/P*	*NEGPEG*	RET_1	Group	*N*	*GSCORE*	*V/P*	RET_1	Group	*N*	*GSCORE*	*NEGPEG*	RET_1
1	4,115	1.66	1.20	−1.19	−4.33%	LL (1, 1)	4,116	2.42	0.44	−7.79%	LL (1, 1)	4,116	2.44	−3.03	−6.13%
25	4,119	6.01	0.62	−2.78	4.75%	HH (5, 5)	4,134	5.21	1.29	7.09%	HH (5, 5)	4,134	5.20	−0.74	7.25%
25 − 1		4.35	−0.58	−1.59	9.08%	HH − LL		2.79	0.85	14.88%	HH − LL		2.76	2.29	13.38%
		(578.69)	(−34.65)	(−38.52)	(8.05)			(288.64)	(78.66)	(11.55)			(293.88)	(66.33)	(10.37)
						Diff. from 25 groups of *GSCORE*				5.80%	Diff. from 25 groups of *GSCORE*				4.30%
										(3.38)					(2.50)

(The table is continued on the next page.)

TABLE 6 (continued)

Panel C: Comparison of *FSCORE* & *V/P* and *GSCORE* & *V/P* with 25 groups of *V/P*

25 groups of *V/P*						Quintiles of *FSCORE* and *V/P*						Quintiles of *GSCORE* and *V/P*					
Group	*N*	*V/P*	*FSCORE*	*GSCORE*	RET_1	Group	*N*	*V/P*	*FSCORE*	RET_1	Group	*N*	*V/P*	*GSCORE*	RET_1
1	4,115	0.22	4.96	4.11	−3.34%	LL (1, 1)	4,115	0.41	3.47	−5.00%	LL (1, 1)	4,116	0.44	2.42	−7.79%
25	4,119	2.80	4.72	3.24	6.88%	HH (5, 5)	4,134	1.66	6.17	10.06%	HH (5, 5)	4,134	1.29	5.21	7.09%
25 − 1		2.58	−0.24	−0.87	10.22%	HH − LL		1.25	2.70	15.06%	HH − LL		0.85	2.79	14.88%
		(107.86)	(−9.77)	(−37.93)	(6.62)			(89.55)	(191.75)	(10.27)			(78.66)	(288.64)	(11.55)
						Diff. from 25 groups of *V/P*				4.84%	Diff. from 25 groups of *V/P*				4.66%
										(2.27)					(2.31)

Panel D: Comparison of *FSCORE* & *NEGPEG* and *GSCORE* & *NEGPEG* with 25 groups of *NEGPEG*

25 groups of *NEGPEG*						Quintiles of *FSCORE* and *NEGPEG*					Quintiles of *GSCORE* and *NEGPEG*				
Group	*N*	*NEGPEG*	*FSCORE*	*GSCORE*	RET_1	Group	*N*	*NEGPEG*	*FSCORE*	RET_1	Group	*N*	*NEGPEG*	*GSCORE*	RET_1
1	4,180	−6.44	5.09	4.33	−1.64%	LL (1, 1)	4,114	−3.15	3.52	−5.12%	LL (1, 1)	4,116	−3.03	2.44	−6.13%
25	4,119	−0.30	4.69	3.23	8.06%	HH (5, 5)	4,134	−0.56	6.15	9.85%	HH (5, 5)	4,134	−0.74	5.20	7.25%
25 − 1		6.14	−0.40	−1.10	9.70%	HH − LL		2.59	2.63	14.97%	HH − LL		2.29	2.76	13.38%
		(135.62)	(−16.40)	(−47.52)	(6.45)			(76.66)	(187.1)	(10.4)			(66.33)	(293.88)	(10.37)
						Diff. from 25 groups of *NEGPEG*				5.27%	Diff. from 25 groups of *NEGPEG*				3.68%
										(2.53)					(2.51)

Notes: Sample consists of 103,494 observations from 1974 to 2015. This table compares hedge returns of the combined strategies with stand-alone strategies formed in 25 equal-sized groups. See section 3 for the definitions of the variables. Figures in parentheses are *t*-statistics for difference of means computed using a pooled estimate of standard error.

TABLE 7
Performance of the combined strategies in value and growth stocks

Strategies	Growth (low *B/M*)	Medium *B/M*	Value (high *B/M*)
FSCORE	7.14%	7.03%	9.33%
	(7.09)	(7.89)	(8.65)
GSCORE	9.15%	5.33%	6.22%
	(10.19)	(6.24)	(6.22)
V/P	4.70%	2.74%	6.17%
	(4.71)	(2.95)	(5.68)
NEGPEG	2.61%	2.15%	6.82%
	(2.54)	(2.36)	(6.57)
FSCORE and *V/P*	13.21%	12.18%	14.42%
	(5.70)	(5.11)	(5.41)
GSCORE and *V/P*	14.97%	6.80%	9.90%
	(7.46)	(3.79)	(3.8)
FSCORE and *NEGPEG*	12.42%	10.50%	14.20%
	(4.63)	(4.54)	(6.04)
GSCORE and *NEGPEG*	14.07%	5.63%	11.06%
	(7.11)	(3.04)	(4.94)
Improvement			
FSCORE and *V/P* vs. *FSCORE*	6.07%	5.15%	5.09%
	(2.40)	(2.02)	(1.77)
FSCORE and *V/P* vs. *V/P*	8.50%	9.43%	8.25%
	(3.37)	(3.69)	(2.87)
GSCORE and *V/P* vs. *GSCORE*	5.83%	1.47%	3.68%
	(2.65)	(0.74)	(1.32)
GSCORE and *V/P* vs. *V/P*	10.27%	4.06%	3.73%
	(4.58)	(2.01)	(1.32)
FSCORE and *NEGPEG* vs. *FSCORE*	5.28%	3.47%	4.87%
	(1.84)	(1.40)	(1.88)
FSCORE and *NEGPEG* vs. *NEGPEG*	9.81%	8.35%	7.38%
	(3.42)	(3.36)	(2.87)
GSCORE and *NEGPEG* vs. *GSCORE*	4.92%	0.30%	4.84%
	(2.27)	(0.15)	(1.97)
GSCORE and *NEGPEG* vs. *NEGPEG*	11.46%	3.48%	4.23%
	(5.14)	(1.68)	(1.71)

Notes: Sample consists of 103,494 observations from 1974 to 2015. This table reports mean hedge returns of stand-alone strategies, the combined strategies, and the pairwise comparisons between stand-alone and combined strategies in terciles partitioned on *B/M* ratio. Figures in parentheses are *t*-statistics computed using a pooled estimate of standard error.

positive, are not always statistically significant. For value stocks, the increases are all statistically significant, except for the *GSCORE* and *V/P* strategy.

To summarize, Table 7 shows that while the combined strategies generally outperform the stand-alone strategies, the improvements are more pronounced when the quality-driven strategies are implemented in the appropriate context (i.e., *FSCORE* for high *B/M* stocks and *GSCORE* for low *B/M* stocks).

Partition analysis: Controlling for information environment and transaction costs

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. These partitions are related to the information environment and transaction costs, as well as the implementability of the hedge strategies. The hedge return of each strategy is presented in Table 8.

The first set of columns presents the returns by partitions of analyst following. Each of the four stand-alone 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 compute intrinsic value. Furthermore, the combined strategies generate economically and statistically significant improvements in hedge returns in both partitions, ranging from 5.22 to 9.68 percent.[9]

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—the *FSCORE* strategy generates 9.18 and 4.53 percent in small and large firms, respectively. However, for both size groups 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 7.02 and 7.59 percent, respectively, relative to the stand-alone *FSCORE* and *V/P* strategies.

The third set of columns partitions the sample by listing exchange. This partition is also related to the implementability of the strategies, as it is easier and cheaper to short NYSE/AMEX stocks than 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 NASDAQ as well as NYSE/AMEX stocks.

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 for firms with high level of institutional ownership by 10.06 and 6.11 percent, respectively, relative to the stand-alone *FSCORE* and *V/P* strategies.

Across the multiple partitions, hedge returns are generally stronger in firms with weaker information environments, consistent with the interpretation in Piotroski (2000) that investor inattention to fundamentals drives the success of fundamental analysis. In addition, hedge returns are also stronger in firms where transaction costs are higher (e.g., smaller firms, NASDAQ stocks, and firms with lower institutional investment). However, the strong performance of the combined strategies in the partitions with low transaction costs (covered firms, large firms, NYSE/AMEX firms, and firms with high institutional ownership) increases our confidence that these strategies are implementable.

Hedge returns across time

While the tables thus far present hedge returns for annual portfolios, the results are pooled over the sample period. We next examine the performance of the strategies across time. Annual hedge returns for both the individual and combined strategies are presented in panel A of Table 9. Although all four strategies generate positive hedge returns for the majority of the sample period, the incidence of negative hedge returns is 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. However, it is striking to see that in recent years (2002 and later), all the strategies generate weaker hedge returns.

9. We use cross-sectional forecasts to estimate *V/P* and *NEGPEG* for our entire sample for consistency. If we use analyst forecasts to calculate *V/P* and *NEGPEG* for firms with analyst following, the results are similar (almost identical return spreads for *NEGPEG* and slightly higher return spreads for *V/P* using analyst forecasts). We use cross-sectional forecasts for all firms for consistency (across followed and non-followed firms) and parsimony.

TABLE 8
Hedge returns by partitions on analyst following, size, listing exchange, and institutional ownership

	Analyst following		Size		Listing exchange		Institutional investment	
Strategies	No	Yes	Small	Large	NYSE/ AMEX	NASDAQ	Low	High
FSCORE	7.93%	6.39%	9.18%	4.53%	5.80%	7.48%	7.93%	3.00%
	(6.83)	(10.08)	(9.71)	(7.34)	(8.69)	(7.87)	(8.45)	(3.57)
GSCORE	8.56%	5.48%	9.08%	4.05%	3.15%	8.86%	6.29%	0.36%
	(7.74)	(9.54)	(10.05)	(7.31)	(5.13)	(9.67)	(6.99)	(0.47)
V/P	8.48%	4.62%	7.19%	3.96%	5.91%	6.68%	10.78%	6.96%
	(6.99)	(7.33)	(7.08)	(6.41)	(8.37)	(6.73)	(10.85)	(8.62)
NEGPEG	7.47%	4.06%	7.19%	2.52%	5.60%	6.88%	9.92%	10.38%
	(6.34)	(6.46)	(7.28)	(4.25)	(8.02)	(7.05)	(9.88)	(12.62)
FSCORE and *V/P*	16.51%	13.88%	16.98%	11.55%	12.90%	16.53%	21.08%	13.06%
	(5.57)	(9.04)	(7.20)	(8.12)	(6.91)	(7.33)	(9.45)	(5.78)
GSCORE and *V/P*	18.16%	12.28%	18.34%	10.18%	10.24%	19.18%	20.72%	8.55%
	(6.44)	(8.94)	(8.62)	(7.56)	(6.16)	(9.56)	(9.84)	(4.36)
FSCORE and *NEGPEG*	14.16%	13.71%	17.76%	11.38%	13.84%	15.37%	21.38%	16.94%
	(5.40)	(8.89)	(7.49)	(8.26)	(7.63)	(6.82)	(9.45)	(7.53)
GSCORE and *NEGPEG*	13.78%	11.73%	18.12%	9.58%	9.51%	18.21%	18.42%	11.40%
	(5.51)	(8.37)	(8.32)	(7.30)	(5.79)	(9.23)	(8.93)	(5.80)
Improvement								
FSCORE and *V/P*	8.58%	7.49%	7.80%	7.02%	7.11%	9.05%	13.14%	10.06%
vs. *FSCORE*	(2.69)	(4.51)	(3.07)	(4.53)	(3.59)	(3.70)	(5.43)	(4.18)
FSCORE and *V/P*	8.04%	9.26%	9.80%	7.59%	7.00%	9.84%	10.29%	6.11%
vs. *V/P*	(2.51)	(5.58)	(3.81)	(4.89)	(3.51)	(4.00)	(4.21)	(2.54)
GSCORE and *V/P*	9.60%	6.80%	9.26%	6.13%	7.09%	10.32%	14.43%	8.18%
vs. *GSCORE*	(3.17)	(4.57)	(4.00)	(4.21)	(4.00)	(4.68)	(6.30)	(3.89)
GSCORE and *V/P*	9.68%	7.66%	11.15%	6.22%	4.33%	12.49%	9.93%	1.59%
vs. *V/P*	(3.16)	(5.07)	(4.73)	(4.20)	(2.40)	(5.58)	(4.27)	(0.75)
FSCORE and *NEGPEG*	6.23%	7.32%	8.57%	6.85%	8.05%	7.89%	13.44%	13.95%
vs. *FSCORE*	(2.17)	(4.39)	(3.36)	(4.54)	(4.16)	(3.23)	(5.49)	(5.80)
FSCORE and *NEGPEG*	6.69%	9.65%	10.57%	8.86%	8.24%	8.49%	11.46%	6.56%
vs. *NEGPEG*	(2.33)	(5.79)	(4.12)	(5.91)	(4.24)	(3.46)	(4.63)	(2.74)
GSCORE and *NEGPEG*	5.22%	6.25%	9.04%	5.53%	6.36%	9.35%	12.13%	11.03%
vs. *GSCORE*	(1.91)	(4.13)	(3.83)	(3.88)	(3.62)	(4.30)	(5.39)	(5.23)
GSCORE and *NEGPEG*	6.31%	7.67%	10.94%	7.06%	3.91%	11.33%	8.50%	1.02%
vs. *NEGPEG*	(2.28)	(4.99)	(4.57)	(4.90)	(2.19)	(5.15)	(3.70)	(0.48)

Notes: Sample consists of 103,494 observations from 1974 to 2015. This table reports mean hedge returns of stand-alone strategies, the combined strategies, and the pairwise comparisons between stand-alone and combined strategies. The results are presented in partitions by analyst following, firm size (market capitalization), exchange listing, and institutional ownership. Figures in parentheses are *t*-statistics computed using a pooled estimate of standard error.

Panel B of Table 9 reports summary statistics of annual hedge returns for all the strategies. Across the entire period, the combined strategies significantly outperform the individual strategies. For example, the *FSCORE* and *V/P* combined strategy earns average annual hedge returns of 14.63 percent, compared to 6.38 percent for *FSCORE* and 7.04 percent for *V/P*. Further, the Sharpe ratio for the combined strategy, at 1.08, is marginally higher than the Sharpe ratio for *FSCORE* (1.05) and considerably higher than the Sharpe ratio for *V/P* (0.48). The *GSCORE* and *V/P* combined strategy earns average annual hedge returns of 14.11 percent (Sharpe ratio = 1.03), compared to 5.23 percent for *GSCORE* (Sharpe ratio = 0.54) and 7.04 percent for *V/P* (Sharpe ratio = 0.48). Similar results are observed in the remaining two combined strategies. The increase in hedge returns and Sharpe ratios suggests that the additional hedge returns are not merely the result of incurring additional risk. The combined strategies also reduce the incidence of negative returns. Over the 42 years in the sample, the stand-alone strategies earn negative returns in 6–14 years. In contrast, the combined strategies earn negative returns in only 4–8 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.

We next partition our sample into an early period (1974–2001) and a later period (2002–2015) and compare the performance of the strategies in these two periods. The performance of all strategies declines sharply after 2002. For example, the mean hedge return and Sharpe ratio of the *FSCORE* strategy are 8.33 percent and 1.69, respectively, in the early period, but decline to 2.48 percent and 0.38, respectively, in the later period. We observe a similar pattern for the *GSCORE* strategy. The decline in performance of the two value strategies is of a lesser magnitude. For example, the mean hedge return and Sharpe ratio of the *V/P* strategy are 8.34 percent and 0.54 in the early period and 4.44 percent and 0.36, respectively, in the later period. The decline in the performance of the individual strategies also affects the combined strategies in the later period. Although all the combined strategies still generate higher hedge returns, the improvements are only statistically significant between *GSCORE* based combined strategies and the *GSCORE* stand-alone strategy.

Figure 1 presents the results graphically by summarizing the sample into six periods of seven years each. In the first four periods, all strategies generate strong returns, with economically meaningful incremental returns for the combined strategies. However, the performance of all strategies declines in the two most recent periods. This mirrors the findings of Green et al. (2017), who find a marked decline in the characteristics-based predictability of the U.S. stock returns since 2002. They surmise that this decline is caused by sophisticated institutional investors (hedge funds) arbitraging away any excess returns, similar to what Green et al. (2011) document for the decline in the accruals anomaly.

A factor that might have contributed to the greater willingness and ability of investors to exploit potential mispricing is the emergence of exchange traded funds (ETFs). Huang et al. (2018) show that ETFs are especially popular with hedge funds, which use them to get systematic long or short exposure to thinly traded stocks. Glosten et al. (2017) and Bhojraj et al. (2018) show that ETF activity leads to timelier incorporation of systematic earnings information and reduced post-earnings announcement drift. Interestingly, these papers document that ETFs started to rise exponentially in assets under management and trading volume around 2002, when the decline in return predictability began.

To test whether ETFs had a potential impact on the efficacy of fundamental analysis, we partition the 2002–2015 subsample into quintiles based on ETF ownership as a percentage of shares outstanding. As ETF ownership is also likely to be associated with size, we subtract the median ETF ownership of the contemporaneous size quintile and then create quintiles based on the adjusted ETF ownership. We then examine the efficacy of the combined strategies across the five quintiles and also compare them to the pre-2002 period, which was also largely a pre-ETF period. The results are not tabulated for brevity but are presented graphically in Figure 2. While the hedge returns for all ETF quintiles in the later period are lower than the average hedge return in the early period, the reduction is especially pronounced for the top quintile of ETF ownership. This is consistent with ETFs reducing the efficacy of fundamental analysis and corroborates the results in Green et al. (2011).

TABLE 9
Performance of hedge strategies across time

Panel A: Annual hedge returns across time

YEAR	*FSCORE* (%)	*GSCORE* (%)	*V/P* (%)	*NEGPEG* (%)	*FSCORE* and *V/P* (%)	*GSCORE* and *V/P* (%)	*FSCORE* and *NEGPEG* (%)	*GSCORE* and *NEGPEG* (%)
1974	12.0	0.4	11.7	18.4	16.5	−10.5	19.1	11.0
1975	8.9	5.2	23.5	16.7	20.9	27.4	18.8	29.2
1976	4.7	−4.9	20.6	12.4	29.8	8.9	23.8	4.3
1977	9.4	16.3	−2.9	2.5	4.6	12.8	13.7	10.2
1978	7.0	−3.6	−4.6	−5.3	4.6	−4.1	7.5	−7.9
1979	11.6	−1.9	−15.4	−9.0	−10.1	−17.9	1.8	−3.8
1980	9.0	19.1	−6.9	−4.8	3.7	9.9	11.3	5.3
1981	5.0	5.5	24.8	17.9	26.2	35.4	26.9	30.5
1982	11.8	17.7	−7.3	2.3	20.9	22.2	35.0	23.5
1983	4.9	−4.8	25.1	17.8	31.9	22.1	24.6	17.7
1984	3.1	−6.0	26.7	15.1	37.3	35.8	28.9	32.5
1985	3.2	−0.6	9.1	0.9	16.0	8.6	18.5	−1.0
1986	8.3	11.5	7.0	5.8	23.4	23.6	19.9	8.0
1987	7.1	3.7	16.4	11.7	30.0	28.6	27.8	17.6
1988	9.5	−1.2	18.6	15.6	28.4	17.3	26.7	12.3
1989	11.3	8.4	−10.5	−5.6	5.7	−1.8	9.3	5.0
1990	9.2	10.8	4.3	3.3	3.1	25.1	2.7	27.7
1991	2.1	6.3	13.2	7.0	22.7	11.6	12.0	14.0
1992	4.2	−0.9	14.5	16.5	19.7	15.4	22.1	14.3
1993	4.3	9.5	10.9	10.4	10.0	26.0	8.0	26.6
1994	9.5	16.2	−5.3	−0.9	5.9	16.8	18.0	19.7
1995	8.3	−3.6	0.8	5.2	29.1	−1.4	26.0	3.0
1996	5.9	1.0	26.1	18.6	27.5	30.9	21.6	27.2
1997	5.5	0.2	15.8	11.2	35.3	18.5	23.8	8.9
1998	15.3	19.6	−3.8	0.3	13.0	27.9	22.7	31.2
1999	27.4	39.1	−33.9	−23.0	18.4	22.9	20.1	28.8

(The table is continued on the next page.)

TABLE 9 (continued)

Panel A: Annual hedge returns across time

YEAR	*FSCORE* (%)	*GSCORE* (%)	*V/P* (%)	*NEGPEG* (%)	*FSCORE* and *V/P* (%)	*GSCORE* and *V/P* (%)	*FSCORE* and *NEGPEG* (%)	*GSCORE* and *NEGPEG* (%)
2000	9.2	17.5	24.9	14.5	21.2	38.2	17.2	23.0
2001	5.8	10.8	30.3	23.8	41.5	39.0	34.8	38.7
2002	4.8	11.3	−13.4	−14.7	−9.3	4.9	−2.6	0.7
2003	−1.6	−3.3	20.4	20.0	9.5	18.5	9.2	18.7
2004	2.6	−11.2	21.3	18.3	18.7	6.9	13.8	0.8
2005	10.4	−5.5	5.1	10.3	24.0	5.0	18.2	6.0
2006	10.5	5.0	1.8	4.9	2.6	−1.1	8.3	−4.0
2007	14.7	7.2	−7.3	−8.5	22.0	1.7	8.4	−1.2
2008	7.9	18.6	−14.7	−17.2	−12.1	11.6	−11.5	13.3
2009	−4.3	3.7	22.1	19.0	13.7	28.1	18.1	28.8
2010	−3.5	−2.3	−2.5	3.5	3.8	−3.9	−0.5	−1.5
2011	−0.1	3.5	5.9	7.8	11.3	8.2	14.6	11.0
2012	−8.0	−8.8	19.6	16.2	−1.1	2.4	0.6	0.0
2013	1.4	1.9	3.4	1.5	5.3	3.7	13.4	−0.1
2014	−1.7	5.4	−2.1	−1.1	−6.6	2.1	−9.1	5.4
2015	1.7	2.8	2.6	6.0	−4.6	15.1	0.3	13.1

(The table is continued on the next page.)

TABLE 9 (continued)

Panel B: Analysis of annual hedge returns

	FSCORE	*GSCORE*	*V/P*	*NEGPEG*	*FSCORE* and *V/P*	*GSCORE* and *V/P*	*FSCORE* and *NEGPEG*	*GSCORE* and *NEGPEG*
Entire time period								
Mean (%)	6.38	5.23	7.04	6.32	14.63	14.11	14.85	13.06
SD (%)	6.08	9.75	14.55	11.02	13.60	13.70	10.98	12.20
Sharpe ratio	1.05	0.54	0.48	0.57	1.08	1.03	1.35	1.07
Negative years	6/42	14/42	14/42	10/42	6/42	7/42	4/42	8/42
Improvement vs. *FSCORE* or *GSCORE*					8.26%	9.62%	8.47%	7.83%
					(3.59)	(3.71)	(4.38)	(3.25)
Improvement vs. *V/P* or *NEGPEG*					7.59%	7.81%	8.53%	6.74%
					(2.47)	(2.53)	(3.56)	(2.66)
Early period (1974–2001)								
Mean (%)	8.33	6.83	8.34	7.11	19.19	17.47	19.37	16.33
SD (%)	4.91	10.31	15.55	10.63	12.32	14.66	8.62	12.26
Sharpe ratio	1.69	0.66	0.54	0.67	1.56	1.19	2.25	1.33
Negative years	0/28	9/28	9/28	6/28	1/28	5/28	0/28	3/28
Improvement vs. *FSCORE* or *GSCORE*					10.86%	10.64%	11.05%	9.50%
					(4.33)	(3.14)	(5.89)	(3.14)
Improvement vs. *V/P* or *NEGPEG*					10.85%	9.13%	12.26%	9.22%
					(2.89)	(2.16)	(4.74)	(3.01)
Later period (2002–2015)								
Mean (%)	2.48	2.02	4.44	4.72	5.52	7.38	5.80	6.50
SD (%)	6.48	7.89	12.42	12.01	11.57	8.51	9.67	9.39
Sharpe ratio	0.38	0.26	0.36	0.39	0.48	0.87	0.60	0.69
Negative years	6/14	5/14	5/14	4/14	5/14	2/14	4/14	5/14
Improvement vs. *FSCORE* or *GSCORE*					3.04%	5.35%	3.33%	4.48%
					(1.21)	(2.44)	(1.51)	(1.93)
Improvement vs. *V/P* or *NEGPEG*					1.08%	2.94%	1.08%	1.78%
					(0.34)	(1.03)	(0.37)	(0.62)

Notes: Sample consists of 103,494 observations from 1974 to 2015. This table reports the summary statistics of annual hedge returns of stand-alone strategies and the combined strategies. Sharpe Ratio is the ratio of the time series mean to the time series SD of hedge returns.

Figure 1 Time-series performance of individual and combined strategies

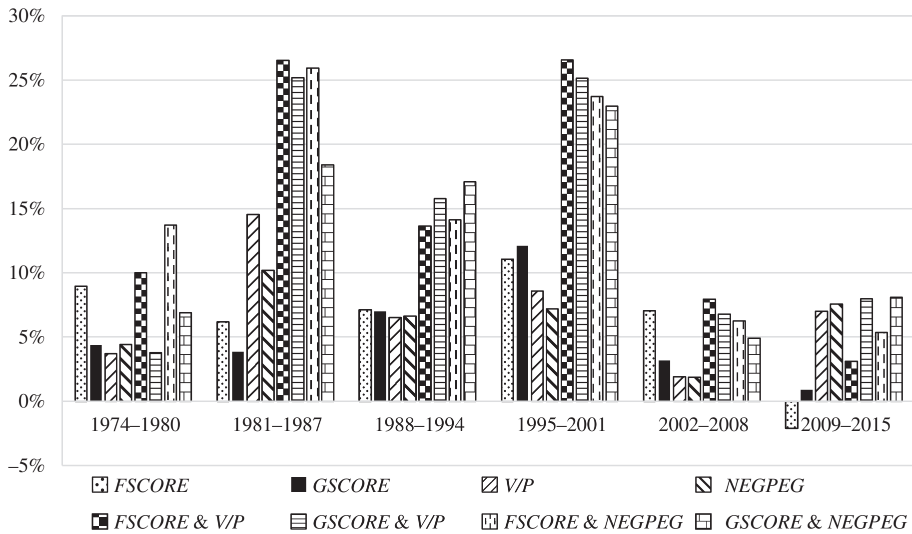
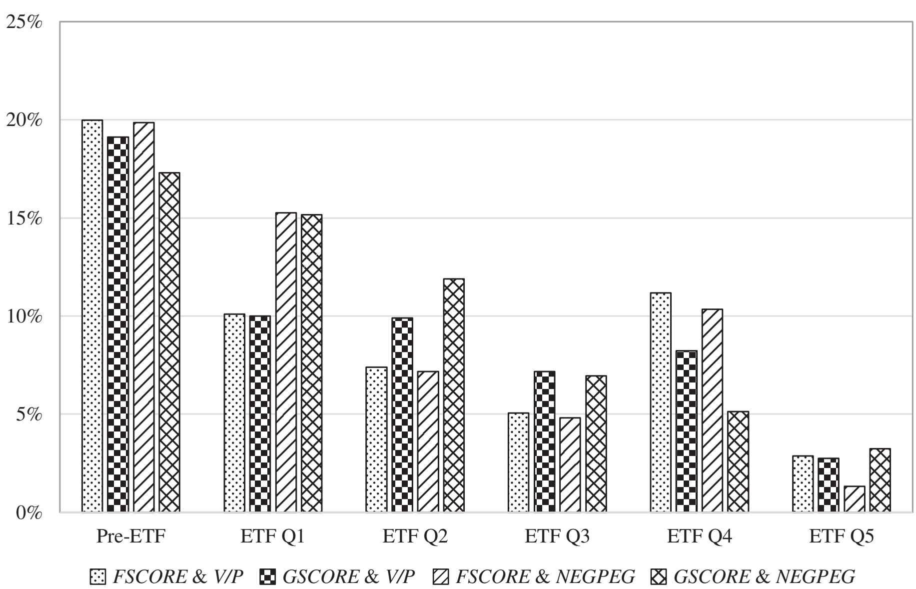


Figure 2 The impact of ETF ownership on hedge returns of combined strategies



5. Alternative explanations

In this section, we examine the alternative explanations for our results. Specifically, we examine whether our results are robust to controlling for known risk factors, other determinants of stock returns, and the incongruent value-glamour strategy of Piotroski and So (2012).

Controlling for risk

To confirm that additional risk does not drive the hedge returns, we run multifactor portfolio models based on the Carhart (1997) four-factor and Fama and French (2015) five-factor models.

We also control for the *QMJ* factor from Asness et al. (2013).[10] We first create hedge portfolios based on the relevant strategies (e.g., long/short in the top/bottom quintile) and run calendar time portfolio regressions 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 10.

Panel A presents the results for the individual strategies. Among the four stand-alone strategies, *FSCORE* generally has the highest alpha. For example, the four-factor adjusted alpha is 0.49 (6.04 percent annualized) for *FSCORE*, 0.41 (5.03 percent annualized) for *GSCORE*, 0.47 (5.79 percent annualized) for *V/P*, and 0.43 (5.28 percent annualized) for *NEGPEG*.[11] The *QMJ* factor loads strongly and positively for the quality strategies (*FSCORE* and *GSCORE*) and negatively for the value strategies (*V/P* and *NEGPEG*), consistent with quality and value working against each other. It is worth noting that the R^2s vary significantly across the strategies. For example, the R^2s for *FSCORE* are 20.2, 16.9, and 21.4 percent for the Carhart (1997) four-factor, Fama and French (2015) five-factor, and Carhart plus QMJ factor models, respectively. In contrast, the corresponding R^2s for *V/P* are 59.0, 58.6, and 59.6 percent, respectively.

Panel B shows that the combined strategies generate substantially higher alphas than the stand-alone strategies. For example, the *FSCORE* and *V/P*, *GSCORE* and *V/P*, *FSCORE* and *NEGPEG*, and *GSCORE* and *NEGPEG* strategies have four-factor adjusted alphas of 1.04 (13.2 percent annualized), 1.06 (13.5 percent annualized), 1.00 (12.7 percent annualized), and 0.92 (11.6 percent annualized), respectively. Results are similar for the other two risk models. Panel C presents the increase in alphas and shows that combining the strategies increases alpha significantly in all comparisons and across all risk models. Hence, the results in Table 10 confirm that the increased returns from combining quality-driven and value-driven approaches are robust to controls for risk.

Controlling for other known determinants of returns

Green et al. (2017) examine 94 determinants of stock returns documented by prior studies and find that only 12 of them are reliably independent determinants in non-microcap stocks—book-to-market, cash, change in the number of analysts, earnings announcement return, one-month momentum, change in six-month momentum, number of consecutive quarters with earnings higher than the same quarter a year ago, annual R&D to market cap, return volatility, share turnover, volatility of share turnover, and zero trading days. In this section, we examine if our results persist after controlling for these 12 independent determinants of stock returns identified by Green et al.

We run monthly weighted least squares regressions (weighted by market cap) using the 1,104,732 monthly observations between January 1980 and December 2015 (i.e., 432 monthly regressions) that are in the intersection of our sample and the sample in Green et al. (2017).[12] The regressions are summarized using the Fama and MacBeth (1973) procedure. We sort firms into quintiles based on each stand-alone strategy and standardize the quintile rankings to lie between zero and one. We then take the average of the standardized quintile rankings of two stand-alone strategies to form the combined strategy (*COMBINE*). The coefficient on *COMBINE* can be interpreted as the hedge return for that strategy.

Similar to Green et al. (2017), we begin by first controlling for the characteristic equivalents of the factors in Carhart (1997), Fama and French (2015), and Hou et al. (2015)—book-to-market,

10. The *QMJ* factors are downloaded from the AQR website: https://www.aqr.com/library/data-sets/quality-minus-junk-factors-monthly.
11. The decline in the performance of *V/P* and *NEGPEG* relative to the portfolio tests in prior tables can be attributed to the strong loadings on size (*SMB*) and book-to-market (*HML*).
12. We thank Jeremiah Green for sharing the data of these variables with us. We do not include change in the number of analysts because this variable is not available prior to 1989 in Green et al. (2017). We set missing values of annual R&D to zero.

TABLE 10
Fama-French regressions for hedge portfolios

Panel A: Fama-French regressions for individual strategies

	Alpha	R_m–R_f	*SMB*	*HML*	*UMD*	*RMW*	*CMA*	*QMJ*	Adj. R^2 (%)
FSCORE	0.49	0.01	−0.06	−0.19	0.10				20.2
	(6.72)	(0.72)	(−2.43)	(−7.38)	(6.28)				
	0.51	0.01	−0.01	−0.27		0.15	0.06		16.9
	(6.75)	(0.51)	(−0.34)	(−7.83)		(4.33)	(1.05)		
	0.42	0.04	−0.02	−0.18	0.09			0.11	21.4
	(5.59)	(2.04)	(−0.70)	(−6.92)	(5.47)			(2.90)	
GSCORE	0.41	0.01	−0.26	−0.21	0.06				23.3
	(4.91)	(0.61)	(−9.42)	(−6.95)	(3.06)				
	0.33	0.04	−0.19	−0.32		0.26	0.15		29.0
	(3.99)	(1.90)	(−6.56)	(−8.55)		(6.91)	(2.70)		
	0.16	0.11	−0.11	−0.16	0.01			0.43	37.6
	(1.99)	(5.80)	(−3.79)	(−6.00)	(0.77)			(10.74)	
V/P	0.47	−0.16	0.41	0.82	0.08				59.0
	(4.40)	(−6.52)	(11.34)	(21.49)	(3.09)				
	0.51	−0.16	0.40	0.72		−0.02	0.17		58.6
	(4.61)	(−6.17)	(10.48)	(14.46)		(−0.41)	(2.23)		
	0.57	−0.20	0.35	0.80	0.09			−0.17	59.6
	(5.10)	(−7.16)	(8.50)	(20.97)	(3.71)			(−2.91)	
NEGPEG	0.43	−0.12	0.66	0.58	0.05				50.1
	(3.65)	(−4.54)	(16.69)	(13.95)	(1.90)				
	0.46	−0.12	0.63	0.48		−0.10	0.22		50.8
	(3.88)	(−4.23)	(15.02)	(8.92)		(−1.86)	(2.63)		
	0.59	−0.19	0.56	0.56	0.08			−0.27	51.9
	(4.86)	(−6.17)	(12.62)	(13.38)	(2.91)			(−4.40)	

Panel B: Fama-French regressions for strategies combining quality and value

	Alpha	R_m–R_f	*SMB*	*HML*	*UMD*	*RMW*	*CMA*	*QMJ*	Adj. R^2 (%)
FSCORE and *V/P*	1.04	−0.16	0.36	0.53	0.17				33.8
	(7.70)	(−5.18)	(8.00)	(11.03)	(5.59)				
	1.10	−0.16	0.39	0.35		0.06	0.25		30.5
	(7.88)	(−4.95)	(7.84)	(5.51)		(0.92)	(2.53)		
	1.12	−0.19	0.31	0.51	0.19			−0.14	34.2
	(7.93)	(−5.46)	(6.05)	(10.65)	(5.89)			(−1.89)	
GSCORE and *V/P*	1.06	−0.19	0.12	0.52	0.12				36.5
	(8.91)	(−7.18)	(3.03)	(12.3)	(4.38)				
	1.02	−0.17	0.18	0.33		0.18	0.30		36.6
	(8.45)	(−6.08)	(4.16)	(6.00)		(3.36)	(3.60)		
	0.89	−0.13	0.22	0.55	0.09			0.29	39.1
	(7.27)	(−4.12)	(5.03)	(13.13)	(3.23)			(4.74)	
FSCORE and *NEGPEG*	1.00	−0.10	0.54	0.33	0.20				30.9
	(7.22)	(−3.33)	(11.7)	(6.77)	(6.26)				
	1.08	−0.10	0.54	0.09		−0.02	0.41		27.8
	(7.52)	(−3.09)	(10.77)	(1.32)		(−0.28)	(4.06)		
	1.15	−0.16	0.45	0.31	0.22			−0.25	32.3
	(7.98)	(−4.59)	(8.61)	(6.26)	(6.95)			(−3.40)	

(The table is continued on the next page.)

TABLE 10 (continued)

Panel B: Fama-French regressions for strategies combining quality and value

	Alpha	$R_m - R_f$	*SMB*	*HML*	*UMD*	*RMW*	*CMA*	*QMJ*	Adj. R^2 (%)
GSCORE and *NEGPEG*	0.92	−0.13	0.35	0.32	0.15				25.3
	(7.32)	(−4.41)	(8.44)	(7.18)	(5.28)				
	0.91	−0.11	0.39	0.08		0.11	0.41		24.4
	(7.07)	(−3.49)	(8.66)	(1.31)		(1.97)	(4.62)		
	0.83	−0.09	0.41	0.34	0.13			0.16	26.0
	(6.29)	(−2.70)	(8.58)	(7.50)	(4.59)			(2.43)	

Panel C: Increase in alpha by combining quality and value

Combined	Stand-alone	FF4	FF5	AQR5	Stand-alone	FF4	FF5	AQR5
FSCORE and *V/P*	*FSCORE*	0.55	0.60	0.69	*V/P*	0.56	0.60	0.55
		(4.15)	(4.40)	(5.06)		(4.81)	(4.98)	(4.44)
GSCORE and *V/P*	*GSCORE*	0.65	0.69	0.73	*V/P*	0.59	0.52	0.32
		(5.41)	(5.7)	(5.83)		(4.85)	(4.23)	(2.64)
FSCORE and *NEGPEG*	*FSCORE*	0.51	0.57	0.72	*NEGPEG*	0.57	0.62	0.55
		(3.48)	(3.87)	(4.79)		(4.98)	(5.21)	(4.63)
GSCORE and *NEGPEG*	*GSCORE*	0.51	0.58	0.67	*NEGPEG*	0.49	0.45	0.23
		(3.69)	(4.17)	(4.68)		(4.11)	(3.71)	(1.97)

Notes: Sample consists of 103,494 observations from 1974 to 2015. Long-short hedge portfolios are formed for the 12 months starting July 1 after the fiscal year-end based on the relevant variables. Hedge returns are regressed on the market ($R_m - R_f$), size (*SMB*), book-to-market (*HML*), momentum (*UMD*), profitability (*RMW*), investment (*CMA*), and quality minus junk (*QMJ*) factors. The regression has 504 monthly observations from July 1974 to June 2016. Figures in parentheses are *t*-statistics.

size, asset growth, operating profitability, return on equity, and 12-month momentum. The results are presented in panel A of Table 11. We observe that our combined strategies strongly predict future returns after controlling for these factors. In addition, all four strategies have *t*-statistics well above the cutoff of 3.00 suggested by Green et al. (2017). Among the four combined strategies, *GSCORE* and *V/P* yields the highest hedge return, with a coefficient on *COMBINE* of 0.72 (*t*-statistic 6.48), equivalent to an annual hedge return of 9.04 percent. The hedge returns of the *FSCORE* and *V/P*, *FSCORE* and *NEGPEG*, and *GSCORE* and *NEGPEG* strategies are 5.90, 5.69, and 8.68 percent, respectively.

In panel B, we regress monthly stock returns on *COMBINE* and the independent determinants in Green et al. (2017). The results show that our combined strategies provide independent information about future stock returns after controlling for these independent determinants. For example, the coefficient on *COMBINE* based on the *FSCORE* and *V/P* strategy is 1.06 (*t*-statistic 11.27), equivalent to an annual hedge return of 13.48 percent.

In panel C, we report the Fama-MacBeth regression coefficient on *COMBINE* of each combined strategy in the early period (1980–2001) and the later period (2002–2015). Consistent with the results in Table 9, we observe a decline in performance of our combined strategies in the later period. However, it is worth noting that our combined strategies still generate positive hedge returns that are mostly significant in this period. Green et al. (2017) find that the number of independent determinants of stock returns falls from 12 in the early period to only 2 in the later period. In the context of the general decline of characteristics-based strategies, our combined strategies still generate significant hedge returns in recent years.

TABLE 11
Firm-level Fama-MacBeth characteristic regressions

Panel A: Controlling for characteristic risk factors

	FSCORE and *V/P*	*GSCORE* and *V/P*	*FSCORE* and *NEGPEG*	*GSCORE* and *NEGPEG*
Intercept	1.66	1.64	1.56	1.47
	(2.99)	(2.97)	(2.94)	(2.74)
COMBINE	**0.48**	**0.72**	**0.46**	**0.70**
	(4.54)	**(6.48)**	**(4.43)**	**(6.27)**
B/M	0.03	0.00	0.03	0.02
	(0.26)	(0.00)	(0.34)	(0.21)
MVE	−0.07	−0.08	−0.06	−0.07
	(−2.19)	(−2.40)	(−1.99)	(−2.02)
AGR	−0.73	−0.71	−0.74	−0.72
	(−8.21)	(−8.31)	(−7.77)	(−7.98)
OPERPROF	0.07	0.06	0.07	0.06
	(2.26)	(2.05)	(2.37)	(2.25)
ROEQ	2.57	2.61	2.69	2.73
	(5.27)	(5.28)	(5.36)	(5.45)
MOM12M	0.55	0.56	0.54	0.54
	(2.75)	(2.79)	(2.72)	(2.73)
Adj. R^2 (%)	3.41	3.41	3.38	3.38
Annualized abnormal return (%)	5.90	9.04	5.69	8.68

Panel B: Controlling for determinants of stock returns in Green et al. (2017)

	FSCORE and *V/P*	*GSCORE* and *V/P*	*FSCORE* and *NEGPEG*	*GSCORE* and *NEGPEG*
Intercept	0.81	0.78	0.85	0.82
	(4.17)	(3.95)	(4.44)	(4.23)
COMBINE	**1.06**	**1.01**	**1.13**	**1.05**
	(11.27)	**(9.19)**	**(10.97)**	**(9.31)**
B/M	0.08	0.14	0.07	0.14
	(1.08)	(1.74)	(0.87)	(1.70)
CASH	0.92	1.01	0.83	0.94
	(4.32)	(4.75)	(3.94)	(4.42)
CHMOM	−0.07	−0.08	−0.06	−0.08
	(−0.75)	(−0.97)	(−0.70)	(−0.92)
EAR	1.88	1.92	1.88	1.91
	(6.74)	(6.89)	(6.73)	(6.86)
MOM1M	−3.85	−3.84	−3.80	−3.81
	(−9.50)	(−9.49)	(−9.38)	(−9.41)
NINCR	0.11	0.11	0.11	0.11
	(7.08)	(7.21)	(7.01)	(7.10)
RD_MVE	3.98	2.97	3.81	2.85
	(4.98)	(3.58)	(4.77)	(3.50)
RETVOL	−16.09	−15.05	−17.75	−16.44
	(−3.97)	(−3.74)	(−4.41)	(−4.05)
STD_TURN	0.08	0.08	0.08	0.08
	(8.64)	(8.58)	(8.57)	(8.51)

(The table is continued on the next page.)

TABLE 11 (continued)

Panel B: Controlling for determinants of stock returns in Green et al. (2017)

	FSCORE and *V/P*	*GSCORE* and *V/P*	*FSCORE* and *NEGPEG*	*GSCORE* and *NEGPEG*
TURN	−0.41	−0.41	−0.41	−0.41
	(−5.31)	(−5.29)	(−5.30)	(−5.24)
ZEROTRADE	−0.02	−0.02	−0.03	−0.03
	(−1.15)	(−1.16)	(−1.34)	(−1.31)
Adj. R^2 (%)	4.96	4.96	4.95	4.94
Annualized abnormal return (%)	13.48	12.78	14.41	13.33

Panel C: Coefficient on *COMBINE* partitioned by time

	FSCORE and *V/P*	*GSCORE* and *V/P*	*FSCORE* and *NEGPEG*	*GSCORE* and *NEGPEG*
Controlling for risk characteristics				
Early period	0.597	0.904	0.532	0.819
(1980–2001)	(4.41)	(6.30)	(4.56)	(5.61)
Later period	0.270	0.405	0.339	0.477
(2002–2015)	(1.63)	(2.33)	(1.67)	(2.88)
Controlling for determinants of returns				
Early period	1.298	1.294	1.366	1.345
(1980–2001)	(11.11)	(9.55)	(10.66)	(9.70)
Later period	0.637	0.500	0.706	0.524
(2002–2015)	(4.17)	(2.78)	(4.22)	(2.82)

Notes: Sample consists of 1,104,732 monthly observations from January 1980 to December 2015 (i.e., 432 monthly regressions). We take the average of the standardized quintile rankings of two stand-alone strategies to form the combined strategy (*COMBINE*). Panel A reports Fama and MacBeth (1973) regressions of monthly returns on *COMBINE*, controlling for the characteristic equivalents of risk factors. Panel B reports Fama and MacBeth (1973) regressions of monthly returns on *COMBINE*, controlling for the independent determinants of stock returns identified by Green et al. (2017): book-to-market (*B/M*), cash (*CASH*), earnings announcement return (*EAR*), one-month momentum (*MOM1M*), change in six-month momentum (*CHMOM*), number of consecutive quarters with earnings higher than the same quarter a year ago (*NINCR*), annual R&D to market cap (*RD_MVE*), return volatility (*RETVOL*), share turnover (*TURN*), volatility of share turnover (*STD_TURN*), and zero trading days (*ZEROTRADE*). See the Appendix in Green et al. for the detailed definition of each variable. Panel C reports the coefficients on *COMBINE* from Fama-MacBeth regressions in the early period (1980–2001) and later period (2002–2015). We run Fama-MacBeth weighted least squares regressions with market cap as weight as suggested by Green et al. Figures in parentheses are *t*-statistics. Bold indicates variables of interest.

Comparison with the incongruent value-glamour strategy of Piotroski and So (2012)

Piotroski and So (2012) show that returns to *FSCORE* can be enhanced by further conditioning on the *B/M* ratio. While the *B/M* ratio is not solely a measure of cheapness and also reflects other factors such as risk, growth, and accounting conservatism, it is likely correlated to our measures of cheapness.[13] We next show that our results are incremental to Piotroski and So (2012). The results are not tabulated for brevity.

13. The Pearson (Spearman) correlation between *V/P* and *B/M* is 0.69 (0.73), while the Pearson (Spearman) correlation between *NEGPEG* and *B/M* is 0.42 (0.71).

We begin with a simplified replication of their approach by dividing our sample independently into terciles based on the *B/M* ratio and *FSCORE.* A strategy that goes long in value firms with high *FSCORE* and short in growth firms with low *FSCORE* generates mean hedge returns of 12.1 percent, significantly greater than a long-short strategy solely on the basis of *FSCORE* terciles, which generate mean hedge returns of 5.0 percent. When we further condition on the basis of *V/P*, the hedge returns increase significantly from 12.1 to 15.6 percent, an increase of 3.5 percent (*t*-statistic 1.96). However, *B/M* increases on the long side (from 1.07 to 1.44) and decreases on the short side (from 0.37 to 0.29), suggesting that conditioning on *V/P* might simply be the same as finer conditioning on *B/M.* To address this concern, we orthogonalize *V/P* from *B/M* ratio, by regressing *V/P* on *B/M* annually and using the residual (*V/P_RES*) as our measure of cheapness. The hedge return to the *FSCORE* strategy conditioned on *V/P_RES* is 15.3 percent, similar to the 15.6 percent using *V/P* and significantly higher than the 12.1 percent using *B/M* (difference of 3.2 percent, *t*-statistic 1.83). This corroborates Frankel and Lee (1998), who show that *V/P* outperforms *B/M.* This is also consistent with the results in Table 7, where the combined strategies work within the value and growth subsets, as well as the results in Table 10, where the alphas remain significant after control for the book-to-market factor (*HML*).

6. Conclusions

Practitioners have long recognized that successful fundamental analysis has two dimensions—the ability to separate good-quality firms from poor-quality firms (quality) and the ability to separate undervalued firms from overvalued firms (value). These two dimensions work against each other, as high-quality stocks tend to have higher valuations, and conversely, lower priced stocks tend to be of lower quality. Successful stock picking hence involves buying high-quality firms that also appear to be underpriced relative to intrinsic value and selling or shorting poor-quality firms that also appear to be overpriced relative to intrinsic value.

Prior approaches used by practitioners to combine quality and value have required either a lengthy time series of information to measure quality or the availability of forecasts to estimate intrinsic value. This article presents a parsimonious approach to combine quality and value for fundamental analysis. For our metrics of quality, we use the easy-to-compute *FSCORE* and *GSCORE* metrics from Piotroski (2000) and Mohanram (2005). For our measures of value, we rely on the recent literature on cross-sectional forecasting to generate measures of intrinsic value, and calculate the *V/P* measure from Frankel and Lee (1998) as well as the *PEG* ratio.

We find that our approach of combining quality and value is very successful in picking winners and losers among stocks. The approach works better than commonly used practitioner stock screens (e.g., the Graham and Dodd screen) and can also be applied to a wider cross section of stocks. A strategy that combines quality with value generates hedge returns that significantly exceed the hedge returns of the stand-alone strategies based on quality or value alone. This superior performance of our approach is not an artifact of smaller portfolio size, evident in a wide variety of partitions related to implementability and transaction costs, persistent across time, and robust to controls for risk factors and other determinants of stock returns. However, we do find a reduction in the ability of our strategies to generate significant incremental returns in the post-2002 period.

The results of this article are directly relevant for practitioners, as it highlights the importance of considering quality and value simultaneously in stock picking. Rather than maximizing on one dimension to the detriment of the other, our strategy asks investors to "satisfice" on the basis of both quality and value.[14]

14. Satisfice is a compound word introduced by Herbert Simon in 1956 that combines the two words satisfy and suffice. Satisficing is a decision-making strategy used in multiobjective optimization problems that entails searching through the available alternatives until an acceptability threshold is met across all objectives.

This article 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 reduced ability of fundamental analysis to generate excess returns in recent years can cause one to question the utility of fundamental analysis. Conversely, Sloan (2018) argues that this should be viewed as a validation of fundamental analysis, which still does well in predicting future earnings, even if it does not predict returns. The reduced ability to predict returns is consistent with investors carrying out such analyses and, more importantly, actively investing in such strategies. Consistent with this, we find the greatest reduction in hedge returns in stocks with the highest ETF ownership, where the costs of implementing such strategies are probably the lowest. These results also suggest that markets are adaptively efficient, as Grossman and Stiglitz (1980) would view it.

Appendix 1

Generating cross-sectional earnings forecasts

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

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

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., $(\Delta WC + \Delta NCO + \Delta FIN)/csho$, 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 10 years. As illustrated by Li and Mohanram (2014, 1158), “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 2

Replicating the Graham-Dodd approach

The Graham and Dodd (1934) approach ranks stocks based on 10 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 are 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 percent of the average PE for all stocks over the last five 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 ($prcc\_f \times csho$).
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; that is, ($dltt + dlc$) < 2 × (act).
9. Historical growth in EPS (over the last five years) > 7 percent.
10. No more than one year of declining earnings over the previous five years.

A score of 1 is given to each condition that is satisfied. Hence, the score ranges from zero to 10, with higher scores indicating better investment.

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