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# THE VALUE IN FUNDAMENTAL ACCOUNTING INFORMATION

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## Abstract

We examine the role of fundamental accounting information in shaping portfolio performance. Using a conditional performance approach, we address the concern that the positive relation between Piotroski's *F Score* and ex post returns is due to risk compensation. Our results show that portfolios of firms with strong fundamental underpinnings generate significant positive and time-varying performance. One potential source of these performance gains is an underreaction to public information (such as momentum and *F Score*) when information uncertainty (proxied by size, illiquidity, and idiosyncratic volatility) is high. In addition, conditional performance benefits seem prevalent in periods of high investor sentiment.

*JEL Classification:* G11, G12, G14, M41

## I. Introduction

There is extensive and long-standing support for the use of fundamental valuation tools in equity choice from the early seminal work of Graham and Dodd (1934) to the current investment philosophy of their modern adherent Warren Buffett.[1] In addition, numerous authors document the potential economic benefits of fundamental analysis through the judicious use of available financial accounting information (cf. Ou and Penman 1989; Lev and Thiagarajan 1993; Haugen and Baker 1996; Asness 1997; Frankel and Lee 1998; Griffin and Lemmon 2002; Piotroski 2000; Mohanram 2005; Piotroski and So 2012; Novy-Marx 2013).

In recent years, the *F Score*, a comprehensive measure of firm fundamentals, has drawn attention from academics and practitioners. Introduced by Piotroski (2000), the *F Score* is constructed from nine accounting signals capturing three aspects of a firm's financial strength: profitability, liquidity, and operating efficiency. Piotroski finds that

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[1] For example, in his 2008 Letter to Shareholders, Buffett quips, "Price is what you pay. Value is what you get." In the Foreword to the First Edition in *The Warren Buffett Way* (Hagstrom 1994), Peter Lynch describes Buffett's thought process regarding company valuation as "the critical investment factor is determining the intrinsic value of a business and paying a fair or bargain price" (p. xxi).



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the *F Score* has strong predictive power for ex post returns. Piotroski and So (2012) further show that the predictability of the *F Score* for ex post returns is stronger when there is substantial disagreement, or incongruence, between a firm's fundamental value (proxied by the *F Score*) and market-perceived value (measured by book-to-market). Walkshäusl (2016) further examines the returns to these incongruent portfolios with strong *F Score*s and large book-to-market ratios. He finds strong unconditional portfolio performance is also present in international markets, and there is some further indirect evidence that the observed predictability is at least partially related to a financing-based mispricing factor.

Although the literature finds a strong relation between *F Score* and ex post returns, the economic rationale for this relation has been debated by multiple authors. In particular, although portfolios of high *F Score* stocks often produce large ex post returns, it is not clear if these returns simply represent appropriate compensation for risk premiums. Fama and French (2006) present a valuation framework to jointly test the relations among expected profitability, expected investment, book-to-market ratio, and expected returns.[2] They conclude that the sources of predictability in expected returns due to *F Score* could be both rational (i.e., high *F Score* stocks are more risky) and irrational (i.e., high *F Score* stocks are more prone to mispricing). Similarly, in a recent survey on accounting anomalies, Richardson, Tuna, and Wysocki (2010) point out that researchers examining the relation between accounting attributes and ex post returns must ensure that plausible risk-based explanations are precluded as alternative explanations.

The extant literature on risk-based pricing is primarily cast in the context of an unconditional asset pricing model in which required asset returns do not vary with changes in the underlying information set. Recent advances in conditional performance evaluation have the ability to assess the impact of information on marginal performance to directly address the risk premium counterargument. For example, Ferson and Schadt (1996) and Christopherson, Ferson, and Glassman (1998) propose conditional alpha measures based on an underlying time-varying beta model. Jha, Korkie, and Turtle (2009) extend this work to provide a conditional alpha that is consistent with an underlying conditional mean–variance decision framework. The resultant conditional alpha has desirable properties and may be readily obtained from a simple unconditional regression. We adopt this framework to examine the importance of fundamental accounting information in conditional performance.

The conditional alpha measures the risk-adjusted return contribution from a conditional model of equilibrium returns. For a given equilibrium model (with

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[2] Through an extension of the basic valuation equation for future expected dividends, and with the addition of a clean surplus accounting condition from Ohlson (1995), they obtain,

$$P_t = \sum_{\tau=1}^{\infty} \frac{E(EPS_{t+\tau} - dB_{t+\tau})}{(1+r)^{\tau}},$$

where $P_t$ is the stock price per share at time $t$, $B_t$ is the book value per share at time $t$, $EPS_{t+\tau}$ is the earnings per share at time $t+\tau$, $dB_{t+\tau} = B_{t+\tau} - B_{t+\tau-1}$ is the similarly indexed change in book value per share, $E(\cdot)$ is the expectation operator, and $r$ is the internal rate of return on expected dividends (cf. Fama and French 2006, p. 492). Dividing both sides of the equation by the book value of equity produces the results discussed.

potentially multiple risk sources), conditional marginal performance is the component of expected return above that required by the conditional asset pricing relation. We use the *F Score* as an information instrument to address the relation between information and equilibrium returns, which rationally change with evolving stock fundamentals and systematic risks.[3] Fundamental accounting information affects time-varying expected returns that also affect the set of available conditional mean–variance opportunities. The approach has the usual mispricing interpretation in conditional mean-conditional standard deviation space. Given this interpretation, our research design has the ability to directly differentiate between marginal performance and a return component that may represent risk compensation. To gauge the statistical significance of the conditional alpha, we also provide a bootstrap approach similar to Kosowski et al. (2006) that admits non-normal disturbances.

Intuitively, our research design compares to the fundamental valuation and anomalies work of Lev and Thiagarajan (1993), and the more recent related work of Piotroski and So (2012). Our work differs from these studies because we also provide conditional performance measures to assess the marginal role of accounting information in performance while controlling for risk. This allows us to address the important question: do improved ex post returns for high *F Score* firms simply reflect risk compensation? Of course, the usual caveat applies in that the resultant conditional alpha is jointly dependent on both the model and the included information instruments.

Our results suggest that portfolio performance improves with fundamental accounting information in a wide variety of asset pricing contexts. Because we examine the marginal value of fundamental accounting information, after controlling for required risk premiums, our results are not subject to the Fama and French (2006) critique.[4] Our annual results find strong post-portfolio-formation returns and suggest evidence of marginal performance that is not solely compensation for increased risk. Observed conditional alphas are often highly significant for portfolios with strong fundamentals, lending support to the *F Score* anomaly explanation.[5]

We also find evidence that investor underreaction is prevalent, especially in high-information-uncertainty cases, consistent with much of the extant literature. Daniel, Hirshleifer, and Subrahmanyam (1998, 2001) present a model in which

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[3] In unreported cross-sectional regressions, the *F Score* provides substantial improvements in return predictability when added to other common firm characteristics (including size, price, return volatility, dividend yield, age, share turnover, book-to-market ratio, S&P 500 membership, concurrent return, and momentum), supporting the use of *F Score* as an instrument variable. Our general approach can also be readily extended to consider other important economic information instruments such as the diversification discount (Mitton and Vorkink 2011), volatility of liquidity (Pereira and Zhang 2010), the dividend–price ratio (Favero, Gozluklu, and Tamoni 2011), and analyst forecast errors (So 2013).

[4] In an earlier draft with further restrictions on admissible firms, we find that unconditional betas increase with *F Scores* for the smallest value firms. This interesting counterexample supports the Fama and French (2006) critique suggesting greater returns may result from greater risk in some instances.

[5] In tangentially related work, Choi and Sias (2012) present evidence showing the role of institutional investors in the relation between *F Score* and ex post returns. In an unconditional setting they find that financial strength predicts future demand by institutional investors. They suggest institutional investors drive some of the observed gradual incorporation of information at least partly because institutional demand drives prices.

overconfident individual investors underreact to public information. In related work, Hong and Stein (1999) and Hong, Lim, and Stein (2000) suggest that information may be slowly disseminated to financial markets in their gradual information diffusion model. Underreaction to information is likely to be most prevalent in opaque firms with greater degrees of information uncertainty. Examples include small firms, illiquid firms, and firms with few analysts. Related empirical support for this general hypothesis is found in Chan (2003), using public news announcements, and Zhang (2006). Zhang considers various measures of information uncertainty and finds that firms with greater information uncertainty have greater positive (negative) returns following good (bad) news.

Given that the relation between returns and the *F Score* could be driven by investor underreaction to accounting information, we examine whether this relation is amplified in firms with greater degrees of information uncertainty. To test this hypothesis, we use the *F Score* and momentum to capture news in firm-specific fundamentals and overall market behavior. Using quarterly accounting data, we find high (low) *F Score* portfolios and previous winners (losers) perform best (most poorly) when portfolios display the greatest information uncertainty. Furthermore, portfolios of firms with greater information uncertainty produce stronger return and marginal performance gains relative to those with less information uncertainty. These findings are robust to multiple measures of information uncertainty including size, illiquidity, and idiosyncratic volatility.

We also examine the performance of *F Score* portfolios in response to changing economic conditions to consider the role of investor underreaction in driving the relation between returns and the *F Score*. Stambaugh, Yu, and Yuan (2012) suggest that short restrictions allow overvaluations to persist (when investor underreaction is common). Thus, they hypothesize that mispricing will be greatest when overvaluation is most likely and that the short side of related long–short portfolios will reveal observed mispricing. Consistent with this hypothesis, we find conditional alphas reveal underreaction related to mispricing in the short component of long–short portfolios around sentiment shocks. That is, predictability due to the *F Score* is amplified during market overreactions in positive sentiment and exuberant periods when prices deviate more from intrinsic values. Counter to the spirit of Stambaugh, Yu, and Yuan, we also find strong evidence that the performance of a long strategy of investing in high *F Score*, high-momentum stocks contributes most to the related long–short strategy built around *F Score* and momentum (with a corresponding short strategy in low *F Score*, low momentum stocks).[6]

Our article contributes to the literature in several ways. First, we consider a conditional model that admits time-varying risk-adjusted returns that rationally change with underlying accounting information. Using this conditional asset pricing framework, we directly address the concern that the predictability of the *F Score* for ex post returns is due to risk premiums associated with fundamental accounting information. Second, we reconcile the debate on whether high *F Score* firms outperform low *F Score* firms: we

[6] Berger and Turtle (2012) provide related evidence regarding sentiment-related mispricing.

find that high *F Score* portfolios provide positive marginal performance both before and after conditional risk adjustments. Finally, we provide new empirical evidence on the interplay between fundamental analysis and information uncertainty. The majority of the performance due to momentum and *F Score* is found in firms with high information uncertainty, consistent with the gradual resolution of information in models such as Daniel, Hirshleifer, and Subrahmanyam (1998, 2001) and with the asymmetric short-related findings in Stambaugh, Yu, and Yuan (2012).

## II. Measuring Marginal Performance

Our general model of excess asset returns follows Campbell (1987), Shanken (1990), and Jha, Korkie, and Turtle (2009). We admit changes in conditional means with the economic environment, as well as with sensitivities to underlying risk factors. Conditional asset excess returns evolve with observable valuation information as:

$$R_{jt} = \gamma_{j0} + \gamma_{j1} F\,Score_{jt-1} + e_{jt}, \tag{1}$$

where excess returns are indexed by $j = 1, 2, \ldots, N$; time intervals are given by $t = 1, 2, \ldots, T$; and for coefficients $\gamma_{j0}$ and $\gamma_{j1}$. Our information instrument, $F\,Score_{jt-1}$, is determined at the beginning of each interval, and disturbances, $e_{jt}$, are assumed independent and identically distributed.[7] The conditional mean for any asset is given by:

$$\mu_{jt} = \gamma_{j0} + \gamma_{j1} F\,Score_{jt-1}. \tag{2}$$

Jha, Korkie, and Turtle (2009) provide conditions to demonstrate that equations (1) and (2) result in a conditional alpha, or marginal performance measure given by:

$$\alpha_{jt} = \alpha_{j0} + \alpha_{j1} F\,Score_{jt-1}. \tag{3}$$

Furthermore, the conditional alpha, $\alpha_{jt}$, from the underlying conditional regression, may be estimated from the simpler familiar unconditional regression:

$$R_{jt} = \alpha_{j0} + \alpha_{j1} F\,Score_{jt-1} + \beta_{j1} F_{1t} + \ldots + \beta_{jK} F_{Kt} + u_{jt}, \tag{4}$$

where the $F\,Score_{jt-1}$ information instrument is known at the beginning of each investment interval for each excess return, and the $K$ risk factors are denoted $F_{1t}, \ldots F_{Kt}$.[8]

[7] The assumption of a linear model for conditional excess returns in information instruments may be justified from an underlying linear model, or through a linear approximation of any given nonlinear model, with a judicious choice of information instruments.

[8] Ferson and Schadt (1996) and Christopherson, Ferson, and Glassman (1998) use $z_t$ to differentiate demeaned instruments from the underlying raw instruments in levels, $Z_t$. We define known information instruments with the subscript $t-1$. For our purposes, demeaning is unnecessary (but not harmful) given the inclusion of a constant.

Unconditional tests of the capital asset pricing model (CAPM) may be implemented as a special case of equation (4) with no information instrument (beyond a constant), and where we include a single excess market return risk factor. In this case, $\alpha_{j0}$ is the unconditional Jensen's (1968) alpha.

We examine the conditional performance of portfolios formed on aggregate firm-specific accounting information after controlling for risk sensitivities. This avenue for investigation dovetails with the examination of Ball, Sadka, and Sadka (2009) who find that common earnings factors explain a large percentage of earnings variability at the firm level. Our strategy is to examine the variability in marginal performance using historical accounting information as a source of readily available and measurable information for investors. The point estimate for the conditional alpha may be directly obtained from equation (4) as:

$$\hat{\alpha}_{jt} = \hat{\alpha}_{j0} + \hat{\alpha}_{j1} F\,Score_{jt-1}. \tag{5}$$

To examine the statistical significance of conditional alphas, it is not sufficient to solely consider the significance of the reported coefficients for the conditional alpha from equation (4) as our estimate of $\alpha_{jt}$ is a function of both coefficient estimates and information instruments.[9] In general, the conditional alpha is a measure of mispricing based on an underlying conditional model of evolving expected returns (as given by equation (2)) and, as such, differs from unconditional alphas in the extant literature, even when they are conditioned on additional information. We provide general inferences from the unconditional regression equation (4) for our estimated conditional alphas based on an empirical bootstrapping approach following Kosowski et al. (2006). One benefit of the bootstrapping approach is that it readily admits diverse multivariate error distributions. We provide details for our bootstrapping procedure in the Appendix.

## III. Empirical Analysis

We present annual and quarterly empirical results. Results are robust to popular choices for risk factors and to various lags between portfolio information measurement and subsequent portfolio performance measurement.

### *Data*

*Annual Data.* Our sample includes all firms with ordinary common shares (excluding American Depositary Receipts, closed-end funds, and real estate investment trusts) with available NYSE, AMEX, and NASDAQ return data from the Center for Research in Security Prices (CRSP) and with available data from the merged Compustat

[9] Intuitively, from equation (4), the conditional alpha can also be viewed as a forecast of the excess return, conditional on the known *F Score* and where all other stochastic regressors are (a priori) set to zero. In an earlier version of the paper, we use this forecast interpretation to create a conceptual inference procedure following Feldstein (1971). Results are qualitatively similar and are omitted for brevity.

annual industrial files for income statement and balance sheet data. Following Piotroski and So (2012), we exclude all financial firms (Standard Industrial Classification [SIC] codes 6000–6999) and those with negative book value of equity or missing market value of equity from our sample. For each firm in the sample and for each year-end in our sample period from 1972 through 2012, we calculate the annual *F Score* following Piotroski (2000) and Fama and French (2006).[10] *F Score* information is then used as a conditioning variable for returns computed over the subsequent post-portfolio-formation period from July 1973 through June 2014. The *F Score* is the sum of nine accounting signals that collectively measure a firm's financial strength and is our conditioning information instrument for subsequent portfolio returns. Each signal is represented by a binary variable that equals 0 or 1. In particular, the corresponding binary variables are equal to 1 if the following conditions are met: (1) positive return on assets, (2) positive change in return on assets, (3) positive cash flow from operations, (4) negative accruals, (5) positive change in turnover, (6) positive change in the gross margin ratio, (7) negative change in financial leverage, (8) positive change in liquidity, and (9) no issuance of common or preferred stocks. To ensure the public availability of financial information for each firm, we allow a time gap of at least six months between the fiscal year-end and measurement of post-portfolio-formation returns. For every fiscal year-end up to December, we wait until the end of the following June to calculate the one-year post-portfolio-formation buy-and-hold return. If a firm delists during the post-portfolio-formation period, we calculate the buy-and-hold portfolio return using the available returns, the delisting returns, and zeros for the post-delisting period. Our final annual sample includes 125,426 firm-year return observations from July 1973 to June 2014.

Following Fama and French (2006), we form 10 size portfolios each year based on each firm's capitalization at the end of June for all fiscal year-ends between January and December of the prior calendar year.

*Quarterly Data.* We also perform analyses based on a quarterly portfolio updating approach. Quarterly data provide an improvement in test power given the substantial increase in observations. For simplicity and ease of interpretation, we retain only firms with fiscal year-ends in March, June, September, or December. We then compute quarterly *F Scores* as the sum of seven accounting signals. The seven accounting signals are similar to the annual *F Score* inputs except for the exclusion of change in financial leverage and the equity issuance indicator variables (due to data availability). After calculating the quarterly *F Score*, we wait three months before forming portfolios for subsequent portfolio return measurement.[11]

In our quarterly analysis, we adopt two portfolio-formation strategies. Our double-sorting strategy forms portfolios at each quarter-end based on momentum and various measures of information uncertainty. For the triple-sorting strategy, we first classify firms into three groups based on the *F Score* at each quarter-end. Then, for each *F Score* category, we wait three months and form portfolios based on momentum and information uncertainty. Following Zhang (2006), momentum for each stock is

[10] Compustat data from 1970 through 1972 are required to calculate the *F Score* for 1972 for each firm-year in the sample.

[11] In our robustness analysis we also consider two- and six-month lags before portfolio formation.

**TABLE 1. Descriptive Statistics for the Fundamental Financial Characteristics of the Sample.**

| Variable | Mean | Std. Dev. | 25th Pctl. | Median | 75th Pctl. | Prop. with Pos. Signal |
|---|---|---|---|---|---|---|
| *Asset* | 1,637 | 7,924 | 33.38 | 133.28 | 662.02 | — |
| *MVE* | 1,661 | 10,100 | 21.57 | 102.5 | 567.44 | — |
| *BM* | 0.898 | 0.782 | 0.386 | 0.684 | 1.138 | — |
| *ROA* | 0.016 | 0.225 | 0.000 | 0.045 | 0.089 | 0.751 |
| Δ*ROA* | −0.005 | 0.262 | −0.035 | 0.000 | 0.025 | 0.808 |
| *CFO* | 0.066 | 0.197 | 0.024 | 0.082 | 0.140 | 0.494 |
| *Accrual* | 0.050 | 0.171 | 0.095 | 0.046 | 0.001 | 0.256 |
| Δ*Turn* | −0.024 | 0.780 | −0.147 | 0.001 | 0.128 | 0.512 |
| Δ*Margin* | −0.299 | 107.853 | −0.020 | 0.000 | 0.019 | 0.472 |
| Δ*Lever* | 0.003 | 0.085 | −0.026 | 0.000 | 0.019 | 0.498 |
| Δ*Liquid* | −0.094 | 9.671 | −0.347 | −0.020 | 0.270 | 0.503 |
| *Issuance* | 18.307 | 118.566 | 0.000 | 0.321 | 4.351 | 0.298 |
| *F Score* | 4.592 | 1.520 | 3.000 | 5.000 | 6.000 | — |

Note: This table reports descriptive statistics for the full sample of accounting information including 125,426 firm-year observations from July 1973 to June 2014. The last column shows the proportion of observations that provide a positive signal according to the *F Score* heuristic. *Asset* is total book value of assets at fiscal year-end ($ millions); *MVE* is market value of equity at fiscal year-end ($ millions); *BM* is book value of equity at fiscal year-end divided by market value of equity at the end of December of *t*; *ROA* is return on assets at fiscal year-end; Δ*ROA* is change in return on assets between fiscal year-ends; *CFO* is cash flow from operations scaled by total assets at fiscal year-end; *Accrual* is net income before extraordinary items less cash flow from operations at fiscal year-end, scaled by beginning-of-year total assets; Δ*Turn* is change in asset turnover between fiscal year-ends; Δ*Margin* is change in gross margin ratio (net sales less cost of goods sold, scaled by net sales) between fiscal year-ends; Δ*Lever* is change in debt-to-assets ratio between fiscal year-ends; Δ*Liquid* is change in current ratio (current assets scaled by current liabilities) between fiscal year-ends; *Issuance* is cash flow from the sale of common and preferred stocks at fiscal year-end ($ millions); *F Score* is *F Score* computed from fiscal year-end accounting information.

calculated as the buy-and-hold return from months $t-11$ to $t-1$ relative to the portfolio-formation period.

Our primary quarterly analysis uses three measure of information uncertainty: market capitalization, illiquidity, and idiosyncratic volatility. These measures are obtained at the beginning of the return measurement interval. Because of quarterly *F Score* data availability, quarterly analysis is conducted over the return period from Q3 1984 to Q4 2014.

### *Descriptive Statistics*

Table 1 provides descriptive statistics for the fundamental financial characteristics of the sample used to construct the *F Score* for 125,426 firm-year observations from 1972 to 2012. Returns are subsequently measured from July 1973 to June 2014. The initial (fourth) column of data reports the sample average (median) value for each data series considered. We note the $1.66 billion average market value of equity is dramatically larger than the median firm market equity value of $0.10 billion, reflecting the familiar right skewness common in many of the original data series. Similarly, the sample mean of $1.64 billion for total book value of assets at fiscal year-end, *Asset*, exceeds even the 75th percentile value of $0.66 billion. The book-to-market ratio, *BM*, yields a sample average (median) of 0.90 (0.68). The sample consists of a large number of small and low book-to-market firms; however, there are also a relatively small number of very large firms that heavily influence reported sample means for many of the *F Score* input variables. In addition to the summary statistics for the nine inputs to the Piotroski and So (2012) heuristic, we also report the mean, standard deviation, and percentiles for the resultant *F Score* heuristic. Although the average and median scores for the nine *F Score* input variables are potentially highly skewed, the resultant *F Score* has a relatively symmetric distribution with a sample mean and median of 4.6 and 5, respectively. Similarly, the interquartile range is from 3 to 6. The simplicity of the *F Score* provides potential for a smoothed measure of information that will mitigate the effect of outliers in later regression analyses.

*Annual One-Year Post-Portfolio-Formation Raw Returns and Conditional Alphas*

Following Piotroski (2000), we begin our empirical analysis by confirming the impact of the *F Score* conditional on firm size. Table 2 presents annual results for one-year post-portfolio-formation raw returns for 10 size portfolios. We form equal-weighted size portfolios of low, mid, or high *F Score* firms, based on firm-specific *F Scores* of 0 to 2, 3 to 6, and 7 to 9, respectively. The first row of the table reports one-year buy-and-hold portfolio returns for all firms and for firms within each size decile. The next three rows present results for each *F Score* category. Below each return entry we report the percentage of sample observations within that *F Score* category in brackets. We observe that most of the firm-year observations are classified in the mid *F Score* group for each of the size portfolios. For example, in the smallest size decile, approximately 26% of firms have low or high *F Scores*, and 74% of all firms have *F Scores* between 3 and 6. In addition, there is a strong positive relation between the *F Score* and one-year post-portfolio-formation raw returns for the size portfolios (for all but the second size portfolio). These results suggest that the *F Score* has the ability to effectively discriminate between high-return firms and low-return firms in an ex ante manner. For example, for the smallest decile of firms, low *F Score* firms provide one-year post-portfolio-formation returns of 19%, and high *F Score* firms have one-year post-portfolio-formation returns of over 26%. This pattern persists for all but the second smallest size portfolio where the high *F Score* portfolio has a slightly smaller return than the mid *F Score* portfolio.[12] Tests of differences in raw returns across *F Score* groups are presented below the reported one-year returns. Consistent with the observed return differences, *t*-tests of differences between high and low *F Score* groups are significant for the full sample, and for 8 of the 10 size portfolios (at the 10% level). Furthermore, we find that every high *F Score* portfolio offers a larger raw return than the corresponding low *F Score* portfolio.

The last column in Table 2 shows that the small firm portfolio provides significantly greater returns than the large firm portfolio for the full sample of raw returns. When partitioning our sample into low, mid, and high *F Score* groups, we also

[12] The relatively large returns to our size portfolios are consistent with the extant literature. Our sample is also constrained by the additional restriction of available ex ante *F Score* data. Because our research design includes firms with market value less than $25 million and book values between 0 and $12.5 million, our results are not directly comparable to Fama and French (2006).

**TABLE 2. One-Year Post-Portfolio-Formation Raw Returns for Size Portfolios.**

| *F Score* Category | Full Sample | Size Decile: Smallest | 2nd | 3rd | 4th | 5th | 6th | 7th | 8th | 9th | Largest | Small vs. Large |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Full sample | 16.89% | 23.63% | 18.13% | 18.34% | 17.14% | 17.69% | 15.06% | 15.38% | 15.39% | 15.15% | 13.02% | 10.61%** |
| | | | | | | | | | | | | (2.57) |
| Low *F Score* | 12.72% | 18.79% | 12.88% | 12.94% | 13.72% | 11.73% | 10.44% | 13.60% | 9.09% | 10.64% | 9.48% | 9.31%* |
| | [8.6%] | [13.0%] | [12.0%] | [10.7%] | [10.8%] | [9.5%] | [8.5%] | [7.3%] | [5.6%] | [4.6%] | [4.1%] | (1.68) |
| Mid *F Score* | 16.82% | 23.83% | 18.38% | 18.36% | 17.29% | 17.53% | 15.31% | 15.01% | 15.54% | 15.10% | 12.93% | 10.90%** |
| | [80.5%] | [74.0%] | [75.8%] | [77.6%] | [78.9%] | [80.2%] | [81.3%] | [83.1%] | [84.1%] | [84.4%] | [85.2%] | (2.56) |
| High *F Score* | 19.45% | 26.40% | 17.75% | 23.72% | 18.01% | 22.28% | 16.06% | 19.53% | 17.63% | 16.21% | 13.77% | 12.64*** |
| | [10.9%] | [13.0%] | [12.1%] | [11.7%] | [10.3%] | [10.3%] | [10.1%] | [9.5%] | [10.3%] | [11.0%] | [10.7%] | (3.07) |
| High vs. low *F Score* | 6.73%*** | 7.62%* | 4.87% | 10.78%*** | 4.29% | 10.55%*** | 5.61%* | 5.93%* | 8.53%*** | 5.58%*** | 4.29%* | |
| | (3.55) | (1.80) | (1.37) | (3.29) | (1.18) | (2.73) | (1.80) | (1.70) | (2.81) | (3.15) | (1.80) | |

Note: This table reports summary statistics describing one-year post-portfolio-formation returns for size decile portfolios. Following Fama and French (2006), size portfolios are formed according to each firm's capitalization at the end of June, for all year-ends between January and December of the previous year. For each period, 10 size portfolios are ranked in the order of smallest to largest and are updated annually. Firms with *F Scores* from 0 to 2 are categorized in the low *F Score* group, whereas those with *F Scores* of 3 to 6, and 7 to 9 are categorized in the mid and high *F Score* categories, respectively. The percentage of low, mid, and high *F Score* firms in the sample and in the 10 size portfolios are indicated in brackets. The final row presents the difference in mean returns between the high and low *F Score* categories (with *t*-statistics in parentheses). We also report the difference in mean returns between the smallest and largest size portfolio in the last column (with *t*-statistics in parentheses).

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

find that the small firm portfolio has significantly greater one-year raw returns than the large firm portfolio (at the 10% level) within each *F Score* group.

Our initial descriptive results confirm many of the findings in the extant literature that portfolios formed with strong accounting fundamentals offer large subsequent mean returns. In the next section, we turn to the main focus of our study and address whether these returns represent superior performance or are merely compensation for portfolios with high risk loadings.

One of the benefits of our method is that we are able to identify marginal conditional performance on a period-by-period basis, with accompanying inference procedures. By examining marginal performance after adjusting for risk sensitivities, we are able to address the concern of Fama and French (2006) that high *F Score* portfolios may generate greater returns as compensation for greater risk. For example, the observed strong performance in returns from Table 2 may be due to positive marginal performance, or due to greater risk in portfolios with strong subsequent returns.

Table 3 presents both annual unconditional and conditional alphas for our sample of firms organized by a size sort. We begin by estimating an unconditional version of equation (4) where we use only a constant as our instrument and six risk factors: the market excess return (MKT), the small-minus-big (SMB) factor, the high-minus-low (HML) factor, the momentum (MOM) factor, the robust-minus-weak (RMW) factor, and the conservative-minus-aggressive (CMA) factor. The latter two factors capture the return spread associated with firm profitability and investment. Fama and French (2015) show that a five-factor model containing MKT, SMB, HML, RMW, and CMA outperforms the Fama and French (1993) three-factor model.

Panel A of Table 3 reports the unconditional alpha estimates and related *t*-statistics for each size portfolio. The general trend toward larger alphas for smaller firms is consistent with the small firm effect (cf. Banz 1981; Reinganum 1981). Our point estimates suggest that firms in the smallest decile generate no significant marginal performance, although the point estimate for the smallest portfolio is economically large (approximately 4.14% per year after controlling for various market risks). The lack of significance of this effect may not be surprising given the unconditional alpha is computed with a robust set of risk factors (including SMB).

Panel B of Table 3 reports time series means and medians (in brackets) for conditional alpha estimates for each size portfolio. To allow direct comparisons with Panel A, we use the same six-factor model augmented with the annual *F Score* as the information instrument. Because each size portfolio produces a time series of conditional alphas, we report the sample average and sample median in brackets for each time series as an initial descriptive statistic. The *F Score* for each portfolio at each point in time is the average of the ex ante *F Scores* for all firms within the portfolio at the beginning of each period.

Results for the conditional model are reported in Panel B of Table 3. Given iterated expectations, we find closely comparable unconditional alphas in Panel A with average conditional alphas in Panel B. The latter rows of Panel B report the sample mean and median conditional alphas for portfolios formed according to both size and *F Score*. Firms with *F Scores* from 0 to 2 are categorized in the low *F Score* group, whereas those with *F Scores* of 3 to 6, and 7 to 9 are categorized in the mid and high *F Score* groups,

**TABLE 3. Annual Unconditional and Conditional Alphas for Size Portfolios.**

| | Size Decile | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Alphas | Smallest | 2nd | 3rd | 4th | 5th | 6th | 7th | 8th | 9th | Largest |
| Panel A. Unconditional Alpha | | | | | | | | | | |
| Unconditional alpha | 4.14% | −0.18% | −0.53% | −0.71% | −1.80% | −2.78% | −0.87% | −0.24% | 0.28% | 0.53% |
| | (1.04) | (−0.08) | (−0.32) | (−0.49) | (−1.11) | (−3.25) | (−0.87) | (−0.22) | (0.22) | (0.55) |
| Panel B. Conditional Alpha | | | | | | | | | | |
| Conditional alpha | 3.84% | −0.48% | −0.61% | −0.82% | −1.75% | −2.78% | −0.88% | −0.26% | 0.31% | 0.51% |
| | [4.17%] | [0.07%] | [−0.60%] | [−0.44%] | [−1.04%] | [−2.79%] | [−0.81%] | [−0.21%] | [0.51%] | [0.49%] |
| Conditional alpha | −3.92% | −5.44% | −2.64% | −4.76% | −7.26% | −7.87% | −1.73% | −3.94% | −5.26% | −2.46% |
| Low *F Score* | [−3.24%] | [−5.42%] | [−2.37%] | [−4.71%] | [−7.44%] | [−7.84%] | [−1.60%] | [−3.98%] | [−4.99%] | [−2.08%] |
| Conditional alpha | 3.76% | −0.01% | −1.09% | −0.88% | −1.96% | −2.75% | −1.41% | −0.58% | 0.33% | 0.37% |
| Mid *F Score* | [4.26%] | [0.99%] | [−0.81%] | [−0.26%] | [−1.25%] | [−2.80%] | [−1.34%] | [−0.56%] | [0.42%] | [0.31%] |
| Conditional alpha | 10.60% | −4.03% | 7.61% | −2.31% | −0.36% | −1.23% | 2.10% | 2.63% | 0.26% | 0.70% |
| High *F Score* | [10.37%] | [−3.89%] | [7.67%] | [−2.38%] | [−0.36%] | [−1.26%] | [1.80%] | [2.56%] | [0.32%] | [0.65%] |

Note: This table presents summary statistics for annual unconditional and conditional alphas for size portfolios. Following Fama and French (2006), size portfolios are formed according to each firm's capitalization at the end of June and updated annually. Unconditional alpha estimates are based on the unconditional regression given by equation (4) with a constant as the information instrument. For the conditional size portfolio regressions, the *F Score* information instrument is given by the average *F Score* for all firms in that size portfolio. Panel A reports annual unconditional alphas (with *t*-statistics given in parentheses) for the six-factor model with risk factors including the market excess return (MKT), the small-minus-big (SMB) factor, the high-minus-low (HML) factor, the momentum (MOM) factor, the robust-minus-weak (RMW) factor, and the conservative-minus-aggressive (CMA) factor. Panel B reports the annual conditional alphas estimated from the six-factor model. Conditional alphas for *F Score* levels are based on a dynamic portfolio-formation strategy. For each point in time, and for each size portfolio, equal-weighted portfolios of low, mid, or high *F Score* firms are formed. Firms with *F Scores* from 0 to 2 are categorized in the low *F Score* group, whereas those with *F Scores* of 3 to 6, and 7 to 9 are categorized in the mid and high *F Score* categories, respectively. The resultant average and median (in brackets) of the time series of conditional alphas are reported for each size group and *F Score*.

respectively. We find a strong monotonic pattern in average conditional alphas across *F Scores* for all size groups except for deciles 2 and 4. For example, the average conditional alpha in the smallest size portfolio shows a low *F Score* conditional alpha of −3.92% and a corresponding high *F Score* conditional alpha of 10.60%. The largest size portfolio appears to display the least variability in means across *F Scores*. These findings address the Fama and French (2006) concern that superior returns associated with *F Score* can be due to both rational and irrational factors. The finding that high *F Score* firms earn greater conditional alphas is consistent with a return–*F Score* anomaly.

*Quarterly Conditional Alphas and Inferences*

Our empirical findings provide point estimates that suggest high *F Score* portfolios provide returns that exceed the required return using the six-factor model. In our remaining empirical analysis, we consider finer quarterly data. Higher frequency data provide additional information that is helpful to describe the temporal evolution of conditional alphas. To calculate conditional alphas, we first create quarter-end *F Scores*, wait three months, and then form portfolios. For each quarterly return, there is a three-month lag between measurement of the *F Score* and construction of the equal-weighted portfolios.[13]

As an illustration of our conditional alpha approach in modeling time-varying asset performance, we begin by examining quarterly conditional alphas for the two extreme size portfolios. Because our research design generates time-varying conditional alphas with accompanying time-varying inferences, our results are naturally presented graphically. Figure I plots the time series of quarterly conditional alphas for the largest (Panel A) and smallest (Panel B) size decile portfolios from Q3 1984 to Q4 2014. Quarterly conditional alphas are estimated from the six-factor model with quarterly ex ante *F Scores*. We display the conditional alpha estimate along with the bootstrapped 90% nonrejection region (assuming zero marginal performance). The solid lines plot the quarterly conditional alphas, whereas the lighter dotted lines show the 90% nonrejection region. A conditional alpha is significantly different from zero at any point in time if it lies outside the nonrejection region.

We observe strong and persistent differences in marginal performance between the large and small firm portfolios. The observed large firm marginal performance varies substantially over time and lies within the 90% nonrejection region for significant portions of the sample period. In contrast, the small firm portfolio displays significant positive marginal performance during almost the entire sample period.[14] Although the portfolio of large firms often shows positive conditional alphas, the magnitude of those alphas is small at approximately 25 basis points per quarter. Small firms exhibit significantly larger positive marginal performance (even after adjusting for the size effect

[13] To ensure robustness, we also consider value-weighted portfolios in our analysis. The portfolio *F Score* in this setup is the value-weighted average *F Score* for all firms in that portfolio. Results are not materially different.

[14] Some portion of the observable performance in Figure I portfolios is likely due to greater small firm returns and equal weighting within portfolios.

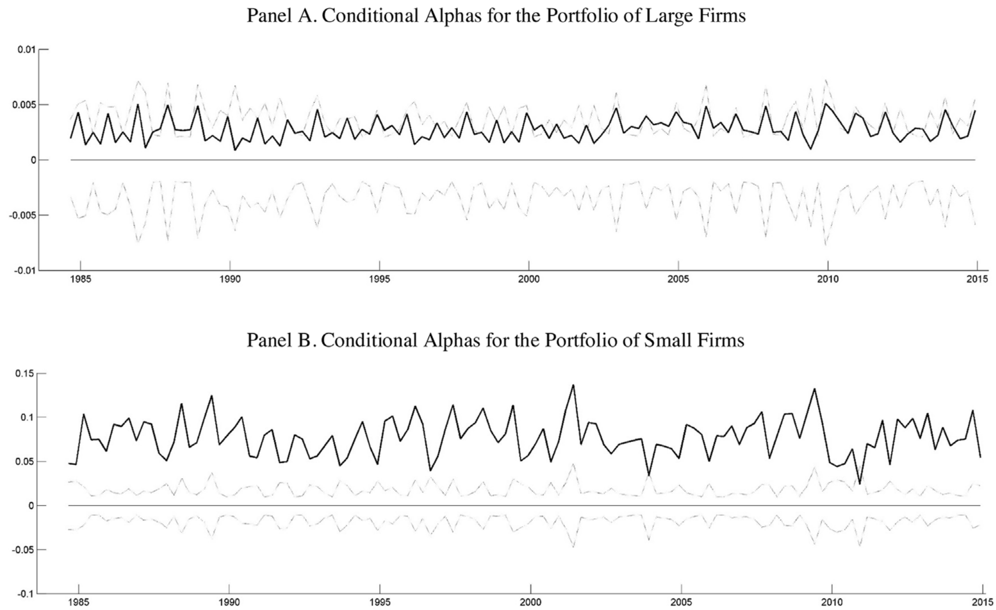


**Figure I. Conditional Alphas for Large and Small Firm Portfolios.** This figure shows the evolution of conditional alphas and the 90% nonrejection regions for the largest and smallest size decile portfolios. Conditional alphas are estimated using the six-factor model and are plotted as solid lines. The bootstrapped 90% nonrejection regions are given by lighter dotted lines. Panel A presents the conditional alphas for the portfolio of large firms. Panel B shows the conditional alphas for the portfolio of small firms.

through SMB), suggesting that in a conditional asset pricing framework, small firms provide consistently superior risk–return characteristics over large firms.[15]

One potential explanation for positive performance in Tables 2 and 3 following large *F Scores* is that investors underreact to firm fundamentals. That is, following large *F Scores*, it may not be surprising to observe underreaction, as prices only partially adjust to new information, resulting in positive conditional alphas. To further examine the underreaction hypothesis, we link our findings to the ambiguity of public information surrounding a firm. We expect underreaction to be greatest in opaque firms whose accounting information is difficult to assess. In the next section, we examine the relation between the marginal performance in high versus low *F Score* portfolios for different levels of information uncertainty.

### *Conditional Alphas and Information Uncertainty*

Information uncertainty may influence the reaction of investors to both good and bad news. Daniel, Hirshleifer, and Subrahmanyam (1998, 2001) suggest that investors may

[15] The quarterly results in Figure I differ from the annual results in Table 3 in two important ways. First, quarterly data provide a richer view of intertemporal performance evolution, and second, quarterly data provide a considerable increase in observations and test power, resulting in more significant conditional alphas.

underreact to public information when investors are overconfident about their private information. Zhang (2006) demonstrates that underreaction, and return predictability, will be greater in firms with greater information uncertainty. Greater information uncertainty should then result in larger positive returns following good news and lower expected returns following bad news. We therefore expect firms with greater information uncertainty to have greater follow-on return effects after informational events. To empirically test this hypothesis, we begin with the framework of Zhang, who double-sorts firms on information uncertainty and price momentum news. We further extend this setup by including the *F Score* as an additional information proxy regarding firm fundamentals.

We begin by confirming the general findings of Zhang (2006) with our quarterly return data. Zhang shows that increases in information uncertainty lead to an underreaction to news. To empirically test this hypothesis, we first sort firms into five quintiles based on stock returns from months $t-11$ to $t-1$. For each momentum quintile, we further sort firms into five groups based on one of three information uncertainty measures obtained at the beginning of the portfolio formation period. We consider three measures to capture firm-level information uncertainty: market capitalization, illiquidity, and idiosyncratic volatility. Market capitalization is calculated as the number of shares outstanding multiplied by the market price per share. Illiquidity is from Amihud (2002) and is defined as the quarterly average of daily ratios of absolute return to dollar value of trading volume. Following Ang et al. (2006), idiosyncratic volatility is measured using the Fama–French (1993) three-factor model.[16] In particular, idiosyncratic volatility is obtained as the quarterly sum of the squared residuals of the regression of daily excess returns on the Fama–French three factors including MKT, SMB, and HML. To diminish the effect of small firms, we remove firms with prices less than \$5 at the portfolio-formation date.[17] We then measure portfolio returns over the quarter following the portfolio-formation period. Portfolios are updated quarterly from Q3 1984 through Q4 2014.

Panel A of Table 4 reports quarterly portfolio returns for our double-sorted portfolios over momentum and size. The upper-leftmost table entry reflects the average portfolio return of 1.69% for an equal-weighted portfolio of the largest quintile of firms with the smallest momentum. In contrast, the equal-weighted portfolio of small, previous winners earns an average quarterly return of 5.17%. The final column reports the returns available to a long–short portfolio that is long previous winners and short previous losers. We observe a tendency for the momentum effect to increase as information uncertainty increases with size categories. The large firm portfolio momentum effects appear smaller and less significant when compared to the observed momentum in high-information-uncertainty portfolios. For example, the

[16] In our empirical analyses, we also consider the six-factor model for estimating idiosyncratic volatility. Our results remain unchanged. For instance, in Table 8 the difference between the conditional alphas from Panel B U5 and Panel A U1 changes from 4.94% $(= 1.73 - (-3.21))$ based on the three-factor model to 4.87% $(= 1.86 - (-3.01))$ based on the six-factor model.

[17] This data filter is included solely to maintain comparability with Zhang (2006) and has little qualitative effect on the empirical results.

**TABLE 4. Portfolio Raw Returns for Double-Sorted Portfolios on Momentum and Information Uncertainty.**

| Information Uncertainty | M1 (Losers) | M2 | M3 | M4 | M5 (Winners) | M5–M1 |
|---|---|---|---|---|---|---|
| | Momentum Quintile | | | | | |
| **Panel A. Uncertainty Proxied by Size** | | | | | | |
| U1 (Large) | 1.69% | 2.79% | 3.05% | 3.18% | 4.02% | 2.33%** (2.19) |
| U2 | 1.85% | 2.76% | 3.34% | 3.39% | 3.30% | 1.45% (1.47) |
| U3 | 1.26% | 3.03% | 3.12% | 3.52% | 3.72% | 2.45%*** (2.68) |
| U4 | 0.81% | 2.57% | 2.91% | 3.87% | 4.89% | 4.08%*** (4.59) |
| U5 (Small) | 0.89% | 2.81% | 3.62% | 4.16% | 5.17% | 4.28%*** (5.21) |
| U5–U1 | −0.80% (−1.24) | 0.02% (0.03) | 0.56% (1.02) | 0.98%* (1.69) | 1.16% (1.62) | |
| **Panel B. Uncertainty Proxied by Illiquidity** | | | | | | |
| U1 (Low) | 1.74% | 2.69% | 2.98% | 3.37% | 3.85% | 2.11%* (1.98) |
| U2 | 1.47% | 2.81% | 3.25% | 2.91% | 3.13% | 1.66%* (1.70) |
| U3 | 1.40% | 2.77% | 3.22% | 3.66% | 3.42% | 2.02%** (2.26) |
| U4 | 1.52% | 2.96% | 3.01% | 4.06% | 4.88% | 3.36%*** (3.75) |
| U5 (High) | 0.88% | 2.97% | 3.67% | 4.37% | 5.63% | 4.76%*** (5.66) |
| U5–U1 | −0.86% (−1.19) | 0.28% (0.52) | 0.69% (1.29) | 0.99%* (1.70) | 1.79%*** (2.63) | |
| **Panel C. Uncertainty Proxied by Idiosyncratic Volatility** | | | | | | |
| U1 (Low) | 2.61% | 3.39% | 3.53% | 3.95% | 4.05% | 1.44%* (1.78) |
| U2 | 2.36% | 2.87% | 3.54% | 3.78% | 4.81% | 2.45%** (2.50) |
| U3 | 2.22% | 3.36% | 3.56% | 3.90% | 5.02% | 2.80%*** (2.91) |
| U4 | 1.03% | 2.70% | 3.44% | 3.81% | 3.98% | 2.95%*** (3.04) |
| U5 (High) | −1.24% | 1.88% | 2.05% | 2.93% | 3.05% | 4.28%*** (4.44) |
| U5–U1 | −3.85%*** (−4.24) | −1.51%* (−1.77) | −1.48%* (−1.82) | −1.02% (−1.11) | −1.01% (−1.07) | |

Note: This table reports quarterly returns for portfolios sorted by price momentum and information uncertainty measured by size (Panel A), illiquidity (Panel B), or idiosyncratic volatility (Panel C). Following Zhang (2006), firms are first sorted into five quintiles based on stock returns from months $t$–11 to $t$–1. For each momentum quintile, the firms are further sorted into five groups based on the market capitalization, illiquidity, or idiosyncratic volatility at the end of month $t$. Equal-weighted portfolio returns are calculated for the next quarter from Q3 1984 to Q4 2014. The $t$-tests of the difference between the mean raw returns in M5 and M1 (U5 and U1) are given in parentheses in the final column (row) of each panel.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

low-information-uncertainty (U1) long–short momentum portfolio earns 2.33%, which is about half the 4.28% average earned by the high-information-uncertainty (U5) long–short momentum portfolio.[18] Except for one case, results across size portfolios within momentum quintiles show no significant differences.

Panels B and C of Table 4 repeat the exercise in Panel A with sorts on illiquidity and idiosyncratic volatility, in place of market capitalization, respectively. Portfolio U1 contains firms with the lowest levels of illiquidity or idiosyncratic volatility, and portfolio U5 includes firms with the highest levels of information uncertainty. We observe qualitatively similar results to those in Panel A. For example, the momentum effect is always more pronounced in high-information-uncertainty firms. The return spread from the momentum effect ranges from 2.11% to 4.76% for illiquidity, and 1.44% to 4.28% for idiosyncratic volatility. Higher previous illiquidity leads to higher future returns for past winners. Similarly, greater previous idiosyncratic volatility is associated with smaller future returns, and this relation is amplified in past losers.

We next compute quarterly conditional alphas for double-sorted portfolios using the six-factor model and the *F Score* as the information instrument. Table 5 reports the time-series averages for all estimated conditional alphas from Q3 1984 to Q4 2014. We find the return differences in Table 4 are not solely attributable to risk corrections. Although (risk-adjusted) conditional alphas are smaller in magnitude than the raw returns in Table 4, the positive relation between information uncertainty and momentum remains. For example, the return spread between past winners and past losers generally becomes larger as we move from low to high levels of information uncertainty.

If the information uncertainty hypothesis is correct, we expect the *F Score* to act as an important measure of good or bad news alongside momentum, with effects being especially prevalent when uncertainty is greatest. Good news events such as positive momentum or high *F Scores* should produce greater conditional marginal performance in high-information-uncertainty firms than similar events for low-information-uncertainty firms.

Table 6 reports results for portfolios sorted on *F Score*, momentum, and three information uncertainty proxies (size, illiquidity, and idiosyncratic volatility). At each quarter-end, we combine firms with quarterly *F Scores* from 0 to 2 in the low *F Score* group, and firms with quarterly *F Scores* from 3 to 4 and 5 to 7 in the mid and high *F Score* groups, respectively. We then wait three months before we further sort firms on momentum and market capitalization. This approach results in a total of 75 quarterly updated portfolios.[19] We report results for both equal-weighted portfolio raw returns and

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[18] These results are comparable to Zhang (2006) after adjusting for the quarterly return measurement interval and the cross-sectional sample restrictions. Korkie and Turtle (2002) discuss related interpretations of long–short portfolios.

[19] Given its persistence, the *F Score* may provide similar evidence to price momentum. Therefore, we control for momentum when examining the return predictability due to *F Score*. Because there are fewer firms with a low *F Score* in our sample, to ensure each triple-sorted portfolio has a reasonable number of firms, we use a dependent sorting approach for momentum and information uncertainty. In unreported tables, we find that our sorting procedure does not result in systematic differences in dispersion of momentum and information uncertainty between low and high *F Score* portfolios. In addition, our results remain quantitatively unchanged when portfolios are formed first on information uncertainty and then on momentum.

**TABLE 5. Portfolio Conditional Alphas for Double-Sorted Portfolios on Momentum and Information Uncertainty.**

| | Momentum Quintile | | | | | |
|---|---|---|---|---|---|---|
| Information Uncertainty | M1 (Losers) | M2 | M3 | M4 | M5 (Winners) | M5–M1 |
| Panel A. Uncertainty Proxied by Size | | | | | | |
| U1 (Large) | −0.41% | −0.10% | −0.14% | −0.16% | 0.57% | 0.98% |
| U2 | −0.23% | −0.16% | −0.09% | −0.19% | −0.28% | −0.05% |
| U3 | −0.59% | 0.16% | −0.21% | 0.17% | −0.03% | 0.56% |
| U4 | −1.25% | −0.47% | −0.25% | 0.29% | 1.10% | 2.35% |
| U5 (Small) | −1.27% | 0.05% | 0.71% | 0.87% | 1.72% | 2.99% |
| U5–U1 | −0.85% | 0.15% | 0.86% | 1.03% | 1.16% | |
| Panel B. Uncertainty Proxied by Illiquidity | | | | | | |
| U1 (Low) | −0.52% | −0.32% | −0.21% | 0.03% | 0.54% | 1.06% |
| U2 | −0.54% | −0.14% | −0.11% | −0.56% | −0.44% | 0.09% |
| U3 | −0.71% | −0.27% | −0.16% | 0.10% | −0.53% | 0.18% |
| U4 | −0.25% | 0.05% | −0.22% | 0.50% | 1.01% | 1.26% |
| U5 (High) | −1.47% | 0.31% | 0.65% | 1.10% | 2.38% | 3.85% |
| U5–U1 | −0.95% | 0.63% | 0.85% | 1.07% | 1.85% | |
| Panel C. Uncertainty Proxied by Idiosyncratic Volatility | | | | | | |
| U1 (Low) | −0.05% | 0.32% | 0.23% | 0.43% | 0.47% | 2.14% |
| U2 | −0.12% | −0.19% | −0.07% | −0.05% | 1.13% | 3.25% |
| U3 | 0.02% | 0.31% | 0.17% | 0.41% | 1.02% | 3.46% |
| U4 | −0.88% | −0.33% | 0.31% | 0.43% | 0.41% | 3.51% |
| U5 (High) | −2.50% | −0.46% | −0.65% | −0.06% | −0.07% | 4.67% |
| U5–U1 | −4.24% | −2.09% | −1.96% | −1.55% | −1.71% | |

Note: This table reports quarterly conditional alphas for portfolios sorted by price momentum and information uncertainty measured by size (Panel A), illiquidity (Panel B), or idiosyncratic volatility (Panel C). Following Zhang (2006), firms are first sorted into five quintiles based on stock returns from months $t$–11 to $t$–1. For each momentum quintile, the firms are further sorted into five groups based on market capitalization, illiquidity, or idiosyncratic volatility at the end of month $t$. Equal-weighted portfolio returns are calculated for the next quarter from Q3 1984 to Q4 2014. Portfolio conditional alphas are computed using risk factors including the market excess return (MKT), the small-minus-big (SMB) factor, the high-minus-low (HML) factor, the momentum (MOM) factor, the robust-minus-weak (RMW) factor, and the conservative-minus-aggressive (CMA) factor. The information instrument for each portfolio is calculated as the average *F Score* for all firms in that portfolio. Time-series averages for all conditional alphas are reported in the table.

equal-weighted portfolio conditional alphas. For brevity, we focus on the smallest and largest quintile portfolios, and portfolios formed with low and high *F Scores*. Results are reported in Panels A and B, respectively.

Our *F Score* results strongly support the information uncertainty hypothesis. When we observe negative public information (bad news) in terms of both momentum and *F Score*, we find a dramatically more responsive negative effect in returns to the high- versus low-information-uncertainty portfolios. For example, in Panel A of Table 6, the small firm portfolio has a sample mean of −0.59%, with a comparable large firm return of 0.82% when both momentum and *F Score* are low. The risk-adjusted marginal performance measures show a comparable difference in the means of conditional alphas

**TABLE 6. Portfolio Raw Returns and Conditional Alphas for Triple-Sorted Portfolios on *F Score*, Momentum, and Information Uncertainty (Proxied by Size, Illiquidity, and Idiosyncratic Volatility).**

| | Raw Returns | | | Conditional Alphas | | |
|---|---|---|---|---|---|---|
| | M1 (Losers) | M5 (Winners) | M5–M1 | M1 (Losers) | M5 (Winners) | M5–M1 |
| Size as an Information Uncertainty Proxy | | | | | | |
| Panel A. Low *F Score* Portfolios | | | | | | |
| U1 (Large) | 0.82% | 2.34% | 1.52% | −0.15% | −0.77% | −0.61% |
| U5 (Small) | −0.59% | 1.79% | 2.38% | −2.03% | −1.09% | 0.94% |
| U5-U1 | −1.41% | −0.55% | | −1.87% | −0.32% | |
| Panel B. High *F Score* Portfolios | | | | | | |
| U1 (Large) | 1.81% | 3.87% | 2.07% | −1.12% | 0.46% | 1.58% |
| U5 (Small) | 2.33% | 7.46% | 5.14% | −0.37% | 3.35% | 3.71% |
| U5–U1 | 0.52% | 3.59% | | 0.75% | 2.89% | |
| Illiquidity as an Information Uncertainty Proxy | | | | | | |
| Panel C. Low *F Score* Portfolios | | | | | | |
| U1 (Low) | 1.37% | 2.03% | 0.65% | 0.54% | −1.38% | −1.91% |
| U5 (High) | −0.51% | 2.40% | 2.90% | −2.64% | −0.18% | 2.47% |
| U5–U1 | −1.88% | 0.37% | | −3.18% | 1.20% | |
| Panel D. High *F Score* Portfolios | | | | | | |
| U1 (Low) | 2.35% | 3.86% | 1.51% | −0.37% | 0.50% | 0.87% |
| U5 (High) | 2.98% | 8.01% | 5.03% | 0.34% | 3.78% | 3.44% |
| U5–U1 | 0.64% | 4.15% | | 0.71% | 3.27% | |
| Idiosyncratic Volatility as an Information Uncertainty Proxy | | | | | | |
| Panel E. Low *F Score* Portfolios | | | | | | |
| U1 (Low) | 1.41% | 3.00% | 1.59% | −0.61% | −0.29% | 0.32% |
| U5 (High) | −2.78% | 0.24% | 3.02% | −3.21% | −1.72% | 1.48% |
| U5–U1 | −4.19% | −2.76% | | −2.60% | −1.43% | |
| Panel F. High *F Score* Portfolios | | | | | | |
| U1 (Low) | 3.21% | 4.46% | 1.25% | 0.26% | 0.33% | 0.07% |
| U5 (High) | 1.74% | 5.65% | 3.91% | −0.27% | 1.73% | 2.01% |
| U5–U1 | −1.47% | 1.19% | | −0.54% | 1.40% | |

Note: This table reports summary statistics for portfolios sorted by *F Score*, momentum, and one of three proxies for information uncertainty (size, illiquidity, and idiosyncratic volatility). To form portfolios, sample firms are first classified into three groups based on *F Score*, where the low *F Score* group contains firms with *F Scores* from 0 to 2, and the high *F Score* group include firms with *F Scores* from 5 to 7. At the end of each quarter, and for each *F Score* category (obtained in the prior quarter), the firms are sorted into five quintiles based on stock returns from months $t-11$ to $t-1$. For each momentum quintile, the firms are further sorted into five groups based on information uncertainty at the portfolio formation date. Time-series averages of conditional alphas for the next quarter from Q3 1984 to Q4 2014 are reported for the six-factor model with risk factors including the market excess return (MKT), the small-minus-big (SMB) factor, the high-minus-low (HML) factor, the momentum (MOM) factor, the robust-minus-weak (RMW) factor, and the conservative-minus-aggressive (CMA) factor. The information instrument for each portfolio is calculated as the average *F Score* for all firms in that portfolio. Panel A reports average one-quarter post-portfolio-formation raw returns as well as conditional alphas for low *F Score* portfolios, when information uncertainty is proxied by market capitalization. Panel B provides similar statistics for high *F Score* portfolios. Panels C and D report low and high *F Score* results, respectively, when information uncertainty is proxied by a measure of illiquidity. Finally, Panels E and F report low and high *F Score* results, respectively, when information uncertainty is proxied by idiosyncratic volatility.

of approximately −1.87%. In the case of positive momentum and *F Score* news, the resultant differences between the large and small firm portfolios are again consistent with the information uncertainty hypothesis. For example, in Panel B we observe that the average return to a high-momentum, high *F Score* portfolio is 7.46% for small firms and only 3.87% for large firms. Comparing average returns or average conditional alphas provides similar findings. In particular, portfolios formed from small, previous winner (high-momentum) firms with high *F Scores* earn nearly 3% more than similar large firm portfolios measured in conditional alphas.

Comparing the differences in marginal performance, we can examine the marginal performance for an investor that is long in a high-momentum, high *F Score* portfolio and short in a low-momentum, low *F Score* portfolio. The average of the time-series alphas in this case is economically meaningful and exceeds 5% (= 3.35 − (−2.03)) per quarter.

Figure II provides a graphical presentation of the six-factor conditional alphas and 90% nonrejection regions over time for our *F Score*, momentum, and size

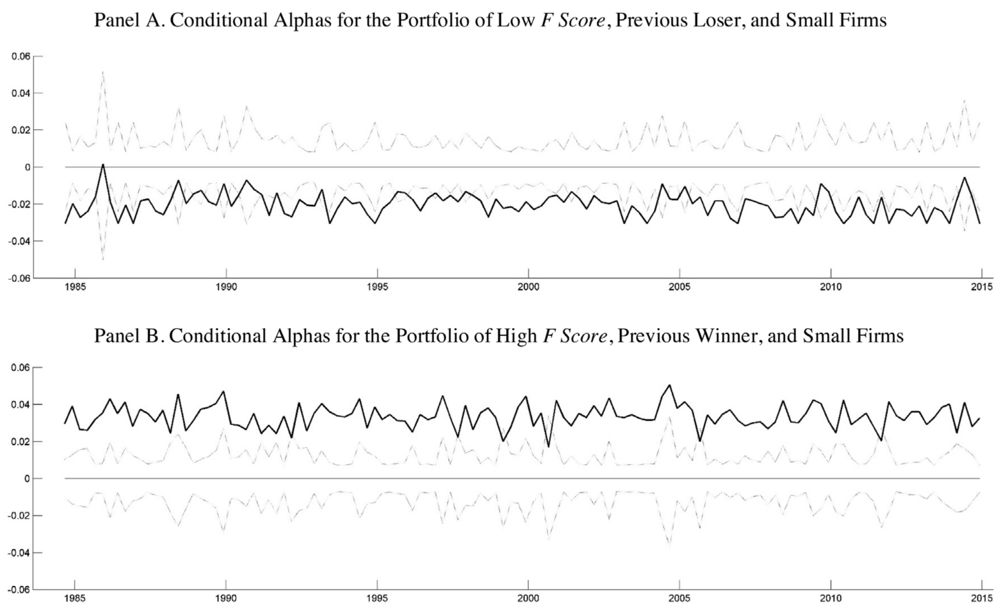


**Figure II. Conditional Alphas for Triple-Sorted Portfolios on *F Score*, Momentum, and Size.** This figure shows the evolution of conditional alphas and 90% nonrejection regions for triple-sorted portfolios on *F Score,* momentum, and size. Conditional alphas are estimated using the six-factor model and are plotted as solid lines. The bootstrapped 90% nonrejection regions are given by lighter dotted lines. Panel A presents the conditional alphas for the portfolio of low *F Score*, previous loser, and small firms. Panel B shows the conditional alphas for the portfolio of high *F Score*, previous winner, and small firms.

triple-sorted portfolios. In Panel A, we present the evolution of conditional alphas for the portfolio of low *F Score*, previous loser, small firms (as averaged and reported in the second row, fourth column of Panel A, Table 6, U5, M1 conditional alpha entry). The observed conditional alphas are consistently (and often significantly) negative. In the lower panel, we see that the portfolio of high *F Score*, previous winner, small firms (as averaged and reported in the second row, fifth column of Panel B, Table 6, U5, M5 conditional alpha entry) consistently generates positive and significant marginal performance. In general, we conclude that higher information uncertainty (small firm) portfolios present a clear opportunity to generate abnormal performance and that the potential gains are persistent and appear strongly significant (both statistically and economically). As is apparent in Figure II, we also note that the positive conditional alphas in Panel B appear economically larger (and are more often statistically significant) relative to the corresponding negative values in Panel A.[20,21]

To confirm that our results are robust to alternative measures of information uncertainty, we repeat the analysis in Panels A and B of Table 6 after replacing the final sorting variable with two alternative measures of information uncertainty: illiquidity or idiosyncratic volatility. Results are shown in Panels C and D, or E and F, respectively. We again find supportive evidence for the information uncertainty hypothesis. For example, when proxying information uncertainty with idiosyncratic volatility, we find the portfolio of high *F Score*, previous winner, and high information uncertainty earns significantly higher marginal performance (Panels D and F, U5, M5 entries), in terms of both raw returns and conditional alphas, than the portfolio of low *F Score*, previous losers, and high information uncertainty (Panels C and E, U5, M1 entries). The difference in conditional alphas between the two extreme portfolios is 6.42% ($= 3.78 - (-2.64)$) per quarter for illiquidity and 4.94% ($= 1.73 - (-3.21)$) per quarter for idiosyncratic volatility. These results suggest that the abnormal gains from a strategy based on underreaction to fundamental value changes under information uncertainty are not subsumed by common risk factors documented in the literature.

To this point, our results on investor underreaction focus on the role of information uncertainty in the cross-section. To further examine the underreaction hypothesis and its relevance to the relation between returns and the *F Score*, we now examine the performance of *F Score* and momentum portfolios in reaction to time-varying macroeconomic conditions.

If investor underreaction explains the return predictability of the *F Score*, we expect this predictability to be more prominent when underreaction is most prevalent. We follow Walkshäusl (2016) and consider two macroeconomic conditions related to investor underreaction (which leads to mispricing): investment sentiment and limits to

[20] Figure II suggests large effects (both economically and statistically) that relate to potential long positions in high *F Score*, high-momentum positions as characterized by the positive conditional alphas in Panel B. Although we later find results consistent with Stambaugh, Yu, and Yuan (2012) regarding the effect of sentiment on performance and the role of short positions, this finding cannot be fully explained by short sale restrictions.

[21] For robustness, and following the guidance of an associate editor, we also examine the behavior of Figure II assuming conditional alphas are generated following the research design of Christopherson, Ferson, and Glassman (1998). Results are economically similar in magnitude compared to Figure II (with less variability in the Panel A conditional alphas).

arbitrage. Stambaugh, Yu, and Yuan (2012) show that investment strategies exploiting mispricing are amplified during periods of strong positive investor sentiment. During periods of positive sentiment, stocks prices deviate more from fundamentals, inflating return anomalies. Furthermore, Stambaugh, Yu, and Yuan argue that the sentiment effect is more pronounced among overvalued stocks whose prices routinely deviate from fundamental values due to short-sale restrictions.[22] Limits to arbitrage are another factor posited to affect mispricing in conjunction with investor sentiment. During periods of scarce arbitrage capital, prices of overvalued stocks are less likely to be corrected, thus attenuating the sentiment effect.

In our context, the portfolio of low *F Score*, previous losers (in terms of momentum) is likely to be most overvalued when the market displays strong investor sentiment. Furthermore, price corrections following overvaluation are expected to occur more quickly when there is an abundance of arbitrage capital. Thus, we expect the portfolio of low *F Score*, previous losers to perform relatively worse during these economic conditions. To test this hypothesis, we run time-series regressions of one-quarter return performance for double-sorted portfolios (over *F Score* and momentum) on marketwide levels of investor sentiment and arbitrage capital. To form portfolios, we first classify firms into low, mid, and high *F Score* groups at each quarter-end. We then wait three months before further sorting each *F Score* group into quintile portfolios based on momentum. We obtain the investor sentiment index from Baker and Wurgler (2006) and the noise index (an inverse measure of arbitrage capital) from Hu, Pan, and Wang (2013).[23] To facilitate coefficient interpretation, we demean index variables and rescale by dividing by 100.

The initial three columns in Table 7 report coefficient estimates and *t*-statistics when portfolio performance is measured by raw returns. For brevity, we report results for the combined portfolio of low *F Score* and previous losers (P1) relative to the portfolio of high *F Score* and previous winners (P5), as well as the long–short portfolio (P5–P1). The intercept for the long–short portfolio is positive and significant, suggesting the strategy of exploiting accounting fundamentals and momentum is profitable. The coefficients on sentiment and noise are broadly in line with the misvaluation hypothesis: the long–short portfolio becomes less profitable when the market becomes more scarce in arbitrage capital (i.e., an increase in noise), and this effect is mostly driven by the short component related to low *F Score*, previous loser firms. During periods of strong sentiment, the long and short components should exhibit larger return spreads, suggesting that market optimism will amplify mispricing. However, we find little support for this hypothesis in raw returns as the long–short portfolio does not have a significant relation to sentiment.

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[22] Strong investor sentiment elevates the prices of all stocks in the market. The underreaction hypothesis posits that low (high) *F Score* stocks tend to have overinflated (underinflated) prices relative to intrinsic values. Therefore, strong sentiment implies that low *F Score* stocks will deviate most from fundamentals.

[23] We thank Jeffrey Wurgler (http://people.stern.nyu.edu/jwurgler/) and Jun Pan (http://www.mit.edu/~junpan/) for making these data available online. We convert the original time series to a quarterly frequency by taking averages within each quarter. Because the noise index begins in Q1 1987, our analysis covers the return period from Q2 1987 to Q4 2014.

**TABLE 7. Performance of *F Score* and Momentum Double-Sorted Portfolios on Investor Sentiment and the Availability of Arbitrage Capital.**

| | Raw Returns$_{q+1}$ | | | Conditional Alphas$_{q+1}$ | | |
|---|---|---|---|---|---|---|
| | P1 (Low *F Score*, Losers) | P5 (High *F Score*, Winners) | P5–P1 | P1 (Low *F Score*, Losers) | P5 (High *F Score*, Winners) | P5–P1 |
| Intercept | −0.003 | 0.049*** | 0.052*** | −0.012*** | 0.015*** | 0.027*** |
| | (−0.20) | (3.71) | (5.09) | (−95.42) | (54.15) | (83.30) |
| Sentiment$_q$ | −4.938* | −3.287 | 1.650 | −0.075*** | 0.073 | 0.148*** |
| | (−1.89) | (−1.47) | (0.96) | (−3.63) | (1.55) | (2.73) |
| Noise$_q$ | 1.309* | −0.053 | −1.362*** | −0.001 | −0.016 | −0.015 |
| | (1.75) | (−0.08) | (−2.76) | (−0.20) | (−1.18) | (−0.95) |

Note: This table reports results from time-series regressions of next-quarter returns to double-sorted portfolios on *F Score* and momentum regressed on investor sentiment and noise. To form portfolios, sample firms are first classified into three groups based on F *Score*, where the low *F Score* group contains firms with *F Scores* from 0 to 2, and the high *F Score* group include firms with *F Scores* from 5 to 7. At the end of each quarter, and for each *F Score* category (obtained in the prior quarter), the firms are further sorted into five quintiles based on stock returns from months *t*–11 to *t*–1. P1 is the portfolio of firms with low *F Score* and previous losers, and P5 consists of firms with high *F Score* and previous winners, and where P5–P1 denotes the long–short portfolio. The first three columns report coefficient estimates from regressing post-one-quarter raw returns on investor sentiment and noise, and the final three columns present similar results for portfolio performance measured by conditional alphas (*t*-statistics are given in parentheses).
***Significant at the 1% level.
*Significant at the 10% level.

The last three columns in Table 7 report results related to the conditional alpha. Consistent with our earlier findings linking performance to the *F Score*, firms with strong accounting fundamentals outperform those with weak fundamentals. The average difference in conditional alphas between the two portfolios is 2.67% per quarter. Consistent with Stambaugh, Yu, and Yuan (2012), we find that investor sentiment enhances the performance of the long–short portfolio, mainly because of the short position in low *F Score* firms and previous losers. The availability of arbitrage capital shows no significant effect on these portfolios.[24] Taken together, these results suggest that after risk compensation, the return predictability of the *F Score* is more sensitive to investor sentiment than limits to arbitrage.[25]

*Robustness Analysis*

In this section we consider two robustness analyses. We begin with an analysis of different time lags between the measurement of the *F Score* and the beginning of the

[24] For robustness, we also consider the market liquidity measure in Pastor and Stambaugh (2003) and find qualitatively similar results.

[25] The results in Table 7 are also consistent with the intertemporal results in Figure II. Because we demean the regressors in Table 7, we can interpret the intercepts in the second and third last columns as the constant portion of the conditional alphas after removing the regressor effects. We again find the strongest effect for the implied long position described by the P5 column. The difference between these portfolios is dampened relative to Figure II, as we now consider the broader double-sorted portfolio.

**TABLE 8. Robustness Results for Two- and Six-Month Portfolio Formation Lags for Triple-Sorted Portfolios.**

| | Two-Month Lag | | | Six-Month Lag | | |
|---|---|---|---|---|---|---|
| Size | M1 (Losers) | M5 (Winners) | M5–M1 | M1 (Losers) | M5 (Winners) | M5–M1 |
| Panel A. Low *F Score* Portfolios | | | | | | |
| U1 (Large) | −0.82% | −0.54% | 0.28% | −1.35% | −0.81% | 0.54% |
| U5 (Small) | −3.81% | −1.68% | 2.13% | −4.12% | −0.33% | 3.79% |
| U5–U1 | −2.99% | −1.14% | | −2.77% | 0.48% | |
| Panel B. High *F Score* Portfolios | | | | | | |
| U1 (Large) | −0.98% | 0.54% | 1.52% | 0.20% | 0.95% | 0.75% |
| U5 (Small) | 0.78% | 4.68% | 3.89% | 1.07% | 3.21% | 2.14% |
| U5–U1 | 1.76% | 4.14% | | 0.87% | 2.26% | |

Note: This table reports average six-factor conditional alphas for portfolios sorted by *F Score*, price momentum, and size, with two- and six-month formation lags. To form portfolios, sample firms are first classified into three groups based on *F Score*, where the low *F Score* group contains firms with *F Scores* from 0 to 2, and the high *F Score* group include firms with *F Scores* from 5 to 7. At the beginning of each portfolio-formation period, and for each *F Score* category (obtained in the prior quarter), the firms are further sorted into quintiles based on momentum and size. Conditional alphas are estimated using the average *F Score* for all firms in each portfolio as the instrument. Reported results reflect a lag of either two or six months between quarter-ends and portfolio-formation date. Time-series averages of conditional alphas based on *F Score* from Q1 1984 to Q2 2014 are reported. Panel A and B report average one-quarter post-portfolio-formation conditional alphas for low and high *F Score* portfolios, respectively.

portfolio-formation period and show that our results are robust to either a two- or six-month lag between *F Score* measurement and portfolio formation.

Because the ability to use *F Score* data depends on the availability of measured accounting data, as a robustness test, we adjust the three-month period between *F Score* measurement and portfolio formation to consider lags of two and six months. If measured accounting data are not available within three months following the quarter-end, our primary results may be overstated. In contrast, if most firms report their 10Q within two months after the quarter-end, the three-month lag between *F Score* measurement and portfolio formation may be too restrictive. To conserve space, in Table 8, we report only results for portfolios sorted on *F Score*, momentum, and market capitalization.[26] Two-month lag results are shown in columns 1–3, followed by six-month lag results in columns 4–6. Our main empirical findings remain with both alternative portfolio formation lags.

In our primary analysis, we focus on triple-sorted portfolios formed on *F Score*, momentum, and information uncertainty because our interest is to see whether the *F Score* provides incremental return predictability beyond the well-documented momentum effect. We use these portfolios to test the hypothesis that the relation between

[26] In unreported tables, we find qualitatively similar results when using illiquidity or idiosyncratic volatility as information uncertainty measures.

**TABLE 9. Portfolio Conditional Alphas for Double-Sorted Portfolios on *F Score* and Information Uncertainty.**

| | *F Score* | | | |
|---|---|---|---|---|
| Information Uncertainty | Low | Mid | High | High–Low |
| Panel A. Uncertainty Proxied by Size | | | | |
| U1 (Large) | −0.08% | 0.26% | −0.03% | 0.05% |
| U2 | −0.76% | −0.29% | 0.54% | 1.30% |
| U3 | −1.09% | −0.23% | 0.18% | 1.27% |
| U4 | −1.36% | −0.38% | 1.11% | 2.47% |
| U5 (Small) | −1.64% | −0.12% | 1.64% | 3.28% |
| U5–U1 | −1.56% | −0.38% | 1.67% | |
| Panel B. Uncertainty Proxied by Illiquidity | | | | |
| U1 (Low) | −0.11% | 0.13% | 0.33% | 0.44% |
| U2 | −1.23% | −0.38% | 0.08% | 1.30% |
| U3 | −0.77% | −0.29% | 0.58% | 1.35% |
| U4 | −1.23% | −0.28% | 0.96% | 2.19% |
| U5 (High) | −1.25% | −0.02% | 1.67% | 2.92% |
| U5–U1 | −1.14% | −0.15% | 1.34% | |
| Panel C. Uncertainty Proxied by Idiosyncratic Volatility | | | | |
| U1 (Low) | −0.11% | 0.01% | 0.25% | 0.36% |
| U2 | −1.23% | −0.24% | 0.39% | 1.61% |
| U3 | −0.77% | 0.66% | 0.98% | 1.75% |
| U4 | −1.23% | −0.04% | 1.17% | 2.40% |
| U5 (High) | −1.25% | −1.14% | 0.86% | 2.11% |
| U5–U1 | −1.14% | −1.15% | 0.62% | |

Note: This table reports quarterly conditional alphas for portfolios sorted by *F Score* and information uncertainty measured by size (Panel A), illiquidity (Panel B), or idiosyncratic volatility (Panel C). To form portfolios, sample firms are first classified into three groups based on *F Score*, where the low *F Score* group contains firms with *F Scores* from 0 to 2, and the high *F Score* group include firms with *F Scores* from 5 to 7. At the end of each quarter, and for each *F Score* category, firms are further sorted into five quintiles based on market capitalization, illiquidity, or idiosyncratic volatility. Equal-weighted portfolio returns are calculated from Q3 1984 to Q4 2014. Portfolio conditional alphas are computed using risk factors including the market excess return (MKT), the small-minus-big (SMB) factor, the high-minus-low (HML) factor, the momentum (MOM) factor, the robust-minus-weak (RMW) factor, and the conservative-minus-aggressive (CMA) factor. The information instrument for each portfolio is calculated as the average *F Score* for all firms in that portfolio. Time-series averages for all conditional alphas are reported in the table.

performance and the *F Score* is driven by investor underreaction to firm fundamentals. Here, we provide a parallel design to Zhang (2006) to examine how *F Score* affects firms that have large versus small information uncertainty (disregarding momentum). To address this issue, at the end of each quarter, we form double-sorted portfolios on *F Score* and information uncertainty. We report quarterly conditional alphas for these portfolios in Table 9. In the final column we observe that high *F Score* firms earn greater conditional alphas than low *F Score* firms, and furthermore, the performance difference is most prominent among high-information-uncertainty firms, again supporting the under-reaction hypothesis of the return predictability of *F Score*.

## IV. Concluding Comments

We apply conditional performance evaluation to fundamental accounting-based information measures in the spirit of Graham and Dodd (1934), Lev and Thiagarajan (1993), and Piotroski and So (2012). We find strong evidence of significant conditional performance after corrections for risk differences. Our approach produces point estimates of performance along with related inferences that vary over time and across economic states. We find little empirical support for the Fama and French (2006) critique that strong fundamental firms may simply offer superior returns as compensation for greater risk.

We address the relation between performance and the *F Score* in the context of the underreaction hypothesis of Daniel, Hirshleifer, and Subrahmanyam (1998, 2001). We find evidence that public information events are only slowly reflected in stock prices and that this effect is more evident among high-information-uncertainty (proxied by size, illiquidity, or idiosyncratic volatility) portfolios and during periods in which asset prices are more detached from intrinsic values. Firms with high (or low) *F Scores* and momentum tend to display especially strong (or weak) ex post performance. In sum, a substantial portion of observed mispricing may be explained by gradual price adjustments in cases of high information uncertainty or market optimism. Results are robust to alternative portfolio-formation strategies.

## Appendix: Marginal Performance Inferences with Bootstrapping

In this Appendix we present our bootstrapping procedure to calculate nonrejection regions for various instrument realizations in the unconditional regression given by equation (4). The bootstrapping approach requires few assumptions regarding the underlying error distribution. A seminal discussion of bootstrapping can be found in Stine (1985), and an excellent application of these approaches in a related context can be found in Kosowski et al. (2006).

Our specific bootstrapping procedure may be described as follows:

1. For any given asset or portfolio, estimate equation (4) using ordinary least squares (OLS) and retain the regressors, the estimated parameter vector, and the model residuals, $e_t$, for $t = 1, 2, \ldots, T$.
2. For each bootstrap replication, draw a pseudo time series of $T$ resampled residuals, defined as $e_{bt}$, for $t = 1, 2, \ldots, T$, and construct a time series of bootstrapped excess returns under the null hypothesis of zero marginal performance, $\alpha_{jt} = 0$. The absence of abnormal performance is equivalent to $\alpha_{j0} = \alpha_{j1} = \ldots = \alpha_{jM} = 0$. The resultant bootstrap replication is then given by

$$R_{bt} = \hat{\beta}_{j1} F_{1t} + \ldots + \hat{\beta}_{jK} F_{Kt} + e_{bt}, \tag{A1}$$

for $t = 1, 2, \ldots, T$. Following Kosowski et al. (2006), our base case bootstrap methodology does not randomize over the risk factors.

3. For each of $b = 1, 2, \ldots, B$, bootstrap replications, we then estimate the model,

$$R_{bt} = \alpha_{jb0} + \alpha_{jb1}Z_{1t-1} + \ldots + \alpha_{jbM}Z_{Mt-1} + \beta_{jb1}F_{1t} + \ldots + \beta_{jbK}F_{Kt} + \varepsilon_{bt}, \tag{A2}$$

and save all estimated model parameters for each replication.

4. The observed empirical distribution of $\hat{\alpha}_{jbt} = \hat{\alpha}_{jb0} + \hat{\alpha}_{jb1}Z_{1t-1} + \ldots + \hat{\alpha}_{jbM}Z_{Mt-1}$ from (A2) may then be used to determine nonrejection regions for given test sizes. In particular, for each point in time and for every instrument realization, we compare the estimated conditional alpha, $\hat{\alpha}_{jt}$, with the bootstrapped distribution under the null hypothesis of no abnormal performance, formed from the empirical distribution of $\hat{\alpha}_{jbt}$.

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