Fundamental Analysis Works

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Abstract

Stock prices cannot be the outcome of a rational efficient market if fundamental analysis based on public information is profitable. Our approach to fundamental analysis estimates the intrinsic fair values of stocks from the most common quarterly balance sheet and income statement items that were last reported in Compustat. Taking the view of a statistician with little knowledge of finance theory, we show that the most basic form of fundamental analysis yields trades with risk-adjusted returns of up to 9% per year. The trading strategy relies on the convergence of market prices to their fair values. The greatest rate of convergence occurs in the month after the mispricing signal and subsequently decays to zero over the subsequent 28 months. Profits from trading are present for both large and small firms in economically significant magnitudes.

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One of the cornerstones of market efficiency is the principle that fundamental analysis should "not work." Trading strategies derived from public information like accounting statements should not earn abnormal profits for the risk they bear. Over the past 35 years, evidence has accumulated about anomalies that seem to violate this maxim. Investments linked to momentum, earnings surprises, stock issuance, accruals, credit risk, gross profit, book-to-market, and a host of other signals have earned abnormal profits in the past.[1] However, unlike basic fundamental analysis, the motivation for studying these signals is not always apparent.[2]

Fundamental analysis is based on the principle that stocks have an intrinsic fair value and that investors can earn abnormal profits from stock-specific signals that indicate deviations from fair value. Abnormal profits arise from convergence to fair value – at one extreme via short-term term price movements towards fair value, or more slowly, via distributions of dividends, takeovers, private buyouts, or asset liquidation. Alternatively, to profit from fundamental analysis, one merely has to subscribe to the seemingly plausible hypothesis that share prices are more likely to converge to fair value than diverge from it.

Despite the popularity of the discounted cash flow technique, fundamental analysis does not necessarily require explicit cash flow forecasts and discount rates. These forecasts and discount

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[1] See, for example, Ball and Brown (1968), Jones and Litzenberger (1970), Joy, Litzenberger, and McEnally (1977), Rendleman, Jones, and Latané (1982), Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989, 1990), Fama and French (1992), Jegadeesh and Titman (1993), Michaely, Thaler, and Womack (1995), Ikenberry, Lakonishok, and Vermaelen (1995), Sloan (1996), Ball and Bartov (1996), Dichev (1998), Fama and French (2006), Pontiff and Woodgate (2008), Campbell, Hilscher, and Szilagyi (2008), Avramov, Chordia, Jostova, and Phillipov (2009), and Novy-Marx (2013).

[2] Both behavioral and risk-based hypotheses have been advanced to explain anomalies like these, but the explanations have generally been developed after the fact. For example, overconfidence and the disposition effect are offered as behavioral explanations for momentum; return covariation within the value and growth categories, embodied in the HML factor, is proposed as a risk-based explanation for the value premium. See Fama and French (1993), Daniel, Hirshleifer, and Subrahmanyam (1998), and Grinblatt and Han (2005).

rates can be implicit in a variety of other approaches that obviate the need for explicit models and parameter estimates. We take a particularly simple and agnostic view of how to compute fair value: Rather than select a specific theoretical model, we approximate a stock's fair value as a linear function of virtually all of its most recently reported income statement and balance sheet items. Our only restriction is that the function's coefficients, which are determined each month, offer the lowest degree of mispricing (as measured by variance) of a randomly selected investment dollar in the economy. This more direct approach to fair value estimation is consistent with the most basic principles of asset pricing theory and turns out to be exceedingly simple to implement: fair values are the predictions of monthly cross-sectional regressions of market capitalizations on firm-level accounting data.

This approach to fundamental analysis is unorthodox, but it avoids the temptation to data snoop across model specifications.[3] With the traditional implementations of fundamental analysis, there are not only multiple models of fair value, but countless approaches to earnings forecasts and discount rate estimation. The freedom to define fair value in so many ways leads to a staggering number of investment strategies one could investigate to test the efficacy of fundamental analysis. We believe that the theorist's license is best suspended when it offers too much discretion over implementation, thus yielding significant results by chance. In contrast, the least squares criterion of the cross-sectional regressions we employ guarantees that the market portfolio is fairly valued at all times, but prevents discretion in the selection or weighting of accounting items that could conceivably relate to future returns.

[3] See, for example, Schulmeister (2009).

After identifying fair values from linear functions of accounting items, we study the profitability of buying undervalued and selling overvalued securities to assess whether fundamental analysis works. Here, we quantify mispricing as the percentage difference of a stock's actual market capitalization from our estimate of its fair value. With extensive controls for risk and major known anomalies, convergence to fair value is the most likely source of the remarkable profitability we uncover from this trading strategy. The abnormal return (alpha) spreads earned from long-short strategies based on quintile sorts for percentage misvaluation are between 5% and 9% per year, depending on the risk adjustment procedure used, and positive in about 60% of the 432 months studied. They are prevalent in large and small firms, evident in all sub-periods, and not explained by the "usual suspects:" industry returns, beta, book-to-market ratios, momentum, short- or long-term reversals, firm size, gross profitability, accruals, earnings surprises, default risk, or a host of other known anomalies. We use both Fama-MacBeth regressions and Black-Jensen-Scholes time-series factor model regressions to implement these controls.

Our approach to fair value estimation, conveniently referred to as the "statistician's approach" to fundamental analysis, is deliberately crude and made even cruder by the accounting inputs used. The cross-sectional regression essentially uses all balance sheet and income items reported by sufficient numbers of firms. The large numbers of highly (or perfectly) collinear variables implies that coefficient signs will flip month-to-month and many of the variables lack any unique coefficient because they are redundant. More precise ways of obtaining fair values certainly exist, but our goal is to be conservative at assessing whether a crude form of fundamental analysis works. The fair value approach used here is unlikely to be a superior mousetrap for capturing the intrinsic values of securities. However, if the crude statistician's approach to fundamental analysis works, then more accurate ways of measuring mispricing should work even better.

Despite the handicaps imposed on fair value estimation, our approach has theoretical roots in the most intuitive of principles that guide fair value: the law of one price. Like fair values obtained from any asset pricing model, the fair values obtained with our approach are the market values of replicating portfolios[4] – "replicating" because each of the latter portfolios' accounting items are identical to those of the firm being valued. Because the number of firms N is large relative to the rank K of an NxK matrix X of all firms' accounting data at a given date, an infinite number of portfolios replicate the accounting data of the firm being valued. Each has a distinct market price that represents an estimate of the target firm's fair value. However, as Appendix A proves, among all these fair value candidates, our unique fair value prediction and the replicating portfolio matrix attached to it can be deduced from three appealing assumptions:

1) The NxN replicating portfolio matrix has weights on stocks that make the average valuation error zero (which is equivalent to assuming that the market portfolio is fairly priced).
2) The replicating portfolio matrix has weights that are functions only of the K-dimensional accounting information and are not functions of firms' market capitalizations, returns, or other variables besides the accounting information.
3) The replicating portfolio matrix minimizes the average squared deviation across securities of any attribute (including market capitalization) not spanned by the K-dimensional accounting attributes.

The set of replicating portfolios satisfying the above criteria forms an NxN idempotent projection matrix $X(X^TX)^{-1}X^T$, tied to the cross-sectional regression described above.

[4] As Ross (1978, p. 455) pointed out in "A Simple Approach to the Valuation of Risky Streams," even the simplest discounting of risk-free cash flows is merely a comparison between the traded price of a quantity of risk-free bonds available in the securities markets and an asset that produces a future risk-free cash flow. In the CAPM, a stock's fairly valued replicating portfolio is a scaling of the market portfolio and risk free asset with the same beta as the stock. In continuous-time asset pricing, fairly priced Arrow-Debreu securities, constructed from dynamic portfolios of fairly priced assets generate the probability-weighted pricing kernels used to obtain fair values of all assets. And even when parameters like risk aversion are estimated from experiments, the lotteries used to obtain those parameters are deemed to be fairly valued.

Note that the idempotent projection matrix, and hence the weights of the replicating portfolios, are constructed without regard for any firm's market capitalization! The accounting variable regressors would generate the same idempotent matrix of replicating portfolio weights if, instead of fitting market capitalization, it was designed to fit earnings growth rates, age of the CEO, or the latitude of the firm's headquarters.[5] Despite market capitalization's nonexistent role in the replicating portfolio, the market values of the replicating portfolios capture all of the dynamics of the relationship between market value and accounting variables. And, in contrast to prior studies that predict returns from specific variables of interest, like Price-to-Earnings, Dividend Yield, or Market-to-Book ratios, our valuation approach has little discretion attached to its variables of interest. We are interested in all accounting variables, and any discretion we demonstrate to estimate fair values is based purely on standard statistical criteria – especially, data availability.

As one quantification of the relative importance of our mispricing signal as a return predictor, consider the paper's Fama-MacBeth cross-sectional regressions of returns on the mispricing signal, beta, size, value, and three non-overlapping intervals of past returns representing the past month (short-term reversal), past year (momentum), and past five years (long-term reversal). The mispricing regressor has a coefficient of the correct sign. Its test statistic is of similar significance as that of the momentum regressor, and it surpasses the greater significance hurdles suggested by Harvey, Liu, and Zhu (2013) and by Green, Hand, and Zhang (2013)[6].

[5] One application of this approach is the use of returns as dependent variable, which provides the return of a portfolio with matched fundamental characteristics along many dimensions (see, e.g., Bessembinder et al., 2015).

[6] In Harvey, Liu and Zhu (2013), newly discovered factors should clear a *t*-ratio of 3.00. Green, Hand and Zhang (2013) study more than 330 anomalies and argue that controlling for a subset of existing factors is sufficient for researchers discovering a new predictive factor.

Admittedly, higher discount rates imply low market values and vice versa, other things equal.[7] The mechanical relationship in the cross-section between market values (or ratios involving values like book-to-market) and expected returns applies to our signal, as it does to many others in the anomalies literature. However, the mere existence of such a mechanical relationship does not identify whether the observed return spreads, tied to this type of anomaly, are due to differences in risk or to pricing errors. We present evidence suggesting that convergence to fair value, rather than risk differences, accounts for the efficacy of our mispricing signal.

1 Related Literature

Indirect study of whether fundamental analysis works – measuring the performance of professional money managers – suggests that the abnormal profits earned by those who arguably make a living from fundamental analysis is relatively small: Risk-adjusted returns are in the order of 0-100 basis points per year before deducting transaction costs, fees, and other expenses.[8] Direct study of whether the estimation of fair market values *per se* leads to trading strategies that can earn abnormal profits is rarer. Bhojraj and Lee (2002), Liu, Nissim and Thomas (2002), and Cooper and Lambertides (2014) study the relative valuation of target and comparable firms in the context of multiples valuation. However, Cooper and Lambertides (2014) find no evidence of predictability, and the other two papers do not investigate whether misvaluation can be used to generate profitable

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[7] This point was elegantly made by Ball (1978), Berk (1995), and the clean surplus accounting arguments in Fama and French (2006) and Novy-Marx (2013).

[8] See, for example, Grinblatt and Titman (1989, 1993, 1994), Daniel, Grinblatt, Titman and Wermers (1997), Chen, Jegadeesh, and Wermers (2000), Wermers (2000), Fama and French (2010), Berk and van Binsbergen (2013), and Grinblatt, Jostova, Petrasek and Philipov (2015). Larger performance is achieved when momentum-based returns are not penalized and with international fund management. Jiang, Verbeek, and Wang (2014) show that stocks heavily over-weighted (compared to the index weight) by actively managed funds greatly outperform those heavily under-weighted after adjustment for risk.

trading strategies.

Ou and Penman (1989) study accounting variables as predictors of future earnings changes and show that the probability of an earnings increase predicts stock returns. Abarbanell and Bushee (1998) study the April to March returns of firms with December fiscal year ends and find that weighted averages of ranks on changes in nine accounting variables predict a firm's return.[9] The discretionary accounting constructs in this latter paper, as well as the weights, are selected because they predict returns in sample. In contrast to our paper, neither of the two aforementioned papers concerns itself with estimation of a firm's fair value and whether deviations from that value have implications for future returns.

The notable exception to the dearth of direct research on fundamental analysis is Frankel and Lee (1998), who study the profitability of trading strategies based on deviations from the residual income model's fair values, obtained from consensus earnings forecasts.[10] In their paper, deviations from fair value predict long-term returns, especially between 24 and 36 months after receiving the mispricing signal. The paper differs from ours in its controls, sample period, and use of a specific forecasting model derived from analyst predictions.

The focus of our paper on the relation between a mispricing signal and returns is also markedly distinct from the vast anomalies literature. Research on anomalies has identified more than

[9] Related papers include Greig (1992), Holthausen and Larcker (1992), Ou and Penman (1989), Lev and Thiagarajan (1993), Abarbanell and Bushee (1997), Piotroski (2000), and Mohanram (2005).

[10] In the same vein, Manaster and Rendleman (1982) show that deviations of observed stock prices from equilibrium stock prices implied in option prices predict future returns for a sample of 172 U.S. stocks. Deviations from fair value have also been used to study misvaluation and Q theories of M&A activity, based on residual income valuation (e.g. Dong, Hirshleifer, Richardson, and Teoh, 2006) or (annual, industry-level) cross-sectional regressions of market capitalization on determinants of fundamental value (e.g. Edmans, Goldstein, and Jiang, 2012; Rhodes-Kropf, Robinson, and Viswanathan, 2005).

300 known predictors of future returns.[11] Their selection, proper mix for a trading signal, and success at publication hinges on the ability of the variable to predict returns. While we relate our signal to future returns, the motivation for our hypothesis is uncomplicated and transparent: deviations from fair value are more likely to contract than expand.

2 Data and Methodology for Fair Value Estimation

We now assess whether fundamental analysis from accounting information, implemented with the rudimentary and mechanical approach of a statistician, contains information about future stock returns. At the market close on the last trading day of every month in the sample, we compute each stock's degree of under- or overvaluation. We then track the returns of stocks over the subsequent month[12] and relate these returns to the stock's beginning-of-month mispricing.

2.1 Sample Period and Data Filters

There are 432 return months in our sample: January 1977 through December 2012, and thus 432 portfolio formation dates, starting Friday, December 31, 1976[13] and ending Friday, November 30, 2012. On the day of mispricing measurement and portfolio formation the stock must:

1) Be in CRSP's Monthly Stock File as the only common equity share class of a U.S. corporation (share classes 10 and 11), and be listed on the NYSE, AMEX, or

[11] See, for example, Green, Hand, and Zhang (2013), Harvey, Liu, and Zhu (2013), and McLean and Pontiff (2013). Kogan and Tian (2013) form pricing factors based on 27 commonly used firm characteristics and show that the relative performance of factor models is highly sensitive to the sample choice and the factor construction methodology, highlighting the challenges of evaluating empirical factor models.

[12] To compute a return for the month starting at date t (also referred to as month $t+1$), we make standard adjustments to the reported CRSP returns for delisting. See, for example, Shumway (1997), Amihud (2002), and Acharya and Pedersen (2005). As delisting is rare, our results are not sensitive to the treatment of delisting.

[13] Quarterly announcement dates are relatively sparse prior to 1976. This dictates the December 31, 1976 start date because portfolio formation requires about one year of these dates.

NASDQ-NMS (exchange codes 1-3) with a share price of at least \$5 and a positive number of common shares outstanding (to compute market capitalization).

2) Have an earnings announcement date within the past 3 months (for a 10Q or 10K reporting positive total assets) that is at least one trading day prior to the portfolio formation date, according to Compustat.
3) Possess an SIC industry code that is not financial services (SIC codes 60-69).
4) Have two prior fiscal years reported on Compustat.[14]

2.2 Estimating fair value and mispricing

As noted earlier, firm *j*'s date *t* fair value is the prediction, $P_j(t)$, from a cross-sectional regression of firms' actual market values, $V_j(t)$, on accounting variables known by market participants at date *t*. For each of the 432 portfolio formation dates *t*, and each stock *j*, we calculate a mispricing signal, $M_j(t) = [P_j(t)\text{-}V_j(t)]/V_j(t)$, the percentage difference between the stock's fair value prediction and its date *t* market capitalization. Underpriced stocks, those with large $M_j(t)$, have low market values relative to the fair values implied by their most recent accounting statements. Such stocks are expected to outperform the overpriced stocks in the future. Conversely, stocks with highly negative $M_j(t)$ are overvalued stocks that are expected to underperform. By construction, the date *t* market-cap-weighted average of $M_j(t)$ is zero.[15]

To economically quantify the effect of mispricing, we rank each of the regression's stocks at the beginning of each month based on the mispricing signal and sort firms into quintile portfolios: Q5 denotes the most underpriced quintile of stock and Q1 the most overpriced quintile. Coefficients from regressing returns on Q2-Q5 dummies can be interpreted as the added return from belonging to the respective mispricing quintile compared to the Q1 quintile.

[14] This filter, used by Fama and French (1993), Cooper, Gulen and Schill (2008) and Cohen, Polk, and Vuolteenaho (2009), avoids possible IPO-related distortions in the Compustat data.

[15] This property is isomorphic to the fair value regression's average least squares residual beings zero.

The regressors for the date t fair value predictions come from stock j's (and other firms') most recently reported 10Q or 10K income or balance sheet items, obtained from the CRSP-merged Compustat Fundamentals Quarterly.[16] We use the prior earnings announcement date from Compustat as the release date of the accounting data. This would be an announcement before December 31, 1976 for the first portfolio formation date in the sample and before November 30, 2012 for the last date in the sample. We deliberately choose the word "before" here because accounting information reported on the last trading day of the month is only considered for the trading signal at the end of the next month. This adjustment controls for month-end information released after the close of trading.[17]

We employ the 28 most commonly reported numerical firm-level[18] Compustat accounting items listed as coming from the balance sheet (14 items) and income statements (14 items) and announced between September 30, 1976 and December 30, 1976. To achieve a 1,000 firm sample at the sample period's start – desirable for statistical precision – 28 items is the maximum number we can use.[19] This coverage-imposed reduction of the accounting data matrix, X^*, to 28 columns is fairly innocuous. Many of the uncommon items are redundant – often perfectly or almost per-

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[16] As is customary when analyzing accounting data, all variables that inform trading positions are winsorized – here, based on their ratio to total assets at the top and bottom 5%, using the sample distribution that exists for that variable from all sample data released prior to month t. Our results are not sensitive to winsorization.

[17] To address the possibility that the accounting data we use are not known at Compustat's earnings report date, we rerun our results with earnings report dates artificially pushed forward by 3 trading days. Our results are robust to this change. Moreover, spot checks of firms' Compustat earnings announcement dates against other sources' dates for the release of accounting data suggest that the occasional differences observed rarely exceed 1 trading day. Using the filing deadlines for 10-Ks and 10-Qs with the SEC as dates when the accounting information was available to investors also has little effect on the results (actual filing dates are only available since 1994).

[18] Many of Compustat's 843 items, like firm name, ticker, and notes are not numerical. Many are titled "per share."

[19] Appendix B lists these 28 items along with details on variables used in the paper as return regression controls.

fectly spanned by linear combinations of the more common items. Thus, including additional accounting items adds little to the pertinent valuation information already contained within the most common 28. There is evidence of this even within the 28 items we use. Six of the 28 accounting items are perfectly spanned by the remaining 22. About 98% of the variation in half of the items is captured by the remaining half of the items. (While this implies that the regression coefficients on many of the items are imprecise and, in six cases, completely indeterminate, the fair value prediction from the 28 items is unique.)

At the start of each trading month, we use the most recently reported 10K and the three most recently reported 10Qs to identify values for these 28 items. The 14 balance sheet items are from the most recently released accounting statement (10K or 10Q); those for the income statement items are sums of the quarterly values from the three most recently released 10Qs and the most recently released 10K. Although summing four quarterly values characterizes the firm over portions of two fiscal years, it eliminates seasonal distortions that plague the quarterly items themselves. For expositional brevity, the "most recent accounting information" henceforth refers to the 14 items in the most recent balance sheet and the sum of the four quarterly values of the 14 items derived from the four most recent income statements.

Each firm's fair value evolves month to month for two reasons. First, market capitalizations, the cross-sectional regression's dependent variable, change, influencing regression coefficients. For example, rising stock prices imply a larger regression intercept even if accounting information or relative fair values do not change. Changes in relative market capitalizations across market sectors also change these coefficients. When firms with low earnings and large R&D suddenly become more valuable than the historical norm, as in the 1998-99 "internet bubble," our cross-sectional approach will capture that change in market tastes. Second, (in some cases) the firm or other firms may report new accounting information during the month. The new information changes the values and coefficients of the regressors used to predict fair value in the next month.

In sum, our approach to fair value takes no stand on changing market preferences for certain types of stocks, or on whether the market as a whole is over- or undervalued at a given point in time. Nor does it rely on a formal theoretical model of fundamental value. Rather, we compare firms to one another. The comparison uses the statistical criterion of goodness of fit to discern how the market values accounting attributes at a given point in time.

All estimates of fair value and mispricing are highly inexact, including ours. The regression's fair market capitalization estimate has R-squareds that vary month-to-month: the minimum R-squared (unadjusted for degrees of freedom) is 74.6% (April 2000), the median is 93.2%, and the average is 91.8%. These R-squareds are unimpressive in light of the fact that market capitalization is on the left hand side and the right-hand side accounting entries tend to scale with firm size. However, there is no bias to the estimation. The noise in our approach only serves to highlight that profits from trading on estimated mispricing can only be improved upon by better mispricing estimation. Nevertheless, the data analysis below will illustrate that even this noisy estimate of mispricing has something interesting to say about market efficiency.[20]

2.3 Summary Statistics for the Overall Sample

Table 1 reports summary statistics describing the relationship of the mispricing variable *M* to firm

[20] Numeric Investors, an institutional asset manager, estimates a fair value measure from a similar type of regression on a daily basis, based on cross-sectional regressions of stock prices on a proprietary set of company fundamentals (see Perold and Tierney, 1997).

size, beta, book-to-market ratio, past returns, earnings surprises, accruals, gross profitability, Merton's (1974) default risk, and past returns over a variety of horizons. It reports the time series average of the cross-sectional means of these variables in the first column, the time series average of the correlation of the variable with *M* in the second column, and the times series averages of the means of the variables within five mispricing quintiles. Quintile 1, in the Q1 column, represents the most overpriced stocks, which have average overpricing of 223%; Quintile 5 (Q5) represents the most underpriced stocks, which have average underpricing of 394%.[21]

As can be seen from Table 1, mispricing is highly related to a number of attributes known to predict returns. Compared to the 20% most overpriced firms, the 20% most underpriced firms are about four times smaller, have a lower beta, lower past returns (at all three horizons), and about twice the book-to-market ratio. With respect to size, only about 13 firms among the 20% most underpriced reside in the top size quintile (using NYSE quintile breakpoints), on average. In short, overpriced stocks tend to be long-term winning large growth stocks, with the opposite true for underpriced stocks, but there are lots of exceptions. The correlations and quintile averages suggest that there is little relationship between the mispricing metric and four other firm characteristics (unexpected earnings surprises (SUE), Gross Profitability, Accruals, and Default Risk) that are known to predict returns.

The negative correlation between beta and estimated mispricing indicates that beta risk could not explain any ability of *M* to forecast average returns. Indeed, except for *M*'s positive correlations with book-to-market, and negative correlation with firm size and past returns, *M* seems

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[21] These figures are large because extreme conditional means sort on sampling error and are therefore biased. However, since much of our later analysis involves ranks, there is little need to adjust for the bias with statistical corrections like Bayesian shrinkage.

relatively unrelated to any of the prominent anomalies in the finance literature. We will also control for the effect of book-to-market, size, and past returns on future average returns. The next section shows that M forecasts returns even with controls for these and other effects.

3 The Mispricing Attribute and the Cross-Section of Expected Returns

This paper's assessment of whether fundamental analysis works has two phases. First, as described in the last section, we construct a mispricing signal M based on deviation from an estimate of fair value. The second phase, tackled in this section, studies the subsequent monthly returns and abnormal (e.g., risk-adjusted) returns of stocks sorted by the mispricing signal. This second stage determines whether stock prices tend to converge to their fair values over time.

3.1 Raw Returns

Table 2, similar in format to Table 1, addresses the mispricing signal's ability to forecasts next-month's return. It reports time series averages of both equal- and value-weighted portfolio returns in the next month, the average correlation between the return and mispricing signal, as well as the average return of portfolios formed from subgroups of stocks stratified by their mispricing signal. The time series averages are reported both overall and for three similar length sub-periods. In addition to the seven columns from Table 1, Table 2 uses the null of efficient markets to test whether the mean return of the most underpriced quintile of stocks (Q5) exceeds that of the most overpriced quintile. The average difference and associated t-statistic (from the time series of paired differences) appear in the two rightmost columns, flanked on their left by the fraction of return differences that are positive.

The average correlation between a firm's signal and its future returns is 0.016. Moreover, average returns are also nearly perfectly monotonic in the mispricing quintiles, both for the full sample period and for sub-periods, using both value- and equal-weighted portfolios. The next-month return spread between the least and most underpriced stock quintiles is 0.68% (0.44% when value-weighted), an annualized return spread of 8.1% per year (5.3% per year for the spread in the value-weighted portfolios). Finally, the Q5-Q1 spread is positive in about 61% of the months (56% when portfolios are value-weighted).

3.2 Fama-MacBeth Cross-Sectional Regressions

Table 2's raw return differences could either be due to differences in expected returns associated with the mispricing signal *per se* or to omitted variables linked to the cross-section of returns. To first analyze the issue, Table 3 cross-sectionally regresses firm j's month t+1 return of on the firm's mispricing signal and control variables known at the end of month t. It then averages the coefficients across all months. For a portfolio formed at the end of month t, the cross sectional regression measures the mispricing signal's efficacy from the coefficient $b(t)$ in the regression

$$R_j(t+1) = a(t) + b(t)M_j(t) + \Sigma_{\{s=1,S\}}\, c_s(t)X_{js}(t) + error_j(t+1)$$

where

$R_j(t+1)$ = stock j's month $t+1$ return

$X_{js}(t)$= end-of-month t value of firm j's control characteristic s known to influence its returns including industry fixed effects.[22]

Table 3's time series averages of coefficients also have t-statistics, computed as in Fama and MacBeth (1973), which appear on their right in brackets. Table 3 reports several specifications

[22] On every portfolio formation date, each firm is classified into one of the 38 industries using classifications from the Kenneth French data library, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The regression coefficients and test statistics without industry adjustment or when we force industry fixed effects coefficients to be one negligibly differ from those reported in Table 3.

to assess the mispricing signal's ability to predict returns, focusing on three sets of variables. The first is the mispricing signal; the second consists of the more classic characteristics of betas, size, book-to-market, and past returns (over three non-overlapping horizons) that correlate with our pricing signal; the third are the four characteristics of gross profitability, accruals, default risk, and earnings surprises, which mispricing is far less correlated with.[23]

Table 3's first specification lacks controls for other characteristics besides industry, the second and third add the six traditional controls, and the fourth and fifth add four additional characteristics known to predict returns. Even-numbered specifications exclude the mispricing regressor; odd-numbered specifications include it. Panel A uses the mispricing signal along with the most commonly used functional forms for the controls. Because we do not know the correct functional form for the mispricing signal in this regression, and want to calibrate its economic effect, Panel B reports on analogous regressions using quintile dummies (Q2, Q3, Q4, and Q5, with Q1 omitted due to the regression intercept) for all of the anomalies studied in Panel A. For brevity, Panel B displays coefficients and test statistics only for the Q5 dummy, which represents the difference in returns from being in Q5 compared to Q1; there are also unreported dummy coefficients for Q2, Q3 and Q4 for each of the characteristics included in the regression.

In all of Panel A and B's specifications, mispricing is a highly significant predictor of next month's return. In Panel A, mispricing's smallest *t*-statistic of 3.37 appears in the rightmost "kitchen sink" Specification 5. This specification has all of the controls including several variables

[23] To facilitate comparisons across specifications, month *t*'s regressions omit firms lacking data for all specifications. Results are highly similar without this restriction.

inferred from the firm's accounting statements. In the more traditional Specification 3, our mispricing signal is a more significant predictor of returns (t = 4.42) than logged book-to-market (t = 3.44). Moreover, if one simply transforms the mispricing variable, whose proper functional form is unknown, to a standard normal variable each month, Specification 3's (5's) t-statistic becomes 6.12 (4.28).[24]

Table 3 Panel B quantifies the economic effect of the mispricing signal by running the same regression using quintile dummies for all regressors. Here, the mispricing quintile dummy coefficients measure the extra return earned from belonging to mispricing quintile q compared to quintile 1 (the overvalued stocks). Panel B's Specification 1 indicates that the average industry-adjusted return of mispricing quintile 5 exceeds that of quintile 1 by 73 basis points per month. M's Q5-Q1 monthly spread drops to 53 basis points with traditional controls (Specification 3), which is twice the book-to-market effect in the same specification, and to 38 basis points in the kitchen sink regression (Specification 5), which is comparable to the same specification's momentum effect (37 basis points). In all cases, the mispricing signal is highly significant, and the coefficients are similar if we do not adjust for industry effects.

Clearly, specifications 5's combination of book-to-market with other less traditional controls captures some of the return predictability attributed to mispricing (and momentum). Yet, despite its kitchen sink of controls, our highly constrained approach to fundamental analysis still generates remarkable performance here. The fact that the accounting variables and their weighting

[24] In unreported results, we also find that the mispricing signal predicts the repurchasing and issuing of shares by companies over the subsequent 3-12 months.

are chosen with no input from future returns suggests that a less ad hoc approach to fundamental analysis is likely to prove even more fruitful than what we have proposed.[25]

The last 20 years of our sample period roughly correspond to the two decades in which the profitability of value and momentum strategies became widely known. Panel C of Table 3 averages Panel B's coefficients for the sub-period of 1993-2012. In the three specifications that employ our mispricing signal, the effect of mispricing in the sub-period seems even stronger than in the full sample period. For example, with both the traditional (Specification 3) and kitchen sink controls (Specification 5), the coefficient on the quintile 5 mispricing dummy is about 10 basis points per month larger in Panel C than in B. By contrast, Panel C shows that in the last 20 years, there is no significant value effect in Specification 3 and no significant momentum effect in Specification 5. The mispricing signal is correlated with value and momentum, but it seems to survive a horse race with them. While Specification 5's kitchen sink of controls resurrects a significant value effect, it is largely because gross profitability is a potent predictor of profitable growth stocks' positive returns, while a value strategy predicts that these growth stocks should have poor returns.

3.3 Factor Model Time-Series Regressions

As an alternative to cross-sectional regressions, we estimate factor model alphas of quintile portfolios of firms constructed from the mispricing signal. Compared to cross-sectional regressions, factor models study value-weighted portfolio returns with greater ease and indicate the degree to

[25] Moreover, the dummy coefficients on mispricing signal Q5 average to a positive number in every single calendar month for Specifications 1 and 3, in 10 out of 12 calendar months for Specification 5, and are positive in 60% of the 432-month sample period. The performance of the strategy is also not statistically different between firms that announce or don't announce earnings in a given month: Fama-MacBeth coefficients on the product of an earnings announcement month dummy and the mispricing signal are negligible when the specifications add this variable and an earning announcement month dummy to the regression; coefficients on the mispricing signal remain of similar magnitude to those reported in Table 3.

which long and short positions contribute to the alpha spreads of pairs of quintile portfolios.

Denote $r_q(t+1)$ to be the industry-adjusted month $t+1$ return on a quintile portfolio based on $Mj(t)$. With L factors, we estimate its alpha as the intercept in the time series regression

$$r_q(t+1) = \alpha_q + \Sigma_{\{i=1,L\}}\beta_{qi}F_i(t+1) + \varepsilon_q(t+1),$$

where $F_i(t+1)$ is the return difference (or excess return) of the i^{th} factor portfolio. If fundamental analysis works, alphas should monotonically increase in the mispricing quintiles. Moreover, the difference in the alphas of the quintile 5 and 1 portfolios – a metric of the mispricing signal's ability to earn abnormal profits – should be significantly positive.

Table 4's industry-adjusted returns are essentially a 0-factor specification. Panel A's industry-adjusted 68 basis point per month spread between mispricing quintiles 5 and 1 is not identical to the 73 basis point spread in Table 3 Panel B. The spreads differ because Table 4 lifts the requirement that firms possess data for all of Table 3's specifications. It also adjusts for industry effects by subtracting the industry return from the dependent variable, while Table 3 employs industry dummies as regressors. The industry-adjusted returns are monotonic. Moreover, the 20% most under- and over-priced quintiles exhibit alphas of similar magnitude (but opposite sign) in Panels A and B. Annualized Sharpe ratios here, and throughout the paper, are obtained by multiplying the *t*-statistics of the intercepts by 0.167, the square root of the ratio of 12 to the number of time series observations (typically, 432). For Panel A, the Sharpe ratios of the quintile 5-1 spreads range from 0.98 (0-factor model) to 1.14 (6-factor model). Our tables omit these ratios for brevity.

Table 4's 6- and 7-factor specifications nest the widely used Fama-French (1993) 3-factor and Carhart (1997) 4-factor models within them. The 6-factor model – Market excess return (Mkt_RF), SMB, HML, Momentum (Mom), a short-term reversal factor (ST_Rev), and a long-term reversal factor (LT_Rev) – represents the broadest factor model available in the Kenneth French data library;[26] Table 4's 7-factor model additionally employs the Novy-Marx (2013) profitability factor, PMU, which is now commonly used in investment management.[27] Appendix B provides more detail on all of the factors used in our analysis.

The six factor betas in Table 4's 6-factor model, (all similar to their 7-factor counterparts), indicate that our mispricing strategy is exposed to four of the model's six dimension of factor risk. Compared to overpriced firms, underpriced firms are more exposed to the returns of small value firms with poor medium- and long-term past returns. These findings are similar to those of Table 1 when studying characteristics across the mispricing quintiles.

Table 4's alphas take out the return contribution of these factor exposures. The fairly monotonic alphas of the 6- and 7-factor models in the top and bottom halves of Panels A, respectively, are similar. The monotonicity strengthens the argument that fundamental analysis works. About 70 basis points per month distinguish the two extreme quintile portfolios' alphas, with both the most under- and over-priced quintiles making economically and statistically significant contributions to the alpha spread. This spread, of the same order of magnitude as the raw return spread from Table 2, is also larger than the HML premium, even after controlling for HML!

Panel B weights returns by market capitalization as of the end of month *t*, which is prior to the return month. At 32 basis points per month, the alpha spreads here are more modest. This could

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[26] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The literature does not give unequivocal guidance on the factors that should be included in the risk model. The two additional return factors in the French data library are motivated by the research in DeBondt and Thaler (1985) and Jegadeesh (1990). The results are robust to adding a liquidity factor (from Pastor and Stambaugh, 2003) and a misvaluation factor (from Hirshleifer and Jiang, 2010).

[27] We obtain PMU from Novy-Marx's data library at http://rnm.simon.rochester.edu/data_lib/index.html.

indicate that large firms are more fairly priced than our mispricing estimate indicates, warranting firm size as an instrument for shrinking (or stretching) a firm's mispricing estimate with commonly accepted statistical methods. However, Panel B's lower spreads for value weighting could also be an artifact of poor diversification. Value-weighted portfolios containing large firms present special inference problems here when they contain a few large firms.[28] The existence of these firms makes portfolio alpha estimates imprecise and largely determined by the firm-specific return realizations of a few large firms rather than the portfolio's true alpha. For example, with less than 1.5% of its stocks from the top NYSE size decile, it is impossible to accurately estimate the value-weighted mean return or alpha of the most underpriced quintile. Typically, only one or two of these megacap firms – often 100 times larger than the typical firm – appear in the most underpriced quintile.[29]

4 Convergence to Fair Value Better Explains the Results than Alternatives

The term "mispricing signal" implies that it is the subsequent convergence to fair value of mispriced stocks – rather than signal-related risk differences – that accounts for the abnormal returns documented in this paper. This section analyzes whether risk differences are a reasonable alternative explanation for the return spreads observed from our mispricing signal.

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[28] This issue is not present in a value-weighted index of all stocks, which achieves diversification by having many large firms.

[29] Size-based portfolio sorts using independent sorting procedures – even with equal weighting – do not overcome the inference problem. For example, in the top NYSE size quintile, the alphas of the 20% most underpriced stocks overall exceed those of the 20% most overpriced by 83 and 86 basis points per month when benchmarked against the 6- and 7- factor model, respectively. Yet spreads of this size, despite being rare in our reading of the literature, fail to attain the 5% significance threshold. The insignificance stands in contrast to the significant negative alphas of the over-priced firms in the same size quintile, despite being of smaller magnitude than the 83 and 86 basis point spreads. The paradox is resolved by recognizing how few highly underpriced firms there are within the largest NYSE quintile of stocks. One cannot have a diversified portfolio with only a handful of stocks. By contrast, many stocks within the top NYSE quintile are estimated to be over-priced.

4.1 Evidence in the paper already controls for known sources of risk

The lower market betas for underpriced stocks (Table 1) represent the first piece of evidence that our signal works because of mispricing and not risk. With multi-factor risk, one compares Specification 1 in Table 3 Panel B with Table 4 Panel A. Specification 1 indicates that the most underpriced quintile's industry-adjusted returns exceed those of the most overpriced quintile by 73 basis points per month. Table 4's alphas control for known sources of multi-factor risk. However, controlling for these factor exposures has virtually no impact on the industry adjusted return spread: alphas are 71 and 69 basis points per month with the 6- and 7-factor models, respectively.

4.2 The Fama-MacBeth Cross-Sectional Coefficients Have No Known Factor Risk

Table 3 Panel B's signal Q5 dummy coefficients control for other characteristics. Fama and MacBeth (1973), among others, note that the coefficient quantifying this effect is the time series average of self-financing portfolio returns. If Z_t is the matrix (number of firms by regressors) representing the data for month t's regressors, the signal Q5 dummy coefficient is the product of the portfolio weights given by the corresponding row of $(Z_t^T Z_t) Z_t^T$ and the column vector of the firms' month t returns. This time series of self-financing portfolio returns holds other characteristics fixed, but could correlate with factor portfolio returns formed from these characteristics. When regressing the times series of these portfolio returns (equivalently, the time series of coefficients) on the factors, the intercept (alpha) negligibly differs from the coefficients in Table 3 Panel B. For example, the coefficient of 53 basis points per month for the signal Q5 dummy in Specification 3 of Table 3 Panel B generates alphas of 56, 58 and 54 basis points per month when the time series of coefficients is regressed on Table 4's 6-factor model, Carhart's (1997) 4-factor model, and Fama and French's (1993) 3-factor model, respectively. For Specification 5, Table 3 Panel B's coefficient of 39 basis points per month generates 7-factor, 6-factor, 4-factor, and 3-factor alphas of 40, 38, 39, and 35 basis points, respectively. These similarities arise because the returns implicit in the Fama-MacBeth coefficients have mostly negligible factor betas.[30] Thus, Table 3's controls for other characteristics largely eliminate known factor risks.

4.3 Undiscovered sources of risk

Characteristics that correlate with market values in the cross-section, like book-to-market, size, or long-horizon past returns may explain the cross-section of expected returns. Other things equal, size is inversely related to risk in a rational market that values stocks as the discounted stream of future dividends. After all, discount rates are expected returns. Our mispricing metric is based on the percentage deviation of a crude fair value estimate from market capitalization. The lower market capitalizations of underpriced firms are isomorphic to larger discount rates for future dividend streams, other things equal. This point, from Berk (1995), is a tautology. But there is nothing in the tautology (or Berk's argument) suggesting that high discount rates have to come from higher risk rather than irrational sentiment. Only data analysis and calibrations can distinguish the risk-based and sentiment-based explanations for our findings.

If our estimate of mispricing "works" because it proxies for an omitted risk factor related to market capitalization, then controlling for size-related risk factors should largely eliminate the abnormal returns earned. However, the 6-factor model gives the same abnormal returns as no controls. Controlling for size-based characteristics rather than factor exposures eliminates about 25% of the paper's documented abnormal returns (as evident in Specification 3 of Table 3 Panel B). However, it still leaves an abnormal return that is on the order of the market risk premium.

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[30] The only significant factor beta here is on the long-term reversal factor. However, the average factor beta (about 0.1) and the relatively small premium of this factor imply that this loading can only alter alpha to a small degree.

Finally, if our results are explained by an omitted risk variable tied to cross-sectional differences in size, stale signals should produce almost the same abnormal returns as fresh signals of estimated mispricing. Cross-sectional differences in book-to-market ratios take years to dissipate. Hence, return differences across firms based on book-to-market ratios are similar irrespective of whether book-to-market ratios are measured at the end of the prior month or one year. By contrast, our accounting-based signal generates ranks that decay more rapidly. The average Spearman rank correlation between the vector of mispricing at month *t* and at *t-1* is 0.92, while the same correlation for the book-to-market ratio is 0.98. Moreover, the rank correlation between months *t* and *t-12* is 0.53 for our mispricing measure, while it is 0.81 for the book-to-market ratio. Hence, if our results were generated by differences in an omitted risk variable, that risk attribute has to change rapidly, and it seems unlikely to be due to a more stable characteristic, like the cross-sectional difference in firm size. Buttressing this argument is evidence on the efficacy of the signal as the signal becomes staler – a topic we turn to next.

4.4 Signal Delay

The quarterly data used to construct our mispricing signal is constantly being refreshed. Estimated mispricing ranks change monthly as some firms report new accounting data and market values change. If the abnormal returns we observe from our mispricing estimate arise from stock prices converging to their fair values, stale signals should be less valuable than fresh signals of fair value. To test this hypothesis, we lag the mispricing signal by up to three years. At a two and a half year lag, most profitability from the signal has disappeared. Figure 1 graphs evidence supporting this hypothesis. Using (for fair comparisons) returns beginning in January 1980, Figure 1 graphs the 6- and 7-factor alpha spreads for equally weighted portfolios of stocks in the extreme mispricing quintiles. These stocks are grouped into quintiles based on lags of the mispricing signal ranging from 0-35 months.[31] The decay in the signal's efficacy is rapid in the first three months. For example, with the 6-factor alpha, the signal's initial ability to earn abnormal returns of 70 basis points over the next month drops to 53 basis points when the mispricing signal is a month old. Between the time the signal is 3 and 12 months old, it can generate only 27 basis points a month, and then only 20 basis points per moth the following year. The 7-factor alphas pattern is highly similar.

Figure 1's evidence on the diminished efficacy of delayed mispricing signals is difficult to reconcile with an omitted risk factor as a source of the efficacy. In particular, if this omitted risk factor is correlated with the market capitalizations in the mispricing signal, the signal's efficacy should not decay so rapidly. The cross-section of market capitalization is relatively stable, and the mispricing ranks of stocks largely change because of changes in relative fair values, not because of changes in market capitalizations. The autocorrelation coefficients for the cross-section of stocks' signal ranks are 0.918, 0.855, and 0.801 at lags 1-3, but are 0.965, 0.939, and 0.917 for fair market values, and 0.996, 0.993, and 0.990 for market capitalizations. Hence, for omitted risk to explain why fresh signals are much more profitable than moderately stale signals, it must be a risk tied to the accounting data and not to each firm's market capitalization.

Figure 2 shows the 6- and 7-factor alphas when updating market capitalization and accounting data, but using stale regression coefficients for weighting the accounting variables to derive fair value. Using weights that are one year old reduces performance by about one third. While both the stale (and most recent) coefficients are estimated with error, averaging the weights

[31] Because of the later start date, the alphas for the 0 lag point differs slightly from the corresponding performance metrics reported in Table 4 Panel A.

over various windows from the past does not prevent the drop in performance, lending further support for the conjecture that mispricing is an anomaly rather than a risk factor.

4.5 The Relaxed Investor Who Reduces Turnover

The signal delay results help to estimate the profitability of a strategy that places signal-based trades and holds them for a full year. In a steady state, a strategy that puts on positions once, estimated more efficiently with overlapping one year returns, is like an equal-weighted combination of 12 strategies obtained from lags for the signal ranging from 0 to 11 months. The average alphas from such a "relaxed strategy," as measured by averaging the first 12 alphas in Figure 1 – namely, 34 basis points per month for both the 6- and 7-factor models – have far lower turnover than a strategy that holds its signal-induced positions for only one month. With a signal that is refreshed every month, a long-short mispricing strategy in the extreme quintiles has turnover of 226% per year, whereas holding positions for one year leads to annual turnover of 59%. There are negligible differences between the turnover ratios of the long and short positions.

Table 5 more properly derives full-sample abnormal returns and test statistics for the 1-year holding positions of the relaxed investor using Jegadeesh and Titman's (1993, 2001) technique. This approach commences the calculation of returns starting in December 1977 (versus 1979 in the paragraph above) with signals from December 1976 (11 month delay) to November 30, 1977 (0 delay). While 2012 signals that are k months prior to the end of 2012 are missing returns for the last $12 - k$ months of the year-long holding period, this is offset by the 1977 signals that are k months before November 30, 1977 (with returns only for the last $12 - k$ months of the 1-year period). Table 5 suggests that portfolio revisions on a yearly rather than a monthly frequency leads underpriced firms to outperform the overprice firms by 34-35 basis points per month.

The strategy's 5% monthly turnover thus requires unrealistically high trading costs of 7% of each dollar traded before such costs offset the 34-35 basis point alpha.

4.6 Revisions to Accounting Items

Our fair value estimates employ accounting figures that sometimes were unavailable to market participants at Compustat's reporting dates. When firms restate values for various income and balance sheets items past the reporting date, Compustat lists only the restated values for the relevant quarter. Our mispricing signal could therefore be a predictor of risk-adjusted returns because it sometimes peers into the future rather than because of true mispricing by the market.

To address whether such revisions explain our results, Table 6 studies the efficacy of the mispricing signal using only the first reported accounting numbers. The alphas from unrevised data were obtained from a separate Compustat database that is not commonly used in research studies.[32] The performance of our trading strategy using as-first-reported accounting information is only marginally weaker (e.g., by 8-9 bp per month according to Table 6) than the performance obtained using restated accounting information. This finding suggests that the effect of a restatement bias is small.

5 What's in the Black Box?

Finance research now documents a large number of firm characteristics that predict returns and risk-adjusted returns, generating what has come to be known as the "anomalies literature." Some

[32] Due to data availability, comparisons between results from Compustat's As First Reported (AFR) database and those from the regular Compustat file can only commence in 1988. Fair value estimates are derived from the 24 of the 28 accounting items that are common to both data sets.

of these return-predicting characteristics may be correlated with our mispricing signal. One cannot help but be curious about what is in the mispricing signal's "black box" and if it resembles anything previously seen in the literature. Table 7 and 8 address these issues. Table 7 first investigates how the mispricing signal relates to a set of 23 documented anomalies and drivers of returns. Table 8 studies the relative importance of the 28 accounting items we use to identify mispriced stocks.

Table 7 reports the 6- (Panel A) and 7-factor (Panel B) alphas of trading strategies formed from the mispricing signal. In contrast to the prior strategies studied, these trades take place within 115 subgroups of stocks that share similar amounts of an alternative characteristic known to predict returns and alphas.[33] Each month, stocks are sorted first into quintiles based on one of 23 predictive characteristics. Within each quintile, stocks are then sorted into quintiles based only on our mispricing variable. The table's alphas represent the abnormal profits of a long-short trading strategy in the extreme mispricing quintiles derived from this sequential sort. If the 23 characteristics are highly related to our mispricing variable, the lack of mispricing signal variation in the sequential sort's second step should eliminate significant alphas from the mispricing signal.

It is apparent from both panels that statistically and economically significant alphas exist in almost all the quintiles of the other characteristics. Of the 115 six-factor alphas in Panel A, there are five scattered exceptions to significance, and only two of them (book-to-market and earnings-to-price) exist in an extreme quintile of the characteristic. Of the 115 seven-factor alphas in Panel B, there also are five scattered exceptions to significance, and only two of the 5 (book-to-market

[33] These include the characteristics already considered in Table 3, i.e., beta, book/market, market capitalization, short-term reversal, momentum, long-term reversal, accruals, earnings surprise (SUE), gross profitability, and default risk. Further predictors are scaled Net Operating Assets (NOA), share issuance, asset growth, capital investment, investment ratio, external financing, Z-Score, leverage, illiquidity, earnings/price, dividends/price, cash flow/price and value/price (Frankel and Lee, 1998).

and dividend-to-price) are in an extreme quintile of the characteristic. Moreover, the alphas control for factors tied to book-to-market and profitability. In short, the correlations between the 23 characteristics and the mispricing signal are unlikely to uncover the drivers of alpha within the mispricing signal's black box.[34, 35]

Directly analyzing the alpha-generating role played by each of the 28 accounting items in the black box is another way to address this issue. Unfortunately, there is no straightforward way to analyze the separate roles of each accounting item. The problem here is that these accounting variables are highly collinear; indeed, seven of them are redundant because (in almost all months) they are perfectly collinear with the remaining 21 accounting items.[36] And at the margin, every one of the 28 accounting items is perfectly or nearly perfectly predicted by the remainder. Thus, all 28, in some sense, have negligible importance.

Table 8 tries to circumvent this thorny issue by applying a modestly different perspective on marginality. Table 8 shows industry- and risk-adjusted performance (using the 6- and 7-factor models) of long-short trading strategies for modified mispricing signals derived from alternative specifications of the fair value regression. Its various specifications address how much each of the 28 accounting items contributed to overall performance by adding (Panel A) or subtracting (Panel

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[34] Table 7 also indicates that that the profitability of the mispricing strategy might be enhanced by focusing on groups of stocks with particular characteristics. These include stocks with small market capitalizations, low past returns (over various horizons), high earnings surprises, profitability, illiquidity, high default risk, and high Z-Scores.

[35] Mispricing estimates employing the staler market capitalizations at fiscal close (as opposed to those at time of the mispricing signal) yield significant abnormal returns that are similar to those presented in the paper. This further rules out the issuance anomaly as a potential driver of our findings. See, e.g., Ikenberry, Lakonishok and Vermaelen (1995), Loughran and Ritter (1995), Mitchell and Stafford (2000), Teoh and Wong (2002), Schultz (2003), Daniel and Titman (2006), Fama and French (2008), Pontiff and Woodgate (2008).

[36] For example, included in the 28 accounting items are *Extraordinary Items*, *Discontinued Operations*, and *Extraordinary Items and Discontinued Operations*, with the latter being the sum of the first two.

B) the accounting items in a particular sequence, determined by coverage. Panel C looks at performance using only the 14 balance sheet items or only the 14 income statement items to determine fair value.

The first two panels list the accounting items in order of coverage. Each of Panel A's 29 fair value regression specifications uses the accounting item listed in its row plus all of the accounting items in the rows above as regressors. Each of Panel B's 29 specifications use all accounting items excluding the accounting items in the rows above.[37] Thus, Panel A's starting point (the first row) are signals from monthly cross-sectional fair value regressions without any accounting variables. One by one, as we subsequently add each of the 28 items, performance from the resulting signal tends to increase, though not entirely monotonically, and sometimes in small and sometimes in larger increments. Performance noticeably increases with the addition of the first (most covered) item (*Assets - Total*, row 2) and the inclusion of the first income item (*Income Before Extraordinary Items – Adjusted for Common Stock Equivalents*). The latter inclusion nearly doubles performance. The bottom of Panel A, as well as the top of Panel B considers all 28 items from the balance sheet and income statement and was reported earlier in Table 4.

As we sequentially drop each accounting item in Panel B, we notice that performance from the mispricing-based trading strategy tends to decline. The two largest declines in the 6- and 7-factor alphas occur when *Current Assets - Total* is dropped from the specification (that includes all of the accounting items below it as regressors) and when *Income Taxes – Total* is dropped from the fair value regression. The three remaining items below (*Non-Operating Income (Expense) –*

[37] For fair comparisons, we require firms to have non-missing data on all 28 accounting items even if we do not use all 28 items in all but one of the alternative fair value regressions.

Total, *Discontinued Operations*, and *Extraordinary Items*), which have the least coverage among the 28, cannot produce significant trading profits without assistance from some of the items listed above them.

Note that signals from fair-value regressions without any accounting variables (the top row of Panel A or the bottom row of Panel B) are effectively “pseudo” signals that capture relative market capitalization. Once we control for SMB and other standard risk factors, we no longer find risk-adjusted returns from this “pseudo-signal.” By contrast, controlling for these risk factors, including SMB, has little effect on the return spreads of the signal with all 28 accounting variables. Consequently, the mispricing signal is unlikely to capture omitted risk factors tied to market capitalization. This finding buttresses our earlier argument that Berk’s critique does not apply here.

Panel C’s two specifications separately analyze the efficacy of the income and balance sheet items separately. Using the 14 balance sheet items generates about 60% of performance from the income statement items alone. Thus, we can say the following from Table 8: First income statement items are more important than balance sheet items in coming up with a profitable trading strategy based on deviations from fair value. Second, 3 the 28 items, *Non-Operating Income (Expense) – Total*, *Discontinued Operations*, and *Extraordinary Items*, have little bearing on the trading strategy’s profitability. Finally, more parsimonious ways of estimating mispricing earn similar profit profits than using all of the remaining 25 variables, but the choice of which specific variables to use appears to be relatively arbitrary given the high degree of multicollinearity between them.

6 Conclusion

Regression-based fitting of accounting data to stock values leads to a mispricing measure constructed from regression residuals. The predicted values are the market values of replicating portfolios that are assumed to be fairly valued. Ranking firms based on their residual-implied percentage mispricing measure predicts returns in the subsequent month and up to two and a half years in the future. The results are not related to the most commonly known predictors of the cross-section of expect returns. Abnormal return spreads based on mispricing metrics formed from accounting data are in the order of 4-9% per year.

Our approach to fundamental analysis uses only information in the most recent accounting statements to see if prices reflect this information. We find they do not. One can earn risk-adjusted returns of a magnitude earned by value and momentum strategies with rudimentary statistical analysis of the most commonly reported accounting information. One could, of course, investigate other potentially valuable information with the type of statistical analysis undertaken here. The other information could include changes in the same item in consecutive accounting statements, analyst forecasts, or corporate actions. It could even combine this information with the information in past price movements. We leave exploration of other sources of information to future research. Our task here was to examine if the most rudimentary form of fundamental analysis works. It seems to work very well, indeed!

Perhaps the most controversial aspect of our results is the claim that the profits obtained are from fundamental analysis. By using the term “fundamental analysis,” we are ultimately telling a behavioral story about mispricing arising from convergence to fair value. We have, however, presented evidence supporting the claim that the abnormal profits earned from fundamental analysis are not due to an omitted risk factor.

We focus only on returns, adjusted for risk factors, rather than more direct measures of convergence, because measuring convergence from returns is a more conservative approach. Our estimate of fair value exhibits regression towards the mean over time, like most other estimates. Hence, direct measure of the dynamics of the distance between fair value and prices leads to stronger convergence estimates than examining returns alone. Holding fair values constant, underpriced stocks that witness price increases and overpriced stocks that witness price decreases converge to the old fair value. Holding prices fixed, fair value estimates that greatly exceed prices tend to decline while those well below the same price tend to increase. Hence, the simple regression to the mean phenomenon implies that direct measurement of convergence is a less conservative approach for making the point that fundamental analysis works, and it has continued to work for more than 35 years.

Because we focus indiscriminately on the most available accounting items, and because of their high degree of collinearity, which renders the exercise extraordinarily difficult, we have not successfully identified which accounting variables are best for determining fair value. We have concluded that income statement items are modestly more important than balance sheet items. Addressing this question more precisely with a try-all-specifications approach is blatant data snooping. It violates the spirit of the paper: an Occam's razor approach that a naïve statistician would take to obtain fair values. Because the accounting data seems to have a factor structure underlying it, it would not surprise us if only a handful of accounting variables could do as well, or improve upon, the strategies derived here. We leave that, as well as improvements in the fair value estimation approach, to future research.

Return-predicting characteristics from the extant finance literature may be correlated with our mispricing signal. Whether or not this is the case has no bearing on the importance of our findings. Our paper is not another anomaly paper because our approach to mispricing differs from the approaches taken by the papers in the anomalies literature. With our approach, best fits with prevailing market capitalizations, rather than best fits with future returns, determines the only discretionary aspect of our signal—the weighting of the accounting items. The selection of accounting items is intended to be universal, except that coverage and statistical power require limitations on the number of accounting items. However, the items we use are not discretionary; the mispricing signal selects them only because they are the most common reported accounting items across firms. It is the absence of discretion that distinguishes our paper from predecessors that study market efficiency and represents its unique contribution to that literature.

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Figure 1: Signal Decay

The figure shows portfolio alphas from 36 pairs of 6- and 7-factor model time-series regressions. Each month, stocks are sorted into quintiles (Q1-Q5) based on a lagged mispricing signal (*M*), lags from 0 to 35 months, and combined into equally-weighted portfolios. Each spread portfolio return (in excess of the industry portfolios based on the 38 Fama French industry classifications) from one of the 36 signals, the difference between the returns of portfolios Q5 and Q1, is regressed on a set of factors: For the 6-factor model, the factors are Mkt_RF, SMB, HML, Mom, ST_Rev and LT_Rev, obtained from the Kenneth French data library; the 7-factor model additionally includes the PMU factor from the Robert Novy-Marx data library. The sample consists of all ordinary common stocks of U.S. nonfinancial firms listed on a major exchange (NYSE, Amex, Nasdaq) with a share price at the beginning of the return month of not less than five dollars. The sample period is 1/1980-12/2012. All variables are defined in Appendix B.

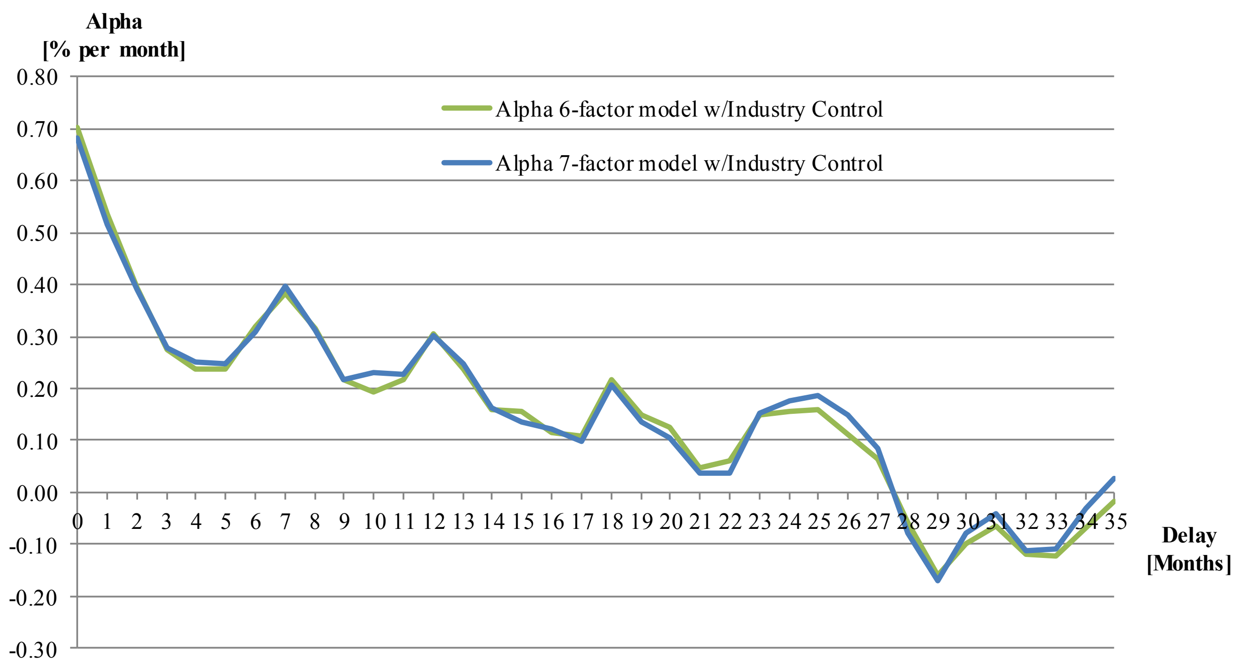

Figure 2: Accounting Weights

The figure shows alphas from 12 pairs of factor model time-series regressions. Stocks are sorted each month into quintiles (Q1-Q5) based on a mispricing signal (*M*) and combined into equally-weighted portfolios. The mispricing signal is based on fair value estimates, derived from cross-sectional regressions, that weight accounting variables. The fair value prediction that determines the 5 quintile portfolios uses coefficients that are from fair value regressions lagged between 0 and 11 months along with the accounting variables from lag 0. Each spread portfolio return (in excess of the industry portfolios based on the 38 Fama French industry classifications) from one of the 12 signals, the difference between the returns of portfolios Q5 and Q1, is regressed on a set of factors: For the 6-factor model, the factors are Mkt_RF, SMB, HML, Mom, ST_Rev and LT_Rev, obtained from the Kenneth French data library; the 7-factor model additionally includes the PMU factor from the Robert Novy-Marx data library. The sample consists of all ordinary common stocks of U.S. nonfinancial firms listed on a major exchange (NYSE, Amex, Nasdaq) with a share price at the beginning of the return month of not less than five dollars. The sample period is 1/1978-12/2012. All variables are defined in Appendix B.

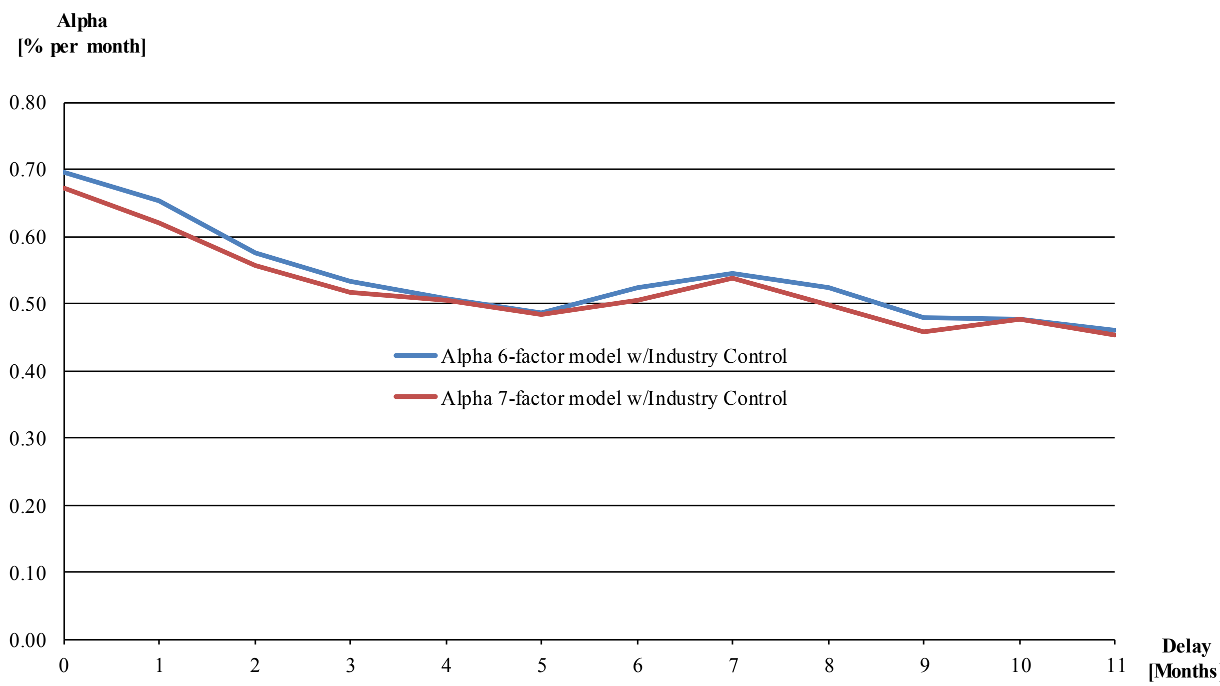

Table 1: Summary Statistics by Mispricing Signal Quintiles

The table reports averages of a number of characteristics of portfolios and firms, including the time-series average of the mean characteristics across all firms ("All"), the average cross-sectional correlation of the characteristic with the mispricing signal *M* ("Correlation"), as well as the average of the mean characteristics across quintiles of firms sorted by the mispricing signal *M* from Q1 (most overpriced) to Q5 (most underpriced). The sample consists of all ordinary common stocks of U.S. nonfinancial firms listed on a major exchange (NYSE, Amex, Nasdaq) with a share price at the beginning of the return month of not less than five dollars. The sample period is 1/1977-12/2012. All variables are defined in Appendix B.

			Signal Quintiles				
	All	Correlation	Q1 (Overvalued)	Q2	Q3	Q4	Q5 (Undervalued)
Mispricing Signal (M)	0.5406	1.000	-2.2251	-0.3213	0.2820	1.0265	3.9403
Market Capitalization	2,326.9	-0.068	2,020.6	4,338.6	3,283.1	1531.7	458.6
Book/Market	0.6736	0.262	0.5666	0.4877	0.5802	0.7203	1.0135
Beta	0.9472	-0.116	1.0112	1.0132	0.9908	0.9306	0.7880
Accruals	0.3190	-0.022	0.3714	0.3643	0.3368	0.2924	0.2388
SUE	0.0023	0.051	-0.0008	0.0018	0.0019	0.0022	0.0068
Gross Profitability	0.3956	0.037	0.3507	0.4092	0.4130	0.4041	0.4007
Default Risk	0.0151	0.033	0.0232	0.0073	0.0064	0.0096	0.0292
Prior Month Return t	2.0892	-0.028	3.1322	2.7201	2.1204	1.4727	1.0015
Return from Month t-1 to t-11	23.439	-0.040	31.077	30.420	24.352	17.502	13.892
Return from Month t-12 to t-59	108.88	-0.040	114.84	125.56	120.37	102.97	80.068

Table 2: Stock Returns and Mispricing Signal Quintiles

The table reports averages and selected test statistics of portfolio returns, including the time-series average of the mean return across all firms ("All"), the average cross-sectional correlation between returns and the mispricing signal *M* ("Correlation"), as well as the average return across quintiles of firms sorted by the mispricing signal *M* from Q1 (most overpriced) to Q5 (most underpriced). The table also shows the time-series average of the spread between the returns of the most undervalued (Q5) and the most overvalued (Q1) firms, as well as the associated *t*-statistics. Moreover, the table reports the fraction of time-series observations of the quintile spread that is greater than zero and the *p*-value of a binomial test against 50%. Panels A and B report results for equal- and value-weighted portfolios, respectively. The sample consists of all ordinary common stocks of U.S. nonfinancial firms listed on a major exchange (NYSE, Amex, Nasdaq) with a share price at the beginning of the return month of not less than five dollars. The sample period is 1/1977-12/2012.

			Signal Quintiles					Q5-Q1 (Undervalued - Overvalued)			
	All	Correlation	Q1 (Overvalued)	Q2	Q3	Q4	Q5 (Undervalued)	Fraction > 0	*p-value*	Average	*t-stat*
Panel A: Equally-weighted Portfolios											
Return in Month t+1	1.2603	0.0159	0.9259	1.0989	1.2748	1.3983	1.6039	61.1	[0.00]	0.6781	[4.85]
Return in Month t+1 (1977-1988)	1.6280	0.0195	1.3151	1.4005	1.5740	1.8172	2.0339	61.8	[0.00]	0.7188	[3.72]
Return in Month t+1 (1989-2000)	1.2095	0.0150	0.7613	1.2274	1.4251	1.3144	1.3190	56.9	[0.10]	0.5577	[1.76]
Return in Month t+1 (2001-2012)	0.9434	0.0132	0.7012	0.6687	0.8255	1.0633	1.4589	64.6	[0.00]	0.7577	[3.82]
Panel B: Value-weighted Portfolios											
Return in Month t+1	1.0105	0.0142	0.9994	0.8564	1.1342	1.3092	1.4416	56.0	[0.01]	0.4422	[2.63]
Return in Month t+1 (1977-1988)	1.2095	0.0194	1.2138	1.0947	1.3504	1.6746	1.9487	59.7	[0.02]	0.7349	[2.52]
Return in Month t+1 (1989-2000)	1.3437	-0.0011	1.1440	1.1446	1.4007	1.2875	1.3585	52.8	[0.50]	0.2145	[0.71]
Return in Month t+1 (2001-2012)	0.4784	0.0241	0.6403	0.3299	0.6515	0.9656	1.0176	55.6	[0.18]	0.3773	[1.33]

Table 3: Fama-MacBeth Cross-Sectional Regressions

The table shows average coefficients and test statistics from Fama MacBeth (1973) regressions of returns on stock characteristics. Across different specifications, returns are regressed against end-of-prior-month values for the mispricing signal *M*, market beta, book-to-market, market capitalization, short-term reversal, momentum, long-term reversal, accruals, SUE, gross profitability, and default risk. Panel A uses values of the characteristics as regressors; Panel B employs quintile dummies for the same characteristics as regressors. Each month's quintiles are determined from sorts of firms with non-missing values for all characteristics. Size quintiles are based on NYSE breakpoints. Panel B's regressions include dummy variables for quintiles 2, 3, 4 and 5 of each characteristic, but only display the coefficients of the quintile dummy with the largest amount of the characteristic (Q5) for brevity. Panel C shows results for the same specifications as Panel B for the 1993-2012 sub-period. All regressions include industry dummy variables based on the 38 Fama French industry classifications. The table also shows the average number of observations and average adjusted R-Squared. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% significance levels, respectively. The sample consists of all ordinary common stocks of U.S. nonfinancial firms listed on a major exchange (NYSE, Amex, Nasdaq) with a share price at the beginning of the return month of not less than five dollars. The sample period is 1/1977-12/2012. All variables are defined in Appendix B.

Panel A: Regressions with Regular Variables

	(1)			(2)			(3)			(4)			(5)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Mispricing Signal (*M*)	0.0903	[5.95]	***				0.0616	[4.42]	***				0.0471	[3.37]	***
Beta				-0.0545	[-0.41]		-0.0475	[-0.36]		-0.0099	[-0.08]		-0.0111	[-0.09]	
Log(Market Capitalization)				-0.0384	[-1.01]		-0.0417	[-1.05]		-0.0327	[-0.87]		-0.0427	[-1.08]	
Log(Book/Market)				0.2710	[4.19]	***	0.2267	[3.44]	***	0.3578	[5.28]	***	0.3199	[4.62]	***
Short-term Reversal				-0.0364	[-10.16]	***	-0.0363	[-10.16]	***	-0.0385	[-10.81]	***	-0.0383	[-10.80]	***
Momentum				0.0055	[4.87]	***	0.0055	[4.84]	***	0.0046	[4.40]	***	0.0046	[4.44]	***
Long-term Reversal				-0.0004	[-2.39]	**	-0.0004	[-2.46]	**	-0.0003	[-1.80]	*	-0.0003	[-1.84]	*
Accruals										-0.2259	[-5.57]	***	-0.2261	[-5.58]	***
SUE										4.0045	[8.49]	***	3.8754	[8.19]	***
Gross Profitability										0.8752	[7.47]	***	0.8575	[7.29]	***
Default Risk										-2.1527	[-3.84]	***	-2.0598	[-3.66]	***
Intercept	1.0568	[3.73]	***	1.3600	[4.08]	***	1.3360	[3.81]	***	0.9960	[2.94]	***	1.0358	[2.91]	***
Observations	1,219			1,219			1,219			1,219			1,219		
Adj. RSquare	0.042			0.076			0.078			0.082			0.084		
Industry Control	Yes			Yes			Yes			Yes			Yes		

(continued)

Table 3: Fama-MacBeth Cross-Sectional Regressions (continued)

Panel B: Regressions with Quintile Dummies

	(1)			(2)			(3)			(4)			(5)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Mispricing Signal (*M*) Q5	0.7292	[5.66]	***				0.5326	[5.75]	***				0.3849	[3.98]	***
Beta Q5				-0.1360	[-0.79]		-0.1428	[-0.84]		-0.0634	[-0.40]		-0.0874	[-0.55]	
Market Capitalization Q5				-0.2177	[-1.25]		-0.2125	[-1.27]		-0.2072	[-1.26]		-0.2260	[-1.41]	
Book/Market Q5				0.4742	[3.54]	***	0.2656	[2.03]	**	0.6894	[4.89]	***	0.5193	[3.69]	***
Short-term Reversal Q5				-1.3278	[-9.62]	***	-1.3151	[-9.58]	***	-1.5540	[-11.64]	***	-1.5400	[-11.60]	***
Momentum Q5				0.9517	[5.70]	***	0.9292	[5.63]	***	0.3713	[2.39]	**	0.3695	[2.40]	**
Long-term Reversal Q5				-0.1864	[-2.05]	**	-0.2364	[-2.63]	***	0.0769	[0.91]		0.0543	[0.65]	
Accruals Q5										-0.7270	[-10.35]	***	-0.7494	[-10.66]	***
SUE Q5										1.2372	[15.18]	***	1.2225	[14.94]	***
Gross Profitability Q5										0.6678	[7.08]	***	0.6234	[6.61]	***
Default Risk Q5										-0.2611	[-2.51]	**	-0.2452	[-2.35]	**
Intercept	0.7690	[2.60]	***	1.1974	[3.23]	***	1.1211	[2.97]	***	0.7616	[2.06]	**	0.8011	[2.13]	**
Observations	1,219			1,219			1,219			1,219			1,219		
Adj. RSquare	0.045			0.078			0.079			0.085			0.086		
Industry Control	Yes			Yes			Yes			Yes			Yes		

(continued)

Table 3: Fama-MacBeth Cross-Sectional Regressions (continued)

Panel C: Regressions with Quintile Dummies for 1993-2012

	(1)			(2)			(3)			(4)			(5)		
	Coef	t-stat		Coef	t-stat		Coef	t-stat		Coef	t-stat		Coef	t-stat	
Mispricing Signal (M) Q5	0.7866	[4.23]	***				0.6519	[4.88]	***				0.5412	[3.91]	***
Beta Q5				-0.1672	[-0.64]		-0.1719	[-0.67]		-0.1210	[-0.50]		-0.1492	[-0.63]	
Market Capitalization Q5				-0.0608	[-0.25]		-0.1770	[-0.75]		-0.0104	[-0.04]		-0.1204	[-0.52]	
Book/Market Q5				0.4818	[2.35]	**	0.2205	[1.12]		0.6999	[3.26]	***	0.4655	[2.20]	**
Short-term Reversal Q5				-1.1009	[-5.08]	***	-1.0877	[-5.06]	***	-1.2632	[-6.09]	***	-1.2449	[-6.05]	***
Momentum Q5				0.6837	[2.60]	***	0.6638	[2.57]	**	0.3237	[1.34]		0.3357	[1.40]	
Long-term Reversal Q5				-0.3162	[-2.42]	**	-0.3725	[-2.92]	***	-0.0635	[-0.53]		-0.0839	[-0.71]	
Accruals Q5										-0.7229	[-7.35]	***	-0.7611	[-7.71]	***
SUE Q5										0.8741	[7.67]	***	0.8474	[7.42]	***
Gross Profitability Q5										0.7963	[5.65]	***	0.7301	[5.20]	***
Default Risk Q5										-0.1260	[-0.85]		-0.1035	[-0.70]	
Intercept	0.3208	[0.78]		0.8730	[1.58]		0.8367	[1.48]		0.4171	[0.74]		0.4939	[0.86]	
Observations	1,397			1,397			1,397			1,397			1,397		
Adj. RSquare	0.047			0.080			0.081			0.087			0.088		
Industry Control	Yes			Yes			Yes			Yes			Yes		

Table 4: Factor Model Time-Series Regressions

The table shows average industry-adjusted portfolio returns (measured by portfolio weighting each stock return in excess of its industry portfolio return based on the 38 Fama-French industry classifications), as well as intercepts, slope coefficients, and test-statistics from time-series regressions of industry-adjusted portfolio returns on 6 or 7 factors. Stocks are sorted each month into quintiles based on the mispricing signal (*M*) and combined into equally-weighted (Panel A) or value-weighted (Panel B) portfolios. The table reports averages and regression statistics separately for each of the five portfolios, Q1-Q5, and for the corresponding times series of return spreads between the most undervalued (Q5) and overvalued (Q1) stock quintiles. Regressors are Mkt_RF, SMB, HML, Mom, ST_Rev, LT_Rev, and PMU, obtained from the data libraries of Kenneth French (the first 6) and Robert Novy-Marx (PMU). The table also shows the average number of observations and adjusted R-Squared. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. The sample consists of all ordinary common stocks of U.S. nonfinancial firms listed on a major exchange (NYSE, Amex, Nasdaq) with a share price at the beginning of the return month of not less than five dollars. The sample period is 1/1977-12/2012. All variables are defined in Appendix B.

(continued)

Table 4: Factor Model Time-Series Regressions (continued)

Panel A: Equal-weighted Portfolios

	Q1 (Overvalued)			Q2			Q3			Q4			Q5 (Undervalued)			Q5-Q1 (Undervalued - Overvalued)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Industry-Adjusted Return	-0.3485	[-3.61]	***	-0.2245	[-1.91]	*	-0.0373	[-0.35]		0.1091	[1.01]		0.3331	[3.51]	***	0.6815	[5.85]	***
Alpha	-0.4500	[-4.94]	***	-0.2615	[-2.47]	**	-0.0975	[-0.99]		0.0312	[0.31]		0.2639	[3.09]	***	0.7139	[6.83]	***
Mkt_RF	0.0424	[1.97]	**	0.0313	[1.25]		0.0375	[1.62]		0.0277	[1.17]		0.0162	[0.80]		-0.0262	[-1.06]	
SMB	-0.1757	[-5.25]	***	-0.2708	[-6.97]	***	-0.2348	[-6.52]	***	-0.2158	[-5.88]	***	-0.0827	[-2.64]	***	0.0931	[2.42]	**
HML	-0.0097	[-0.27]		-0.1560	[-3.73]	***	-0.0028	[-0.07]		0.2119	[5.36]	***	0.3233	[9.57]	***	0.3330	[8.05]	***
Mom	0.1753	[8.63]	***	0.2066	[8.76]	***	0.1803	[8.25]	***	0.1092	[4.90]	***	0.0120	[0.63]		-0.1634	[-7.01]	***
ST_Rev	-0.0110	[-0.40]		-0.0569	[-1.77]	*	-0.0606	[-2.03]	**	0.0084	[0.28]		0.0180	[0.69]		0.0290	[0.91]	
LT_Rev	0.0400	[0.98]		0.0711	[1.50]		-0.0126	[-0.29]		-0.1305	[-2.90]	***	-0.1643	[-4.28]	***	-0.2042	[-4.35]	***
RSquare	0.20			0.27			0.24			0.24			0.27			0.28		
Observations	432			432			432			432			432			432		
Alpha	-0.5355	[-5.82]	***	-0.3423	[-3.18]	***	-0.2158	[-2.21]	**	-0.1236	[-1.27]		0.1561	[1.84]	*	0.6916	[6.44]	***
Mkt_RF	0.0502	[2.37]	**	0.0387	[1.56]		0.0484	[2.15]	**	0.0419	[1.86]	*	0.0260	[1.33]		-0.0242	[-0.98]	
SMB	-0.1580	[-4.77]	***	-0.2541	[-6.56]	***	-0.2103	[-5.97]	***	-0.1837	[-5.23]	***	-0.0603	[-1.97]	**	0.0977	[2.52]	**
HML	0.0384	[1.03]		-0.1107	[-2.53]	**	0.0636	[1.60]		0.2988	[7.55]	***	0.3838	[11.14]	***	0.3455	[7.92]	***
Mom	0.1759	[8.82]	***	0.2071	[8.88]	***	0.1811	[8.54]	***	0.1103	[5.22]	***	0.0127	[0.69]		-0.1632	[-7.00]	***
ST_Rev	-0.0218	[-0.80]		-0.0671	[-2.10]	**	-0.0756	[-2.60]	***	-0.0112	[-0.39]		0.0044	[0.17]		0.0262	[0.82]	
LT_Rev	0.0171	[0.42]		0.0495	[1.04]		-0.0442	[-1.02]		-0.1719	[-3.99]	***	-0.1931	[-5.15]	***	-0.2102	[-4.43]	***
PMU	0.1589	[4.05]	***	0.1500	[3.27]	***	0.2197	[5.27]	***	0.2875	[6.91]	***	0.2002	[5.53]	***	0.0414	[0.90]	
RSquare	0.23			0.29			0.29			0.31			0.32			0.28		
Observations	432			432			432			432			432			432		

(continued)

Table 4: Factor Model Time-Series Regressions (continued)

Panel B: Value-weighted Portfolios

	Q1 (Overvalued)			Q2			Q3			Q4			Q5 (Undervalued)			Q5-Q1 (Undervalued - Overvalued)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Industry-Adjusted Return	-0.2773	[-1.85]	*	-0.42271	[-2.44]	**	-0.2191	[-1.30]		0.02479	[0.17]		0.22593	[1.86]	*	0.50318	[3.35]	***
Alpha	-0.1737	[-1.34]		-0.1902	[-1.58]		-0.0845	[-0.74]		0.0442	[0.39]		0.1480	[1.33]		0.3216	[2.19]	**
Mkt_RF	0.0957	[3.13]	***	-0.0272	[-0.96]		-0.0333	[-1.23]		0.0410	[1.52]		0.1139	[4.35]	***	0.0182	[0.52]	
SMB	-0.5796	[-12.19]	***	-0.8892	[-20.13]	***	-0.8457	[-20.08]	***	-0.6228	[-14.88]	***	-0.3162	[-7.76]	***	0.2635	[4.89]	***
HML	-0.0914	[-1.78]	*	-0.2384	[-5.01]	***	-0.1215	[-2.68]	***	0.0972	[2.15]	**	0.2310	[5.26]	***	0.3224	[5.55]	***
Mom	0.0890	[3.08]	***	0.1523	[5.68]	***	0.2050	[8.02]	***	0.1064	[4.19]	***	0.0424	[1.72]	*	-0.0466	[-1.42]	
ST_Rev	-0.1268	[-3.22]	***	-0.1483	[-4.06]	***	-0.0607	[-1.74]	*	0.0637	[1.84]	*	0.0327	[0.97]		0.1596	[3.57]	***
LT_Rev	0.0232	[0.40]		0.1553	[2.87]	***	0.0833	[1.62]		-0.0494	[-0.96]		-0.0828	[-1.66]	*	-0.1060	[-1.61]	
RSquare	0.33			0.57			0.58			0.44			0.25			0.15		
Observations	432			432			432			432			432			432		
Alpha	-0.2983	[-2.29]	**	-0.2864	[-2.35]	**	-0.2724	[-2.45]	**	-0.1451	[-1.32]		0.0249	[0.22]		0.3233	[2.14]	**
Mkt_RF	0.1072	[3.56]	***	-0.0183	[-0.65]		-0.0160	[-0.63]		0.0583	[2.30]	**	0.1252	[4.89]	***	0.0180	[0.52]	
SMB	-0.5538	[-11.77]	***	-0.8693	[-19.75]	***	-0.8068	[-20.14]	***	-0.5836	[-14.69]	***	-0.2907	[-7.26]	***	0.2631	[4.83]	***
HML	-0.0214	[-0.40]		-0.1845	[-3.72]	***	-0.0160	[-0.35]		0.2035	[4.55]	***	0.3001	[6.65]	***	0.3215	[5.24]	***
Mom	0.0899	[3.17]	***	0.1529	[5.77]	***	0.2063	[8.56]	***	0.1077	[4.50]	***	0.0432	[1.79]	*	-0.0466	[-1.42]	
ST_Rev	-0.1426	[-3.67]	***	-0.1605	[-4.42]	***	-0.0845	[-2.56]	**	0.0397	[1.21]		0.0172	[0.52]		0.1598	[3.56]	***
LT_Rev	-0.0101	[-0.18]		0.1296	[2.40]	**	0.0330	[0.67]		-0.1001	[-2.06]	**	-0.1157	[-2.36]	**	-0.1056	[-1.58]	
PMU	0.2315	[4.16]	***	0.1786	[3.43]	***	0.3490	[7.36]	***	0.3516	[7.47]	***	0.2285	[4.82]	***	-0.0031	[-0.05]	
RSquare	0.35			0.58			0.63			0.51			0.29			0.15		
Observations	432			432			432			432			432			432		

Table 5: Buy-and-Hold Returns

The table shows average industry-adjusted portfolio returns, as well as intercepts, slope coefficients, and test-statistics from time-series regressions of industry-adjusted portfolio returns on 6 or 7 factors. Following Jegadeesh and Titman (1993, 2001), the table measures the monthly performance of a portfolio held for 12 months with the following non-overlapping returns methodology: Stocks are sorted each month into 12 sets of quintiles based on a mispricing signal (*M*) that is delayed from 0 to 11 months and combined into equally-weighted portfolios within the same signal delay cohort. The industry-adjusted monthly return that is averaged over all months or used in the regression equally weights the twelve portfolios that belong to the same quintile. The table reports averages and regression statistics separately for each of the five portfolios, Q1-Q5, and for the corresponding times series of return spreads between the most undervalued (Q5) and overvalued (Q1) stock quintiles. Regressors are Mkt_RF, SMB, HML, Mom, ST_Rev, LT_Rev, and PMU, obtained from the data libraries of Kenneth French (the first 6) and Robert Novy-Marx (PMU). The table also shows the average number of observations and adjusted R-Squared. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. The sample consists of all ordinary common stocks of U.S. nonfinancial firms listed on a major exchange (NYSE, Amex, Nasdaq) with a share price at the beginning of the return month of not less than five dollars. The sample period is 1/1977-12/2012. All variables are defined in Appendix B.

(continued)

Table 5: Buy-and-Hold Returns (continued)

	Q1 (Overvalued)			Q2			Q3			Q4			Q5 (Undervalued)			Q5-Q1 (Undervalued - Overvalued)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Industry-Adjusted Return	-0.1926	[-2.35]	**	-0.1343	[-1.37]		-0.0220	[-0.22]		0.0605	[0.58]		0.1530	[1.67]	*	0.3457	[3.18]	***
Intercept	-0.2348	[-2.91]	***	-0.1284	[-1.42]		-0.0545	[-0.58]		-0.0127	[-0.13]		0.1074	[1.40]		0.3422	[3.61]	***
Mkt_RF	0.0402	[2.12]	**	0.0203	[0.96]		0.0378	[1.71]	*	0.0389	[1.76]	*	0.0001	[0.00]		-0.0401	[-1.80]	*
SMB	-0.1735	[-5.87]	***	-0.2743	[-8.27]	***	-0.2710	[-7.87]	***	-0.2113	[-6.12]	***	-0.0813	[-2.88]	***	0.0922	[2.65]	***
HML	-0.0535	[-1.67]	*	-0.1767	[-4.93]	***	0.0132	[0.35]		0.2461	[6.59]	***	0.3472	[11.39]	***	0.4007	[10.65]	***
Mom	0.0793	[4.45]	***	0.1144	[5.72]	***	0.1147	[5.52]	***	0.0734	[3.52]	***	0.0095	[0.56]		-0.0698	[-3.32]	***
ST_Rev	0.0530	[2.18]	**	0.0314	[1.15]		-0.0174	[-0.62]		-0.0190	[-0.67]		-0.0427	[-1.84]	*	-0.0957	[-3.35]	***
LT_Rev	-0.0033	[-0.09]		0.0296	[0.73]		-0.0355	[-0.84]		-0.1118	[-2.64]	***	-0.1722	[-4.98]	***	-0.1689	[-3.96]	***
RSquare	0.13			0.23			0.22			0.27			0.37			0.32		
Observations	421			421			421			421			421			421		
Intercept	-0.3339	[-4.16]	***	-0.2094	[-2.29]	**	-0.1750	[-1.88]	*	-0.1643	[-1.80]	*	0.0082	[0.11]		0.3421	[3.51]	***
Mkt_RF	0.0493	[2.67]	***	0.0277	[1.32]		0.0489	[2.28]	**	0.0528	[2.52]	**	0.0092	[0.52]		-0.0401	[-1.79]	*
SMB	-0.1548	[-5.37]	***	-0.2590	[-7.88]	***	-0.2483	[-7.41]	***	-0.1828	[-5.56]	***	-0.0626	[-2.28]	**	0.0922	[2.63]	***
HML	-0.0010	[-0.03]		-0.1337	[-3.61]	***	0.0771	[2.04]	**	0.3265	[8.83]	***	0.3998	[12.95]	***	0.4008	[10.14]	***
Mom	0.0791	[4.58]	***	0.1143	[5.81]	***	0.1145	[5.71]	***	0.0732	[3.72]	***	0.0094	[0.57]		-0.0698	[-3.32]	***
ST_Rev	0.0405	[1.72]	*	0.0212	[0.79]		-0.0326	[-1.19]		-0.0381	[-1.42]		-0.0552	[-2.46]	**	-0.0957	[-3.33]	***
LT_Rev	-0.0275	[-0.78]		0.0099	[0.24]		-0.0649	[-1.58]		-0.1488	[-3.69]	***	-0.1964	[-5.84]	***	-0.1689	[-3.92]	***
PMU	0.1823	[5.34]	***	0.1490	[3.83]	***	0.2216	[5.59]	***	0.2789	[7.17]	***	0.1824	[5.62]	***	0.0002	[0.00]	
RSquare	0.19			0.26			0.28			0.35			0.41			0.32		
Observations	421			421			421			421			421			421		

Table 6: Revisions in Accounting Data

The table shows average industry-adjusted portfolio returns, as well as intercepts and *t*-statistics from time-series regressions of industry-adjusted portfolio returns on 6 or 7 factors. Stocks are sorted each month into quintiles based on one of two mispricing signals (*M*) and combined into equally-weighted portfolios. The mispricing signals are derived from fair values based on either the Regular or the As First Reported (AFR) Compustat databases. In each case, we compute fair values from the 24 accounting variables (of the 28 previously used) available in both databases. The table report averages and regression statistics separately for each of the five portfolios, Q1-Q5, and for the corresponding times series of return spreads between the most undervalued (Q5) and overvalued (Q1) stock quintiles. Regressors are Mkt_RF, SMB, HML, Mom, ST_Rev, LT_Rev, and PMU, obtained from the data libraries of Kenneth French (the first 6) and Robert Novy-Marx (PMU). *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. The sample consists of all ordinary common stocks of U.S. nonfinancial firms listed on a major exchange (NYSE, Amex, Nasdaq) with a share price at the beginning of the return month of not less than five dollars. The sample period is 1/1977-12/2012. All variables are defined in Appendix B.

	Q1 (Overvalued)			**Q2**			**Q3**			**Q4**			**Q5 (Undervalued)**			**Q5-Q1 (Undervalued - Overvalued)**		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Regular Compustat																		
Industry-Adjusted Return	-0.4625	[-3.69]	***	-0.1802	[-1.19]		-0.0140	[-0.10]		0.0985	[0.70]		0.3121	[2.41]	**	0.7746	[5.10]	***
6-Factor Alpha	-0.6063	[-5.41]	***	-0.3232	[-2.56]	**	-0.1281	[-1.04]		0.0285	[0.23]		0.2978	[2.71]	***	0.9041	[7.18]	***
7-Factor Alpha	-0.6762	[-5.91]	***	-0.4002	[-3.10]	***	-0.2498	[-2.03]	**	-0.1263	[-1.05]		0.1954	[1.76]	*	0.8716	[6.72]	***
As First Reported Compustat																		
Industry-Adjusted Return	-0.4224	[-3.32]	***	-0.1021	[-0.67]		-0.0427	[-0.30]		0.0500	[0.36]		0.2712	[2.13]	**	0.6935	[4.64]	***
6-Factor Alpha	-0.5748	[-5.12]	***	-0.2319	[-1.81]	*	-0.1501	[-1.26]		-0.0142	[-0.12]		0.2397	[2.18]	**	0.8145	[6.77]	***
7-Factor Alpha	-0.6387	[-5.57]	***	-0.3169	[-2.42]	**	-0.2800	[-2.36]	**	-0.1646	[-1.37]		0.1432	[1.29]		0.7819	[6.31]	***

Table 7: Mispricing Strategies and Other Anomalies

The table shows intercepts and *t*-statistics from time-series regressions of the industry-adjusted portfolio returns of a mispricing-based spread portfolio on 6 (Panel A) or 7 (Panel B) factors. Stocks are first sorted each month into quintiles, designated by column heading, based on the row's firm characteristic. Within each of the former quintiles, stocks are further sorted into quintiles based on the mispricing signal and combined into equally-weighted portfolios. The industry-adjusted return difference of the most underpriced and overpriced stocks within each cell are then regressed on Mkt_RF, SMB, HML, Mom, ST_Rev, LT_Rev, and PMU, obtained from the data libraries of Kenneth French (the first 6) and Robert Novy-Marx (PMU. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. The sample consists of all ordinary common stocks of U.S. nonfinancial firms listed on a major exchange (NYSE, Amex, Nasdaq) with a share price at the beginning of the return month of not less than five dollars. The sample period is 1/1977-12/2012. All variables are defined in Appendix B.

Panel A: 6-Factor Alphas

	Q1			Q2			Q3			Q4			Q5		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Beta	0.7381	[5.66]	***	0.4590	[3.38]	***	0.6482	[4.80]	***	0.5277	[3.58]	***	0.5773	[3.29]	***
Book/Market	0.2536	[1.32]		0.2904	[1.77]	*	0.5926	[4.32]	***	0.7813	[5.64]	***	0.7801	[5.18]	***
Market Capitalization	0.8777	[7.03]	***	0.8992	[6.51]	***	0.6276	[4.31]	***	0.4161	[3.03]	***	0.4141	[3.24]	***
Short-term Reversal	0.8342	[4.98]	***	0.8060	[6.21]	***	0.6621	[4.90]	***	0.4792	[3.87]	***	0.4855	[3.06]	***
Momentum	1.1539	[6.77]	***	0.6287	[4.80]	***	0.5981	[4.65]	***	0.6296	[4.61]	***	0.5380	[3.15]	***
Long-term Reversal	0.8215	[5.12]	***	0.7705	[5.46]	***	0.5269	[3.88]	***	0.7317	[5.70]	***	0.6518	[4.05]	***
Accruals	0.7392	[4.65]	***	0.6899	[4.72]	***	0.6993	[4.97]	***	0.6296	[4.00]	***	0.6831	[4.16]	***
SUE	0.7003	[4.27]	***	0.7225	[5.54]	***	0.4999	[3.84]	***	0.7359	[5.28]	***	1.0949	[7.15]	***
Gross Profitability	0.7531	[5.07]	***	0.5765	[4.41]	***	0.6250	[4.40]	***	0.8870	[5.76]	***	0.5432	[3.63]	***
Default Risk	0.7907	[5.24]	***	0.3636	[2.77]	***	0.4995	[4.10]	***	0.9138	[6.31]	***	1.1563	[7.00]	***
Scaled NOA	0.7874	[4.51]	***	0.6846	[4.68]	***	0.7131	[5.04]	***	0.8039	[5.34]	***	0.7040	[4.97]	***
Share Issuance	0.5006	[4.05]	***	0.7176	[5.21]	***	0.7054	[4.84]	***	0.5793	[3.77]	***	0.6935	[4.25]	***
Asset Growth	0.6495	[4.36]	***	0.5061	[3.62]	***	0.8122	[6.27]	***	0.6692	[4.79]	***	0.6833	[4.28]	***
Capital Investment	0.8179	[2.68]	***	0.5525	[3.49]	***	0.5994	[4.55]	***	0.7675	[5.09]	***	0.7430	[4.27]	***
Investment Ratio	0.7680	[5.43]	***	0.7005	[5.00]	***	0.6374	[4.93]	***	0.8033	[5.91]	***	0.6066	[3.84]	***
External Financing	0.5839	[4.46]	***	0.6065	[4.05]	***	0.7451	[5.83]	***	0.5034	[3.28]	***	0.4461	[2.33]	**
Z-Score	0.5150	[3.43]	***	0.5010	[3.71]	***	0.5146	[3.59]	***	0.7967	[5.55]	***	0.8748	[5.43]	***
Leverage	0.4216	[2.34]	**	0.7854	[5.30]	***	0.5594	[4.08]	***	0.6607	[5.11]	***	0.8158	[5.64]	***
Illiquidity	0.6886	[5.31]	***	0.4925	[3.65]	***	0.6552	[4.59]	***	0.3487	[2.51]	**	0.8206	[5.10]	***
Earnings/Price	0.3591	[2.31]	**	0.3088	[1.92]	*	0.3087	[2.26]	**	0.0821	[0.67]		0.4396	[3.29]	***
Dividends/Price	0.5700	[1.58]		0.6393	[3.04]	***	0.5146	[1.73]	*	0.7247	[5.58]	***	0.5515	[4.30]	***
Cash Flow/Price	0.3365	[2.05]	**	0.2365	[1.57]		0.1954	[1.50]		0.5296	[4.04]	***	0.7228	[5.46]	***
V/P	0.5867	[3.47]	***	0.4560	[3.11]	***	0.4464	[3.47]	***	0.3750	[3.21]	***	0.6634	[4.78]	***

(continued)

Table 7: Mispricing Strategies and Other Anomalies (continued)

Panel B: 7-Factor Alphas

	Q1			Q2			Q3			Q4			Q5		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Beta	0.7310	[5.45]	***	0.4507	[3.23]	***	0.6006	[4.33]	***	0.3975	[2.67]	***	0.4510	[2.53]	**
Book/Market	0.0434	[0.23]		0.1709	[1.02]		0.5550	[3.94]	***	0.8112	[5.70]	***	0.8035	[5.19]	***
Market Capitalization	0.8982	[7.00]	***	0.7863	[5.62]	***	0.4777	[3.26]	***	0.3001	[2.16]	**	0.3668	[2.79]	***
Short-term Reversal	0.7911	[4.60]	***	0.8217	[6.16]	***	0.7165	[5.17]	***	0.5119	[4.03]	***	0.4137	[2.55]	**
Momentum	1.1674	[6.66]	***	0.6086	[4.52]	***	0.5813	[4.39]	***	0.6137	[4.37]	***	0.5338	[3.03]	***
Long-term Reversal	0.7722	[4.68]	***	0.7776	[5.36]	***	0.5009	[3.59]	***	0.6749	[5.13]	***	0.6886	[4.17]	***
Accruals	0.7244	[4.43]	***	0.6850	[4.56]	***	0.7219	[4.99]	***	0.5990	[3.70]	***	0.6682	[3.96]	***
SUE	0.7053	[4.18]	***	0.6770	[5.06]	***	0.4681	[3.50]	***	0.7674	[5.36]	***	1.0377	[6.60]	***
Gross Profitability	0.6705	[4.42]	***	0.5362	[4.00]	***	0.6594	[4.52]	***	0.9497	[6.02]	***	0.6093	[3.97]	***
Default Risk	0.8271	[5.33]	***	0.3083	[2.29]	**	0.4812	[3.84]	***	0.8051	[5.47]	***	1.1527	[6.78]	***
Scaled NOA	0.7790	[4.34]	***	0.6749	[4.48]	***	0.6618	[4.56]	***	0.7891	[5.10]	***	0.7344	[5.05]	***
Share Issuance	0.5647	[4.46]	***	0.7391	[5.22]	***	0.6117	[4.12]	***	0.5598	[3.55]	***	0.6832	[4.07]	***
Asset Growth	0.5691	[3.73]	***	0.5016	[3.49]	***	0.7917	[5.94]	***	0.7220	[5.04]	***	0.6503	[3.96]	***
Capital Investment	0.9034	[2.89]	***	0.5795	[3.54]	***	0.5916	[4.37]	***	0.7888	[5.06]	***	0.7329	[4.07]	***
Investment Ratio	0.7711	[5.30]	***	0.6525	[4.53]	***	0.5935	[4.47]	***	0.8263	[5.91]	***	0.5706	[3.51]	***
External Financing	0.5910	[4.37]	***	0.6787	[4.41]	***	0.7469	[5.68]	***	0.5036	[3.17]	***	0.3916	[1.98]	**
Z-Score	0.4773	[3.10]	***	0.4719	[3.40]	***	0.5640	[3.83]	***	0.8904	[6.09]	***	0.9809	[5.98]	***
Leverage	0.3373	[1.83]	*	0.7718	[5.06]	***	0.5702	[4.04]	***	0.6207	[4.68]	***	0.8343	[5.61]	***
Illiquidity	0.6301	[4.74]	***	0.3776	[2.76]	***	0.5653	[3.88]	***	0.2449	[1.74]	*	0.8742	[5.30]	***
Earnings/Price	0.3912	[2.45]	**	0.3141	[1.90]	*	0.3669	[2.62]	***	0.1192	[0.95]		0.5191	[3.81]	***
Dividends/Price	0.0625	[0.15]		0.6918	[3.19]	***	0.6353	[2.05]	**	0.6834	[5.11]	***	0.5378	[4.05]	***
Cash Flow/Price	0.3936	[2.34]	**	0.2580	[1.66]	*	0.2114	[1.58]		0.5200	[3.85]	***	0.8026	[5.94]	***
V/P	0.5423	[3.13]	***	0.4635	[3.07]	***	0.4553	[3.44]	***	0.4086	[3.41]	***	0.7082	[4.97]	***

Table 8: Signal Additions and Deletions

The table shows average industry-adjusted portfolio returns, as well as intercepts and *t*-statistics from time-series regressions of industry-adjusted portfolio returns on 6 or 7 factors. Each row uses alternative constructions of the mispricing signal that vary with the set of accounting items used to obtain fair value. In Panel A, the accounting items listed in the first column are sequentially added as regressors in the fair value regression. In Panel B, the accounting items listed are sequentially dropped from the fair value regression. Panel C shows results separately for fair value regressions with balance sheet and income statement items. Stocks are sorted each month into quintiles based on the mispricing signal (*M*) and combined into equally-weighted portfolios. The table reports averages and regression statistics for the corresponding times series of return spreads between the most undervalued (Q5) and overvalued (Q1) stock quintiles. Regressors are Mkt_RF, SMB, HML, Mom, ST_Rev, LT_Rev, and PMU, obtained from the data libraries of Kenneth French (the first 6) and Robert Novy-Marx (PMU). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% significance levels, respectively. The sample consists of all ordinary common stocks of U.S. nonfinancial firms listed on a major exchange (NYSE, Amex, Nasdaq) with a share price at the beginning of the return month of not less than five dollars. The sample period is 1/1977-12/2012. All variables are defined in Appendix B.

Panel A: Signal Additions

	Industry-Adjusted Return			6-Factor Alpha			7-Factor Alpha		
Sequentially Added Variable	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
none (just regression intercept)	0.2526	[1.74]	*	0.0314	[0.30]		0.0916	[0.85]	
Assets - Total	0.3912	[2.40]	**	0.2226	[1.71]	*	0.2452	[1.83]	*
Liabilities and Stockholders Equity - Total	0.3912	[2.40]	**	0.2226	[1.71]	*	0.2452	[1.83]	*
Stockholders Equity > Parent > Index Fundamental > Quarterly	0.3605	[2.51]	**	0.3004	[2.60]	***	0.3345	[2.82]	***
Liabilities - Total and Noncontrolling Interest	0.3826	[2.62]	***	0.3150	[2.68]	***	0.3497	[2.89]	***
Liabilities - Total	0.3830	[2.61]	***	0.3228	[2.72]	***	0.3574	[2.93]	***
Assets - Other - Total	0.3493	[2.43]	**	0.3326	[2.87]	***	0.3681	[3.10]	***
Property Plant and Equipment - Total (Net)	0.3202	[2.39]	**	0.3078	[2.75]	***	0.3209	[2.79]	***
Liabilities - Other	0.3721	[2.94]	***	0.3443	[3.20]	***	0.3451	[3.11]	***
Common/Ordinary Equity - Total	0.3362	[2.63]	***	0.3108	[2.85]	***	0.3181	[2.83]	***
Preferred/Preference Stock (Capital) - Total	0.3335	[2.61]	***	0.3113	[2.86]	***	0.3155	[2.82]	***
Long-Term Debt - Total	0.3699	[2.92]	***	0.3951	[3.68]	***	0.3861	[3.50]	***
Current Liabilities - Total	0.4659	[3.77]	***	0.4619	[4.46]	***	0.4572	[4.30]	***
Current Assets - Total	0.4223	[3.36]	***	0.4259	[3.96]	***	0.4173	[3.78]	***
Non-Current Assets - Total	0.3955	[3.13]	***	0.3973	[3.65]	***	0.3920	[3.50]	***
Common Stock Equivalents - Dollar Savings	0.3871	[3.07]	***	0.3882	[3.58]	***	0.3851	[3.45]	***
Dividends - Preferred/Preference	0.3655	[2.93]	***	0.3699	[3.47]	***	0.3617	[3.30]	***
Income Before Extraordinary Items - Adjusted for Common Stock Equivalents	0.6940	[5.65]	***	0.7014	[6.55]	***	0.6488	[5.92]	***
Income Before Extraordinary Items	0.6558	[5.31]	***	0.6668	[6.15]	***	0.6276	[5.64]	***
Income Before Extraordinary Items - Available for Common	0.6281	[5.06]	***	0.6440	[5.92]	***	0.6104	[5.46]	***
Extraordinary Items and Discontinued Operations	0.6293	[5.14]	***	0.6582	[6.11]	***	0.6186	[5.60]	***
Net Income (Loss)	0.6426	[5.27]	***	0.6711	[6.27]	***	0.6399	[5.82]	***
Revenue - Total	0.6088	[5.00]	***	0.6158	[5.78]	***	0.5990	[5.47]	***
Sales/Turnover (Net)	0.6088	[5.00]	***	0.6158	[5.78]	***	0.5990	[5.47]	***
Pretax Income	0.6376	[5.40]	***	0.6573	[6.21]	***	0.6494	[5.97]	***
Income Taxes - Total	0.6385	[5.40]	***	0.6592	[6.24]	***	0.6469	[5.95]	***
Non-Operating Income (Expense) - Total	0.6922	[5.92]	***	0.7154	[6.83]	***	0.6928	[6.44]	***
Discontinued Operations	0.6997	[5.99]	***	0.7173	[6.82]	***	0.6942	[6.43]	***
Extraordinary Items	0.6815	[5.85]	***	0.7139	[6.83]	***	0.6916	[6.44]	***

(continued)

Table 8: Signal Additions and Deletions (continued)

Panel B: Signal Deletions

	Industry-Adjusted Return			6-Factor Alpha			7-Factor Alpha		
Sequentially Dropped Variable	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
none (signal with all variables)	0.6815	[5.85]	***	0.7139	[6.83]	***	0.6916	[6.44]	***
Assets - Total	0.6815	[5.85]	***	0.7139	[6.83]	***	0.6916	[6.44]	***
Liabilities and Stockholders Equity - Total	0.6846	[5.93]	***	0.7215	[6.98]	***	0.7005	[6.59]	***
Stockholders Equity > Parent > Index Fundamental > Quarterly	0.6814	[5.95]	***	0.7162	[6.98]	***	0.6996	[6.63]	***
Liabilities - Total and Noncontrolling Interest	0.7109	[6.13]	***	0.7344	[7.10]	***	0.7015	[6.60]	***
Liabilities - Total	0.7115	[6.09]	***	0.7307	[7.05]	***	0.6955	[6.54]	***
Assets - Other - Total	0.7112	[6.08]	***	0.7228	[7.01]	***	0.6961	[6.57]	***
Property Plant and Equipment - Total (Net)	0.7128	[6.10]	***	0.7346	[7.11]	***	0.7078	[6.67]	***
Liabilities - Other	0.6943	[5.97]	***	0.7248	[7.04]	***	0.6945	[6.57]	***
Common/Ordinary Equity - Total	0.7011	[6.03]	***	0.7539	[7.22]	***	0.7449	[6.94]	***
Preferred/Preference Stock (Capital) - Total	0.6824	[5.85]	***	0.7330	[6.98]	***	0.7266	[6.73]	***
Long-Term Debt - Total	0.6231	[5.33]	***	0.6603	[6.25]	***	0.6682	[6.15]	***
Current Liabilities - Total	0.6845	[5.65]	***	0.7280	[6.92]	***	0.7343	[6.79]	***
Current Assets - Total	0.6533	[4.93]	***	0.5532	[4.90]	***	0.5265	[4.53]	***
Non-Current Assets - Total	0.6763	[5.02]	***	0.5674	[4.85]	***	0.5281	[4.40]	***
Common Stock Equivalents - Dollar Savings	0.6695	[4.96]	***	0.5608	[4.79]	***	0.5217	[4.34]	***
Dividends - Preferred/Preference	0.6755	[4.97]	***	0.5572	[4.74]	***	0.5145	[4.27]	***
Income Before Extraordinary Items - Adjusted for Common Stock Equivalents	0.6880	[4.98]	***	0.5666	[4.75]	***	0.5217	[4.27]	***
Income Before Extraordinary Items	0.6753	[4.90]	***	0.5482	[4.71]	***	0.5119	[4.28]	***
Income Before Extraordinary Items - Available for Common	0.6789	[4.85]	***	0.5534	[4.72]	***	0.5200	[4.32]	***
Extraordinary Items and Discontinued Operations	0.6747	[4.81]	***	0.5437	[4.64]	***	0.5049	[4.19]	***
Net Income (Loss)	0.6959	[4.94]	***	0.5668	[4.80]	***	0.5367	[4.43]	***
Revenue - Total	0.6959	[4.94]	***	0.5668	[4.80]	***	0.5367	[4.43]	***
Sales/Turnover (Net)	0.5419	[3.87]	***	0.4278	[3.60]	***	0.3826	[3.14]	***
Pretax Income	0.5491	[3.81]	***	0.3887	[3.18]	***	0.3511	[2.80]	***
Income Taxes - Total	0.2539	[1.77]	*	0.0582	[0.54]		0.1359	[1.23]	
Non-Operating Income (Expense) - Total	0.2569	[1.77]	*	0.0444	[0.42]		0.1051	[0.97]	
Discontinued Operations	0.2564	[1.76]	*	0.0356	[0.34]		0.0949	[0.88]	
Extraordinary Items (just regression intercept)	0.2526	[1.74]	*	0.0314	[0.30]		0.0916	[0.85]	

Panel C: Balance Sheet and Income Statement Items

	Industry-Adjusted Return			6-Factor Alpha			7-Factor Alpha		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
All Balance Sheet Items	0.3955	[3.13]	***	0.3973	[3.65]	***	0.3920	[3.50]	***
All Income Statement Items	0.6763	[5.02]	***	0.5674	[4.85]	***	0.5281	[4.40]	***

Appendix A: Discussion and Proof of Result in the Paper's Introduction

For a given date, let X^* denote the NxK matrix of K accounting variables for each of N firms, with $K < N$. The accounting variables are reported (or transformed) at the firm level (*i.e.*, earnings, dividends, depreciation, and book equity for the firm as a whole rather than per share), preserving the linearity of valuation.[1] Thus, the accounting items that would be reported for an investment represented by the $1xN$ vector w in the N firms would be the $1xK$ vector wX^*. More generally, for N distinct investments given by the rows of the NxN matrix W, the accounting statements of the investments would be given by the rows of the NxK matrix WX^*. Thus, the N replicating investments must satisfy $WX^* = X^*$, and if the associated fair value estimates are further required to have average mispricing of zero, then W must satisfy $WX = X$, where the $Nx(K+1)$ matrix X is X^* augmented by a (first) column of 1's.[2] With entries that are functions of X, W's rank deficiency leads to an infinite number of Ws that perfectly replicate each of the N targets' accounting items while producing zero average mispricing.

Proposition: There is a unique W of rank K+1 that is a function of X that produces zero average mispricing and also minimizes the mean-squared prediction error of any non-accounting attribute v of the targets. This is the one given by the idempotent projection matrix statisticians are so familiar from linear regression.

[1] For example, the revenue of an investment that buys up 100 per cent of two firms is the sum of their revenues; the earnings of an investment that is 50% of investments A and B is the average of A and B's earnings. Linearity in the portfolio mathematics of accounting items from firm combinations views these combinations as ETFs rather than as full-fledged mergers or acquisitions. Mergers often have synergies, and purchase accounting treatment allocates goodwill to the balance sheet items of the target. Such synergies and accounting treatments generally violate the linearity discussed here.

[2] This means that the N eigenvalues of W consist of K+1 "1"s and N-K-1 "0"s. Moreover, the eigenvectors of W associated with the eigenvalue of 1 consist of the cross-section of each of the K accounting variables and an N-vector of 1's, as well as any linear combination of these eigenvectors. The 1 vector as eigenvector implies W's "weights" sum to one, which is isomorphic to a market portfolio that is never estimated as mispriced.

Proof: Project any variable y not spanned by X onto X, which decomposes $y = X(X^TX)^{-1}X^Ty + \varepsilon$, with the vector ε orthogonal to X. Then, the quadratic minimization problem of finding W with eigenvectors X for eigenvalue 1 that minimizes the sum of squared errors simplifies to choosing the weight matrix W that minimizes $[(X(X^TX)^{-1}X^T - W)y + \varepsilon]^T[(X(X^TX)^{-1}X^T - W)y + \varepsilon]$, which trivially forces W to be the least squares projection matrix, irrespective of the value of the vector y. Since ε is orthogonal to X and mean zero in sample, it must be orthogonal to W if W is assumed to depend only on X.■

Setting

$$W = X(X^TX)^{-1}X^T$$

predicts a cross-section of the attribute v, denoted P, that is the least squares prediction, *i.e.*,

$$P = Wv = X(X^TX)^{-1}X^Tv.$$

Appendix B: Variable Definitions

The table shows the variable name (or mnemonic), the description (or construction) of the data item, as well as the source (database). CRSP and Compustat are from the merged database on WRDS.

Variable	Definition	Source
ATQ	Assets - Total	Compustat
IBADJQ	Income Before Extraordinary Items - Adjusted for Common Stock Equivalents	Compustat
IBCOMQ	Income Before Extraordinary Items - Available for Common	Compustat
IBQ	Income Before Extraordinary Items	Compustat
LSEQ	Liabilities and Stockholders Equity - Total	Compustat
DVPQ	Dividends - Preferred/Preference	Compustat
NIQ	Net Income (Loss)	Compustat
SEQQ	Stockholders Equity > Parent > Index Fundamental > Quarterly	Compustat
REVTQ	Revenue - Total	Compustat
SALEQ	Sales/Turnover (Net)	Compustat
XIDOQ	Extraordinary Items and Discontinued Operations	Compustat
CSTKEQ	Common Stock Equivalents - Dollar Savings	Compustat
PPENTQ	Property Plant and Equipment - Total (Net)	Compustat
DLTTQ	Long-Term Debt - Total	Compustat
CEQQ	Common/Ordinary Equity - Total	Compustat
PSTKQ	Preferred/Preference Stock (Capital) - Total	Compustat
NOPIQ	Non-Operating Income (Expense) - Total	Compustat
DOQ	Discontinued Operations	Compustat
XIQ	Extraordinary Items	Compustat
LTMIBQ	Liabilities - Total and Noncontrolling Interest	Compustat
LTQ	Liabilities - Total	Compustat
LCTQ	Current Liabilities - Total	Compustat
ACTQ	Current Assets - Total	Compustat
ANCQ	Non-Current Assets - Total	Compustat
PIQ	Pretax Income	Compustat
TXTQ	Income Taxes - Total	Compustat
AOQ	Assets - Other - Total	Compustat
LOQ	Liabilities - Other	Compustat
SharePrice	Stock price (in dollar and cents)	CRSP
Number of Shares Outstanding	Number of shares outstanding (in millions)	CRSP
Return	Monthly Stock Return	CRSP
Beta	Annual Market Beta	CRSP
Industry Classification	38 industries	Ken French website
Industry Portfolios	Monthly returns on 38 industry portfolios	Ken French website
Mkt_RF	Monthly market index return net of risk-free rate	Ken French website
SMB	Monthly Small Minus Big (SMB) portfolio return	Ken French website
HML	Monthly High Minus Low (HML) portfolio return	Ken French website
Mom	Monthly Momentum portfolio return	Ken French website
ST_Rev	Monthly Short-term reversal portfolio return	Ken French website
LT_Rev	Monthly long-term reversal portfolio return	Ken French website
PMU	Monthly profitability factor	Novy-Marx website

(continued)

Appendix B: Variable Definitions (continued)

Variable	Definition
SUE	Quarterly earnings surprise based on a rolling seasonal random walk model (Livnat and Mendenhall, 2006, page 185)
Accruals	Accruals = [NOA(t)-NOA(t-1)]/NOA(t-1), where NOA(t) = Operating Assets (t) - Operating Liabilities (t). Operating Assets is calculated as total assets (ATQ) less cash and short-term investments (CHEQ). Operating liabilities is calculated as total assets (ATQ) less total debt (DLCQ and DLTTQ) less book value of total common and preferred equity (CEQQ and PSTKQ) less minority interest (MIBTQ) (Richardson et al., 2001, p. 22)
Gross Profitability	(Revenue(REVTQ) - Cost of Goods Sold(COGSQ))/Total Assets(ATQ) (Novy-Marx 2013)
Default Risk	Default probability from Merton (1974) model
Market Capitalization	Stock Market Capitalization of Common Stock, calculated as product of Share Price(PRC) * Number of Shares Outstanding(SHROUT)
Book/Market	(Book Equity(CEQQ) + Deferred Taxes Balance Sheet(TXDBQ))/MarketCapitalization
Mispricing Percentage (M)	-1 * Residual/ MarketCapitalization
Short-term Reversal	Return in prior month
Momentum	Return in prior year excluding prior month
Long-term Reversal	Return in prior five years excluding prior year
Scaled NOA	Scaled NOA (Hirshleifer, Hou, Teoh, and Zhang, 2004)
Share Issuance	Share issuance (Daniel and Titman, 2006)
Asset Growth	Asset growth (Cooper, Gulen and Schill, 2008)
Capital Investment	Abnormal capital investment (Titman, Wei, and Xie, 2004)
Investment Ratio	Investment ratio (Lyandres, Sun, and Zhang, 2008)
External Financing	External financing (Bradshaw, Richardson, and Sloan, 2006)
Z-Score	Z-Score (Ferguson and Shockley, 2003)
Leverage	Leverage (Ferguson and Shockley, 2003)
Illiquidity	Illiquidity (Amihud, 2002)
Earnings/Price	Earnings/Price (Penman, Richardson, Riggoni, and Tuna 2014)
Dividends/Price	Dividends/Price (Fama and French, 1992)
Cash Flow/Price	Cash flow/Price (Hou, Karolyi, and Kho, 2011)
V/P	Value/Price (Lee, Myers, and Swaminathan, 1999)