Mispricing Factors

by*

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Abstract

A four-factor model with two "mispricing" factors, in addition to market and size factors, accommodates a large set of anomalies better than notable four- and five-factor alternative models. Moreover, our size factor reveals a small-firm premium nearly twice usual estimates. The mispricing factors aggregate information across 11 prominent anomalies by averaging rankings within two clusters exhibiting the greatest co-movement in long-short returns. Investor sentiment predicts the mispricing factors, especially their short legs, consistent with a mispricing interpretation and the asymmetry in ease of buying versus shorting. Replacing book-to-market with a single composite mispricing factor produces a better-performing three-factor model.

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1. Introduction

Modern finance has long valued models relating expected returns to factor sensitivities. A virtue of such models is parsimony. Once factors are constructed, the only additional data required to compute implied expected returns in standard applications are the historical returns on the assets being analyzed. Moreover, the number of factors has typically been small. For many years only a single market factor was popular, following the CAPM of Sharpe (1964) and Lintner (1965). Fama and French (1993) spurred widespread use of three factors, motivated by violations of the single-factor CAPM related to firm size and value-versus-growth measures.

Numerous studies identify a wide range of anomalies that violate the three-factor model. Only occasionally, though, does the literature entertain anomalies as additional factors, given the virtue of parsimony.[1] Recently, however, two additional factors have received significant attention. Hou, Xue, and Zhang (2015a) propose a four-factor model that combines market and size factors with two new factors based on investment and profitability. Fama and French (2015) add somewhat different versions of investment and profitability factors to their earlier three-factor model (Fama and French (1993)), creating a five-factor model. Both studies provide theoretical motivations for the new factors: Hou, Xue, and Zhang (2015a) rely on an investment-based pricing model, while Fama and French (2015) invoke comparative statics of a present-value relation. At the same time, it should be noted that both investment and profitability are two of the numerous anomalies documented earlier in the literature.[2] In subsequent studies, Fama and French (2014) and Hou, Xue, and Zhang (2015b) examine their models' abilities to explain other anomalies.

We also propose two new factors based on anomalies, but we take a different approach. Clearly an important dimension on which a parsimonious factor model is judged is its ability to accommodate a wide range of anomalies. Our approach exploits that range when forming the factors. Rather than construct a factor using stocks' rankings on a single anomaly variable, such as investment, we construct a factor by averaging rankings across the set of 11 prominent anomalies examined by Stambaugh, Yu, and Yuan (2012, 2014, 2015). In constructing two such factors, we average rankings within two clusters of anomalies whose

[1] A notable example subsequent to Fama and French (1993) is the momentum anomaly documented by Jegadeesh and Titman (1993), which motivates the frequently used momentum factor proposed by Carhart (1997).

[2] Titman, Wei, and Xie (2004) and Xing (2008) show that high investment predicts abnormally low returns, while Fama and French (2006), Chen, Novy-Marx, and Zhang (2010), and Novy-Marx (2013) show that high profitability predicts abnormally high returns.

long-short return spreads exhibit the greatest co-movement. We combine these two factors with market and size factors to obtain a four-factor model. We find that this four-factor model's overall ability to accommodate a wide range of anomalies exceeds that of both the four-factor model of Hou, Xue, and Zhang (2015a) and the five-factor model of Fama and French (2015). This conclusion obtains not only within the set of anomalies used to construct the factors but also for the substantially larger set of 73 anomalies examined previously by Hou, Xue, and Zhang (2015a, 2015b). Also, if our two new factors are replaced by a single factor that simply averages rankings across the set of 11 anomalies, rather than within clusters, the resulting three-factor model substantially outperforms the three-factor model of Fama and French (1993).

Our size factor is constructed using stocks least likely to be mispriced, as identified by the measures used to construct our mispricing factors. Our resulting SMB delivers a small-firm premium of 46 bps per month over our 1967–2013 sample period, nearly twice the premium of 25 bps implied by the familiar SMB factor in the Fama-French three-factor model. Consistent with mispricing exerting less effect on our size factor, the investor sentiment index of Baker and Wurgler (2006) exhibits significant ability to predict the Fama-French SMB but not our SMB.

The basic concepts motivating our approach are that anomalies in part reflect mispricing and that mispricing has common components across stocks, often characterized as sentiment. Both concepts are consistent with empirical evidence. A mispricing interpretation is consistent with evidence that anomalies are stronger among stocks for which price-correcting arbitrage is deterred by greater risks and impediments. The effects of these deterrents are especially strong among stocks for which the anomaly variables predict negative alphas, consistent with arbitrage risks and impediments being especially significant in dampening short selling that would otherwise correct overpricing. See, for example, Stambaugh, Yu, and Yuan (2015) and Drechsler and Drechsler (2014). A mispricing interpretation of anomalies is also consistent with the evidence of McLean and Pontiff (2015), who observe that following an anomaly's academic publication, there is greater trading activity in the anomaly portfolios, and anomaly profits decline. Evidence consistent with a common sentiment-related component of mispricing is provided, for example, by Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2012). The latter study finds that the short-leg returns for long-short spreads associated with each of 11 anomalies are significantly lower following a high level of investor sentiment. By combining information across anomalies, we aim to construct factors capturing common elements of mispricing.

Factor models can be useful whether expected returns reflect risk or mispricing. Factors can capture systematic risks for which investors require compensation, or they can capture common sources of mispricing, such as market-wide investor sentiment. Kozak, Nagel, and Santosh (2015), for example, emphasize this point. Moreover, there need not be a clean distinction between mispricing and risk compensation as alternative motivations for factor models of expected return. For example, DeLong, Shleifer, Summers, and Waldman (1990) explain how fluctuations in market-wide "noise-trader" sentiment create an additional source of systematic risk for which rational traders require compensation.

When expected returns reflect mispricing and not just compensation for systematic risks, some of the mispricing may not be driven by pervasive sentiment factors but may instead be asset specific. In other words, a correctly specified factor model may not exist, as discussed for example by Daniel and Titman (1997). In that sense the concept of "mispricing" factors potentially embeds some inconsistency. On the other hand, mispricing does appear to exhibit commonality across stocks, as discussed above, and the extent to which our factors help describe expected returns is an empirical question. A parsimonious factor model that outperforms feasible alternatives seems useful from a practical perspective, as no model can be entirely correct.

The remainder of the paper proceeds as follows. Section 2 explains the construction of our factors and examines their empirical properties. The resulting four-factor model is compared to notable alternative factor models in Section 3. Section 4 constructs a single mispricing factor and compares the resulting three-factor model to the three-factor model of Fama and French (1993). Section 5 illustrates a shared limitation of the factor models, showing how they can seem to explain the idiosyncratic volatility puzzle if the role of mispricing is not considered. Section 6 reviews our conclusions.

2. Anomalies and Factors

The first factor in our four-factor model is the excess market return. Constructing the remaining three factors—a size factor and two mispricing factors—involves averaging stocks' rankings with respect to various anomalies. We use the same 11 anomalies analyzed by Stambaugh, Yu, and Yuan (2012, 2014, 2015). While the number of anomalies used to construct the factors could be expanded, we use this previously specified set to alleviate concerns that a different set was chosen to yield especially favorable results for this study. Appendix A provides brief descriptions of the 11 anomalies: net stock issues, composite equity issues, accruals, net operating assets, asset growth, investment-to-assets, distress, O-score, momentum, gross profitability, and return on assets.

Rather than constructing a five-factor model by adding our two mispricing factors to the three factors of Fama and French (1993), we opt for only four factors. That is, we do not include a book-to-market factor and instead include only a size factor in addition to the market and our mispricing factors. Our motivation here is parsimony and the long-standing recognition that firm size enters many dimensions of asset returns, such as average return, volatility, liquidity, and sensitivities to macroeconomic conditions.[3]

2.1. The Mispricing Factors

The initial step in constructing the mispricing factors is to separate the 11 anomalies into two clusters. Identifying an anomaly requires a benchmark model. As Stambaugh, Yu, and Yuan (2012) explain, the 11 prominent anomalies that we use here are shown in the literature to have average long-short return spreads that violate the three-factor model of Fama and French (1993). We maintain that model as the benchmark when estimating comovement of the anomaly returns for the purpose of forming clusters. To form clusters, for each anomaly i we first compute the spread, $R_{i,t}$, between the value-weighted returns in month t on stocks in the first and tenth NYSE deciles of the ranking variable in a sort at the end of month $t-1$ of all NYSE/AMEX/NASDAQ stocks with share prices greater than \$5, where the ordering produces a positive estimated intercept in the regression

$$R_{i,t} = \alpha_i + b_i MKT_t + c_i SMB_t + d_i HML_t + u_{i,t}, \tag{1}$$

and MKT_t, SMB_t, and HML_t are the market, size, and value factors constructed by Fama and French (1993).[4] Next we compute the correlation matrix of the estimated residuals in equation (1). Our sample period runs from January 1967 through December 2013, except data for the distress anomaly begin in October 1974, and data for the return-on-assets

[3]For example, see Banz (1981) on average return, Amihud and Mendelson (1989) on volatility and liquidity, and Chan, Chen, and Hsieh (1985) on sensitivities to macroeconomic conditions.

[4]For the anomaly variables requiring Compustat data from annual financial statements, we require at least a four-month gap between the end of month $t-1$ and the end of the fiscal year. When using quarterly reported earnings, we use the most recent data for which the reporting date provided by Compustat (item RDQ) precedes the end of month $t-1$. When using quarterly items reported from the balance sheet, we use those reported for the quarter prior to quarter used for reported earnings. The latter treatment allows for the fact that a significant number of firms do not include include balance-sheet information with earnings announcements and only later release it in 10-Q filings (see Chen, DeFond, and Park (2002)). For anomalies requiring return and market capitalization, we use data recorded for month $t-1$ and earlier, as reported by CRSP.

anomaly begin in November 1971. To deal with the heterogeneous starting dates, we compute the correlation matrix using the maximum likelihood estimator analyzed by Stambaugh (1997). Using this correlation matrix, we form two clusters by applying the same procedure as Ahn, Conrad, and Dittmar (2009), who combine a correlation-based distance measure with the clustering method of Ward (1963). The first cluster of anomalies includes net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment to assets; the second cluster includes distress, O-score, momentum, gross profitability, and return on assets.

We next average a stock's rankings with respect to the available anomaly measures within each of the two clusters. Thus, each month a stock has two composite mispricing measures, $P1$ and $P2$. Our averaging of anomaly rankings closely follows the approach of Stambaugh, Yu, and Yuan (2015), who construct a single composite mispricing measure by averaging across all 11 anomalies.[5]

We construct the mispricing factors by applying a 2×3 sorting procedure resembling that of Fama and French (2015). The approach in that study generalizes the approach in Fama and French (1993), and a similar procedure is applied in Hou, Xue, and Zhang (2015a). Specifically, each month we sort NYSE, AMEX, and NASDAQ stocks (excluding those with prices less than \$5) by size (equity market capitalization) and split them into two groups using the NYSE median size as the breakpoint. Independently, we sort all stocks by $P1$ and assign them to three groups using as breakpoints the 20th and 80th percentiles of the combined NYSE, AMEX, and NASDAQ universe. We similarly assign stocks to three groups according to sorts on $P2$. To construct the first mispricing factor, UMO_1 (underpriced minus overpriced), we compute value-weighted returns on each of the four portfolios formed by the intersection of the two size categories with the top and bottom categories for $P1$. The value of UMO_1 for a given month is then the simple average of the returns on the two low-$P1$ portfolios (underpriced stocks) minus the average of the returns on the two high-$P1$ portfolios (overpriced stocks). The second mispricing factor, UMO_2, is similarly constructed from the low- and high-$P2$ portfolios.

One might note that for the breakpoints of $P1$ and $P2$, we use the 20th and 80th percentiles of the NYSE/AMEX/NASDAQ, rather than the 30th and 70th percentiles of the NYSE, used by the studies cited above that apply a similar procedure to different variables. These modifications reflect the notion that relative mispricing in the cross-section is likely

[5]Stambaugh, Yu, and Yuan (2015) also report a robustness exercise that employs a clustering approach similar to that reported above.

to be more a property of the extremes than of the middle. Stambaugh, Yu, and Yuan (2015) find, for example, that the negative (positive) effects of idiosyncratic volatility for overpriced (underpriced) stocks are consistent with the role of arbitrage risk deterring the correction of mispricing, and those authors show that such effects occur primarily in the extremes of a composite mispricing measure and are stronger for smaller stocks. Subsection 3.3 explains that our main results are robust to the various deviations we take from the more conventional factor-construction methodology tracing to Fama and French (1993). Appendix B reports detailed results of those robustness checks.

2.2. The Size Factor

When constructing our size factor, we depart more significantly from the approach in Fama and French (2015) and other studies cited above. The stocks we use to form the size factor in a given month are the stocks not used in forming either of the mispricing factors. Specifically, to construct our size factor, SMB (small minus big—that we keep), we compute the return on the small-cap leg as the value-weighted portfolio of stocks present in the intersection of both small-cap middle groups when sorting on $P1$ and $P2$. Similarly, the large-cap leg is the value-weighted portfolio of stocks in the intersection of the large-cap middle groups in the sorts on the mispricing measures. The value of SMB in a given month is the return on the small-cap leg minus the large-cap return.

Each 2×3 sort on size and one of the mispricing measures produces six categories, so in total twelve categories result from the sorts using each of the two mispricing measures. If we were to follow the more familiar approach of Fama and French (2015) and others, we would compute SMB as the simple average of the value-weighted returns on the six small-cap portfolios minus the corresponding average of returns on the six large-cap portfolios. By averaging across the three mispricing categories, that approach would seek to neutralize the effects of mispricing when computing the size factor. The problem is that such a neutralization can be thwarted by arbitrage asymmetry—a greater ability or willingness to buy than to short for many investors. With such asymmetry, the mispricing within the overpriced category is likely to be more severe than the mispricing within the underpriced category. Moreover, this asymmetry is likely to be greater for small stocks than for large ones, given that small stocks present potential arbitrageurs with greater risk (e.g., idiosyncratic volatility).[6] Thus, simply averaging across mispricing categories would not neutralize the effects of mispricing, and the resulting SMB would have an overpricing bias. This bias is a concern

[6]See Stambaugh, Yu, and Yuan (2015) for supporting evidence.

not just when sorting on our mispricing measures but when sorting on any measure that is potentially associated with mispricing. Some studies argue that book-to-market, for example, contains a mispricing effect (e.g., Lakonishok, Shleifer, and Vishny (1994)), so one might raise a similar concern in the context of the version of SMB computed by Fama and French (1993). By instead computing SMB using stocks only from the middle of our mispricing sorts, avoiding the extremes, we aim to reduce this effect of arbitrage asymmetry.

Consistent with the above argument, our approach delivers a small-cap premium that significantly exceeds not only the value produced by the above alternative method but also the small-cap premium implied by the version of SMB in the three-factor model of Fama and French (1993). For our sample period of January 1967 through December 2013, our SMB factor has an average of 46 bps per month. In contrast, the alternative method discussed above gives an SMB with an average of 28 bps, close to the average of 25 bps for the three-factor Fama-French version of SMB. The differences between our estimated small-cap premium and these alternatives are significant not only statistically (t-statistics: 3.99 and 4.19) but economically as well, indicating a size premium that is nearly twice that implied by the familiar Fama-French version of SMB. This result is similar to the conclusion of Asness, Frazzini, Israel, Moskowitz, and Pedersen (2015), who find that the size premium becomes substantially greater when controlling for other stock characteristics potentially associated with mispricing. Those authors conclude that explaining a significant size premium presents a challenge to asset pricing theory. Such a challenge is beyond the scope of our study as well. Even though the size premium is a fundamentally important quantity, our comparison below of factor models' abilities to explain anomalies is not sensitive to the method used to construct the size factor. (We present further discussion and evidence of this point in subsection 3.3 and in Appendix B.)

2.3. Factor Betas, Arbitrage Asymmetry, and Sentiment Effects

Table 1 gives parameter estimates from our four-factor model for the individual long-short strategies based on the anomaly measures used above as well as book-to-market. Panel A contains the alphas and factor sensitivities ("betas") of the long-short spreads between the value-weighted portfolios of stocks in the long leg (bottom decile) and short leg (top decile). Panel B gives corresponding estimates for the long legs, and Panel C reports estimates for the short legs. The breakpoints are based on NYSE deciles, but all NYSE/AMEX/NASDAQ stocks with share prices of at least \$5 are included.[7] For anomalies in the first cluster, the long-short betas on the first mispricing factor, UMO_1, are positive with t-statistics between 6.09 and 18.12, whereas the same anomalies' long-short betas on the second factor, UMO_2, are uniformly lower and have t-statistics of mixed signs that average just 1.27. Similarly, for anomalies in the second cluster, the long-short betas on UMO_2 are positive with t-statistics between 5.02 and 24.10, while the betas on UMO_1 have mixed-sign t-statistics averaging -0.17. These results confirm that averaging anomaly rankings within a cluster produces a factor that captures common variation in returns for the anomalies in that cluster. Not surprisingly, for each anomaly with respect to its corresponding factor, the short-leg beta is significantly negative and the long-leg beta is significantly positive, with the long leg for accruals being the only exception.

Also observe in Table 1 that the short-leg betas are generally larger in absolute magnitude than their long-leg counterparts. With the first-cluster anomalies, for example, the average short-leg UMO_1 beta is -0.46, whereas the average long-leg UMO_1 beta is 0.20. Similarly, for the second-cluster anomalies, the short-leg UMO_2 betas average -0.49 as compared to 0.30 for the long legs. If the factors indeed capture systematic components of mispricing, a greater short-leg sensitivity is consistent with the arbitrage asymmetry discussed above. This arbitrage asymmetry leaves more uncorrected overpricing than uncorrected underpricing, implying greater sensitivity to systematic mispricing for overpriced (short-leg) stocks than for uncerpriced (long-leg) stocks.

Arbitrage asymmetry is also consistent with the relation between investor sentiment and anomaly returns. For each of the anomalies we use to construct our factors, Stambaugh, Yu, and Yuan (2012) observe that the short leg of the long-short anomaly spread is significantly more profitable following high investor sentiment, whereas the long-leg profits are less sensitive to sentiment. We observe similar sentiment effects for our factors. Table 2 reports the results of regressing each factor as well as its long and short legs on the previous month's level of the investor sentiment index of Baker and Wurgler (2006). The slope coefficients on both the long and short legs are uniformly negative, consistent with sentiment effects, but the slopes for the short legs are two to three times larger in magnitude. The short-leg coefficients for the two factors are nearly identical, as are the t-statistics of -2.06 and -2.05. The long-leg t-statistics, in contrast, are just -0.98 and -1.29.

The stronger sentiment effects for the short legs are consistent with sentiment-driven

[7] NYSE breakpoints are also used, for example, by Fama and French (2014) and Hou, Xue, and Zhang (2015a).

mispricing coupled with arbitrage asymmetry, as Stambaugh, Yu, and Yuan (2012) explain. Given that many investors are less willing or able to short stocks than to buy them, overpricing resulting from high investor sentiment gets corrected less by arbitrage than does underpricing resulting from low sentiment. The significantly positive t-statistics in Table 2 for the sentiment sensitivity of each long-short difference (i.e., each mispricing factor) confirm the greater sentiment effect on the short-leg returns. Overall, the long-short asymmetry in factor betas (Table 1) and sentiment effects (Table 2) is consistent with a mispricing interpretation of our factors.

Sentiment does not exhibit much ability to predict our size factor. In Table 2, the t-statistic is -1.60 for the slope coefficient when regressing the long-short spread (SMB) on lagged sentiment, and the t-statistics for the long and short legs (small and large firms) are -1.72 and -1.17. If sentiment affects prices, then periods of high (low) sentiment are likely to be followed by especially low (high) returns on overpriced (underpriced) stocks, especially among smaller stocks, which are likely to be more susceptible to mispricing. Baker and Wurgler (2006) report evidence consistent with this hypothesis, which implies a negative relation between lagged sentiment and the return on a spread that is long small stocks and short large stocks—if mispriced stocks are included, especially in the small-stock leg. The lack of a significant relation between our SMB factor and sentiment suggests some success in our attempt to avoid mispriced stocks when constructing the factor. In contrast, for example, sentiment does exhibit a significant ability to predict the familiar SMB factor from the three-factor model of Fama and French (1993). The slope coefficient is nearly 50% greater in magnitude (-0.32 versus -0.22) and has a t-statistic of -2.31. In fact, the t-statistic for the difference in slopes of -0.10 is -1.68, which is significant at the 5% level for the one-tailed test implied by the alternative hypothesis that our SMB factor is less affected by mispricing.

3. Comparing Factor Models

Fama and French (2014) explore the ability of the five-factor model of Fama and French (2015) to accommodate various return anomalies. Hou, Xue, and Zhang (2015b) compare that model to the four-factor model of Hou, Xue, and Zhang (2015a) by investigating the two models' abilities to explain a range of anomalies. We evaluate our four-factor model relative to both of those models, also including the three-factor model of Fama and French (1993) in the comparison as a familiar benchmark.[8] In subsection 3.1, we compare the models' relative abilities to explain a range of individual anomalies, both the set of 12 anomalies examined in Table 1 as well as the substantially wider set of 73 anomalies analyzed by Hou, Xue, and Zhang (2015a, 2015b). Subsection 3.2 then reports pairwise model comparisons that evaluate each model's ability to explain factors present in another. Results of robustness investigations are summarized in subsectin 3.3 (with details reported in Appendix B).

3.1. Comparing models' abilities to explain anomalies

Table 3 reports alphas from the various factor models for each of the 12 anomalies in Table 1. For convenience, we denote the factor models as follows:

FF-3: three-factor model of Fama and French (1993)

FF-5: five-factor model of Fama and French (2015)

q-4: four-factor "q-factor" model of Hou, Xue, and Zhang (2015a)

M-4: four-factor mispricing-factor model introduced here

For each anomaly, we construct the difference between the value-weighted monthly return on stocks ranked in the bottom decile and the return on those in the top decile. (The highest rank corresponds to the lowest three-factor Fama-French (1993) alpha.) We then use each long-short return as the dependent variable in 12 regressions of the form

$$R_{i,t} = \alpha_i + \sum_{j=1}^{K} \beta_{i,j} F_{j,t} + u_{i,t}, \tag{2}$$

where the $F_{j,t}$'s are the K factors in a given model. Panel A reports the estimated α_i's for each model. Also reported (first column) are the averages of the $R_{i,t}$'s. Panel B reports the corresponding t-statistics.

The alternative models—FF-3, FF-5, and q-4—exhibit at best only modest ability to accommodate the anomalies. Consistent with having been identified as anomalies with respect to the FF-3 model, the first 11 produce FF-3 alphas that are significant both economically and statistically. The monthly alphas range from 0.32% (asset growth) to 1.59% (momentum), and the t-statistics range from 2.83 to 5.70. Model FF-5 lowers all but one of the FF-3 alphas for the first 11 anomalies, but only the alpha for asset growth—essentially the investment factor in FF-5—drops to insignificance (0.06%, t-statistic: 0.58). Ten alphas

[8] We are grateful to all of these authors for providing time series of their factors.

remain economically and statistically significant, ranging from 0.32% (net stock issues) to 1.35% (momentum), with the t-statistics ranging from 2.29 to 4.12. Model q-4 does a somewhat better job than FF-5. Asset growth—also essentially the investment factor in q-4—is similarly accommodated, while the alphas on three additional anomalies—distress, momentum, and return on assets—drop to levels insignificant from at least a statistical perspective (t-statistics ranging from 0.72 to 1.40). At the same time, though, seven anomalies have both economically and statistically significant q-4 alphas ranging from 0.32% (investment to assets) to 0.65% (accruals), with t-statistics ranging from 2.50 to 4.30.

Model M-4, true to its intent, does the best job of accommodating the anomalies. Of the nine positive M-4 alphas, all but one are lower than any of the corresponding alphas for the other models. The sole exception is return on assets, for which model q-4 produces a smaller alpha (0.10% versus 0.27%)—unsurprising given that model q-4 includes a profitability factor. Only two of the M-4 t-statistics exceed 2.0 (a third has a t-statistic of 1.90). The alphas for asset growth and distress flip to negative values in model M-4 (with t-statistics of -1.96 and -1.03).

Table 4 compares the models on several measures that summarize abilities to accommodate the set of anomaly long-short spreads: average absolute alpha, average absolute t-statistic of alpha, the number of anomalies for which the model produces the lowest absolute alpha among the four models being compared, and the Gibbons, Ross, and Shanken (1989) "GRS" test of whether all alphas equal zero.[9] Panel A reports these measures for the set of 12 anomalies examined above. Because two of the anomaly series start at later dates than the others, as noted earlier, we compute two versions of the GRS test. The first, denoted GRS_{10}, uses the ten anomalies with full-length histories. The second, GRS_{12}, uses all of the anomalies for the shorter sample period with complete data on all 12. The relative performance of the models is consistent across all of the summary measures. For each measure, we see M-4 performs best, followed in decreasing order of performance by q-4, FF-5, and FF-3. (The values in the first column correspond to a zero-factor model, with alphas equal to average excess returns.) The average absolute alpha of 0.18% for M-4 is

[9]For T time-series observations on the N long-short spreads and the K factors, define the multivariate regression $R = X\Theta + U$, where R and U are $T \times N$, X is $T \times (K+1)$ and Θ is $(K+1) \times N$. The first column of X contains ones, and the remaining K columns contain the factors. The least-squares estimator is $\hat{\Theta} = (X'X)^{-1}X'R$, where the first row of $\hat{\Theta}$, transposed to a column vector, is the $N \times 1$ vector $\hat{\alpha}$. Compute the unbiased residual covariance-matrix estimator, $\hat{\Sigma} = \frac{1}{T-K-1}(R - X\hat{\Theta})'(R - X\hat{\Theta})$, and let $\omega_{1,1}$ denote the 1,1 element of $(X'X)^{-1}$. Then

$$F = \frac{T-N-K}{N(T-K-1)}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}/\omega_{1,1}$$

has an F distribution with degrees of freedom N and $T - N - K$.

about half of the next best value of 0.34%, achieved by q-4, and slightly more than a third of the 0.45% value for FF-5. The average absolute t-statistics follow a similar pattern, with M-4 having an average of only 1.29, compared to values of 2.34 and 2.93 for q-4 and FF-5. For nine of the anomalies, model M-4 achieves the lowest absolute alpha, compared to two anomalies for model q-4, one for FF-5, and none for FF-3. The GRS tests, if judged by the p-values, deliver perhaps the sharpest differences between M-4 and the other models. For example, for M-4 the GRS_{10} test produces a p-value of 0.05. In other words, at a significance level of 5% or less, the test does not reject the hypothesis that all ten full-sample anomalies are accommodated by this four-factor model. In contrast, the corresponding p-value is only 0.00000001 for q-4 and just 0.0000000007 for FF-5. For the GRS_{12} test the M-4 p-value is 0.03, but the p-values for q-4 and FF-5 are just 0.000008 and 0.000006.

We also examine a substantially larger set of anomalies. Panels B and C of Table 4 report the same measures as Panel A but for the 73 anomalies examined by Hou, Xue, and Zhang (2015a, 2015b). Those authors construct two sets of long-short returns for each anomaly. The first set, analyzed in Hou, Xue, and Zhang (2015a), uses NYSE deciles as the breakpoints for allocating stocks in forming value-weighted portfolios. The second set, constructed in Hou, Xue, and Zhang (2015b), excludes stocks with market capitalizations below the NYSE 20th percentile and then uses deciles of the remaining NYSE/AMEX/NASDAQ universe to form equally weighted portfolios.[10]

Panel B of Table 4 reports results for the first set of long-short spreads for the 73 anomalies. Here again we compute two GRS tests, one with the 51 anomalies whose data begin by January 1967, and another with the 72 anomalies with data beginning by February 1986.[11] The relative performance of the three models is the same as for the smaller set of anomalies analyzed in Panel A: model M-4 performs best, followed in order by q-4, FF-5, and FF-3. While the margin between M-4 and q-4 narrows somewhat, M-4 again has a smaller absolute alpha (0.18 versus 0.20) and a smaller absolute t-statistic (0.99 versus 1.15), and M-4 produces lower absolute alphas for nearly twice as many anomalies (37 versus 19). Model M-4 again does better on the GRS test as well. For the test with the set of full-sample anomalies, GRS_{51} delivers p-value for model M-4 of 0.10, failing to reject the hypothesis that all 51 anomalies are accommodated by the model. In contrast, the corresponding q-4 p-value is 0.003.

[10] We are grateful to the authors for generously providing us with both sets of these data.

[11] The reason for using only 72 anomalies instead of 73 is that the data for one anomaly, corporate governance (G), are available only from September 1990 through December 2006, so we exclude it to avoid substantially shortening the sample period for the GRS tests.

Panel C of Table 4 reports results using the second set of 73 long-short spreads. Models q-4 and M-4 are closer here, but model M-4 again produces the lowest average absolute alpha (0.22 versus 0.23) and average absolute t-statistic (1.38 versus 1.44), and it achieves a lower absolute alpha on more anomalies (32 versus 23). The GRS statistics are very close, with each of models q-4 and M-4 doing slightly better on one of the two. Both models again enjoy substantial margins over FF-5 and FF-3.

Given that model q-4 is the closest competitor to model M-4 in Table 4, we also consider a modified challenge. Specifically, we reduce the set of 73 anomalies by excluding those most highly correlated with the factors in these two models. For each of four factors—those in models q-4 and M-4 other than the market and size factors—the five anomalies whose long-short returns are most highly correlated with the factor are eliminated. This procedure could eliminate up to 20 anomalies, but somewhat fewer are actually eliminated due to some overlap across factors. (The anomalies eliminated are detailed in Appendix A.)

When using the first set of 73 long-short returns analyzed in Panel B of Table 4, 16 anomalies are eliminated, and the results using the remaining 57 are reported in Panel A of Table 5. For the second set of long-short returns analyzed in Panel C of Table 4, 19 anomalies are eliminated, and Panel B of Table 5 presents results for the remaining 54 anomalies. The results in Table 5 deliver essentially the same message as those in Table 4, though the margin of M-4 over q-4 increases a bit. In Panel A of Table 5, as compared to Panel B of Table 4, the gap widens for the average absolute t-statistic. In addition, M-4 produces p-values for the GRS statistic of 0.13 and 0.01, whereas those for q-4 are less than 0.01.

For the second set of 73 anomalies, in Panel B of Table 5, as compared to Panel C of Table 4, the gaps for the average absolute alpha and t-statistic widen slightly, while the GRS statistics for q-4 and M-4 are again close, with the latter slightly better on the set of 40 anomalies with longer histories and the former slightly better on the set of 53 with shorter histories. In the head-to-head comparison of q-4 and M-4 shown in the last row, M-4 produces the smallest alpha for 33 of the 54 anomalies, compared to 21 for q-4. As before, the margin of M-4 over q-4 is generally smaller than the margin of q-4 over FF-5 and FF-3.

Two additional four-factor models are used in a number of studies. The model of Carhart (1997), MOM-4, adds a momentum factor to FF-3, while the model of Pástor and Stambaugh (2003), LIQ-4, adds a liquidity factor. Table 6 reports the results of including these additional four-factor models in the same comparisons summarized in Table 4. (The sample period begins a year later, in January 1968, which is the initial month for the Pástor-Stambaugh liquidity factor.) Including a liquidity factor barely improves, at best, the three-factor model's ability to explain anomalies. In Panel A, using 12 anomalies, the average $|\alpha|$, average $|t|$, and GRS_{10} statistic for LIQ-4 are slightly lower than those for FF-3, but the GRS_{12} statistic is higher. In Panels B and C, the results are similarly mixed. This outcome is perhaps unsurprising, as LIQ-4 is the only model of the six considered here whose additional factor is not formed by ranking on a characteristic producing a return anomaly in an earlier study.[12] The improvement over FF-3 produced by MOM-4 is greater than what LIQ-4 produces, but the ability to explain anomalies falls short of that for M-4, q-4, and, generally, FF-5.

3.2. Comparing models' abilities to explain each other's factors

We next investigate whether the factors unique to one model produce non-zero alphas with respect to another model. That is, we explore the extent to which one model can price the factors of the other. Panel A of Table 7 reports the alphas and corresponding t-statistics for (i) the FF-5 factors HML (book-to-market), RMW (profitability), and CMA (investment), (ii) the q-4 factors I/A (investment) and ROE (profitability), and (iii) the M-4 factors UMO_1 and UMO_2. For each of these three sets, Panel B reports the GRS statistic and p-value testing whether all of the alphas with respect to an alternative model jointly equal zero.

Both models q-4 and M-4 appear to price fairly well the three FF-5 factors—HML, RMW, and CMA. Those factor produce M-4 alphas of 0.11 or less in absolute magnitude, with t-statistics of 1.35 or less in magnitude. The GRS p-value equals 0.58 for the test of whether all three M-4 alphas for HML, RMW, and CMA equal zero. The q-4 model does even better with the FF-5 factors, producing alphas less than 0.04% in magnitude and a GRS p-value of 0.87. This latter result seems not so surprising, given that q-4 contains just different versions of the profitability and investment factors in FF-5.

The FF-5 model fails to price the factors of model M-4 and, somewhat suprisingly, even the factors of model q-4. The FF-5 alphas for the two q-4 factors (I/A and ROE) are 0.12% and 0.45%, with t-statistics of 3.48 and 5.53; the GRS p-value for the joint test is less than 10^{-8}. The FF-5 alphas for the two M-4 factors are even larger, 0.33% and 0.64%, with t-statistics of 4.93 and 4.17; the GRS p-value for the joint test is less than 10^{-10}. Overall, the FF-5 model fares least well in the comparisons reported in Table 7.

[12] The Pástor-Stambaugh (2003) factor is constructed by ranking stocks on their betas with respect to a market-wide liquidity measure. Such betas were previously unexamined in the literature, and as Pástor and Stambaugh explain, they are quite distinct, both conceptually and empirically, from measures of individual stock liquidity. The latter have also been related to average returns (e.g., Amihud and Mendelson (1989)).

The comparison of models q-4 and M-4 in Table 7 provides a more even match in which M-4 finishes modestly ahead. Model M-4 is unable to price the ROE factor of model q-4; the alpha estimate is 0.36% with a t-statistic of 4.00. This significant alpha for the profitability factor of model q-4 seems consistent with the fact that the ROA profitability anomaly is one of the few anomalies in Table 3 not well accommodated by model M-4. The other q-4 factor seems not to present a big problem for M-4, as the alpha estimate for I/A is only 0.09% with a t-statistic of 1.57. In contrast, neither factor of model M-4 is priced by model q-4. The alpha estimates are 0.36% and 0.35%, with t-statistics of 4.54 and 2.24. The GRS tests confirm that neither q-4 nor M-4 can price both factors of the other model, as the p-values are small. At the same time, the rejection is more extreme for model q-4, given its GRS statistic is 72% larger (and the degrees of freedom are the same in both tests).

In sum, model FF-5 accommodates neither the factors of model q-4 nor those of model M-4. In contrast, both of those models appear to price the FF-5 factors, in that the latter factors do not have significant alphas with respect to either model. Models q-4 and M-4 are more evenly matched, as each fails to price all of the other's factors. Model M-4 appears to have the edge, though, in that it accommodates one of the two factors in model q-4 fairly well, whereas the latter model fails to price either of the factors in model M-4.

3.3. Robustness

As discussed earlier, a number of the methodological choices we make when constructing our factors deviate somewhat from conventions that originate with Fama and French (1993) and are adopted in later studies such as Fama and French (2015) and Hou, Xue, and Zhang (2015a). None of these choices are crucial to our model's relative performance in explaining anomalies and the other models' factors. For example, because we believe that the extremes of our mispricing measure best identify mispricing, we use breakpoints of 20% and 80% rather than the conventional 30% and 70%. If we recompute Tables 4, 5, and 7 using 30% and 70%, however, our conclusions remain unchanged. Model M-4 maintains its edge over model q-4 and continues to outperform model FF-5 by a substantial margin. The same holds true if we apply the 20% and 80% breakpoints to just the NYSE universe, instead of to the NYSE/AMEX/NASDAQ universe that covers a broader range of the mispricing scores. The results in Tables 4, 5, and 7 are also not affected much by replacing our SMB, which uses only stocks in the middle category of the mispricing-score rankings, with the more standard version that averages returns across all three categories. If we make all of the above changes simultaneously, again the model comparisons do not change materially. Appendix B reports all of these results.

In cases where annual data are used to construct factors in model FF-3 of Fama and French (1993), model FF-5 of Fama and French (2015), and model q-4 of Hou, Xue, and Zhang (2015a), the authors of those studies require a gap after the end of the fiscal year of at least 6 months and potentially up to 18 months. When using annual data, we instead require a gap of at least 4 months, following precedent in the accounting literature (e.g., Hirshleifer, Hou, Teoh, and Zhang (2004). Thus, one potential source of performance differences between our model, M-4, and models FF-5 and q-4 is this difference in timing used to contruct factors. To explore this possibility, we reconstruct the factors SMB and HML in model FF-3, SMB, HML, RMW, and CMA in model FF-5, and I/A in model q-4, which rely on annual data, by imposing the minimum gap of 4 months for information from annual statements, while using immediate prior-month values of market capitalization. Again our key results—Tables 4, 5, and 7—are not very sensitive to modifying models FF-5 and q-4 in that fashion. Appendix B reports these results as well.

4. An Alternative Three-Factor Model

It is not surprising that FF-3, the three-factor model of Fama and French (1993), does not accommodate anomalies as well as the models with four or five factors. One could argue that a fairer comparison would be FF-3 versus an alternative three-factor model. We construct the latter, denoted as M-3, by replacing the two mispricing factors in M-3 with a single mispricing factor. We construct this single factor in a manner similar to the two factors it replaces. The main difference is that, instead of separating the 11 anomalies into two groups, we simply average each stock's rankings across all 11 anomalies. We then use this mispricing measure, along with firm size, to construct a size factor and a mispricing factor, applying a 2×3 sorting procedure similar to that used by Fama and French (1993) to construct SMB and HML, with the deviations explained earlier. That is, SMB is constructed using only stocks in the middle mispricing category, as opposed to averaging across all three categories. Also, the mispricing-measure breakpoints are the 20th and 80th percentiles of NYSE/AMEX/NASDAQ, rather than the 30th and 70th percentiles of the NYSE. None of the results are sensitive to these deviations, however.

Table 8 compares models FF-3 and M-3 using the same measures reported in Table 4. Model M-3, with the single mispricing factor, dominates FF-3 on all of the measures. In Panel A, model FF-3's average $|\alpha|$ is more than twice as large as that of model M-3 (67 versus

28 bps), and the FF-3 value of GRS_{12} is also more than twice as large. Model M-3 produces a smaller $|\alpha|$ for 11 of the 12 anomalies. For the wider range of 73 anomalies analyzed in Panels B and C, M-3 also dominates FF-3 by a substantial margins on all measures. When using value-weighted portfolios formed on NYSE breakpoints, model M-3 produces the lower absolute alpha for 55 of the 73 anomalies (Panel B). With equally weighted portfolios formed using NYSE/AMEX/NASDAQ breakpoints while excluding microcaps, model M-4 produces the smaller alpha for 58 of the anomalies (Panel C). It appears that replacing book-to-market with a composite mispricing measure delivers a three-factor model with substantially greater ability to accommodate a wide range of anomalies.

5. Arbitrage Risk and the Factor Models

Idiosyncratic volatility (IVOL) represents risk for arbitrageurs seeking to exploit mispricing (e.g., Pontiff (2006)). IVOL also presents a return anomaly, in that stocks with high (low) IVOL have negative (positive) alphas with respect to the CAPM of Sharpe (1964) and Lintner (1965) as well as the three-factor model of Fama and French (1993). (See, for example, Ang, Hodrick, Xing, and Zhang (2006).) Some of the models with additional factors appear to explain this IVOL anomaly, but as we show below, such results prove illusory when recognizing that IVOL represents arbitrage risk.

As explained by Stambaugh, Yu, and Yuan (2015), since higher IVOL implies greater arbitrage risk, mispricing should get corrected less among stocks with high IVOL. Among overpriced stocks, the relation between IVOL and alpha should therefore be negative, as arbitrage eliminates less overpricing in high-IVOL stocks. Among underpriced stocks, the relation between IVOL and alpha should be positive, as less underpricing is eliminated in high-IVOL stocks. With arbitrage asymmetry, however, the negative relation among overpriced stocks should be stronger, resulting in the overall negative relation between alpha and IVOL—the IVOL anomaly. Stambaugh, Yu, and Yuan (2015) report results consistent with these predictions. Panel A of Table 9 essentially repeats their analysis with just a slightly longer sample period. As in that study, stocks are sorted independently with respect to IVOL and a mispricing measure that averages the rankings for the 11 anomalies.[13] We obtain similar results. The last row of Panel A displays the familiar negative relation between IVOL and FF-3 alpha, and the negative IVOL effect among overpriced stocks is stronger

[13]We compute individual stock IVOL, following Ang, Hodrick, Xing, and Zhang (2006), as the standard deviation of the most recent month's daily benchmark-adjusted returns. The latter returns are computed as the residuals in a regression of each stock's daily return on the three factors in model FF-3.

than the positive relation among underpriced stocks.

Panel B of Table 9 repeats the analysis, using the same mispricing and IVOL rankings as in Panel A, but with alphas computed with respect to FF-5. The negative IVOL-alpha relation among the overpriced stocks is stronger than the positive relation among the underpriced stocks. Thus the overall IVOL-alpha relation in the bottom row of the panel is again negative, though it is substantially weaker than in Panel A. In the latter case the difference between the highest and lowest IVOL portfolio alphas is -81 bps per month (t-statistic: -6.04), as compared to the corresponding value in Panel B of -33 bps (t-statistic: -2.69).

Panels C and D of Table 9 repeat the same analysis for models q-4 and M-4. Both of these models appear to explain the IVOL anomaly, given the results in the last row of each panel. For model q-4, the difference between the highest and lowest IVOL portfolio alphas is -23 bps per month, about one-third smaller than that for FF-5, and the t-statistic of -1.58 is insignificant at conventional levels. For model M-4, reported in Panel D, the highest-versus-lowest IVOL difference is -12 bps, and the t-statistic is just -0.79. We can see, however, that these results in the last row of each panel obscure important IVOL effects. For both models, the relation between IVOL and alpha is strongly negative (positive) among the overpriced (underpriced) stocks. The insignificance of the overall IVOL-alpha relation simply reflects a lower degree of asymmetry in the strength of the IVOL effects in the overpriced and underpriced segments.

In short, some of the factor models appear to explain the IVOL anomaly produced by the one-way sort on IVOL shown in the last row of each panel in Table 9. None of the factor models can accommodate the cross-sectional role played by IVOL, as we see from the results for the 25 portfolios reported in the other rows. The latter results are consistent with the presence of mispricing and the importance of arbitrage risk. The seeming ability of some of the factor models to explain the IVOL anomaly stems simply from a failure to distinguish the opposing directions in which IVOL enters, depending on whether stocks are overpriced or underpriced. The apparent strength of the IVOL anomaly declines monotonically when proceeding through models FF-3, FF-5, q-4, and M-4, with the alpha spread between the high- and low-IVOL portfolios (last rows of each panel in Table 9) taking values in bps of -81, -33, -23, and -12. We can also see, however, that this decline in the strength of the IVOL anomaly simply reflects corresponding reductions in the asymmetry of the IVOL effects among overpriced and underpriced stocks.

6. Conclusions

Popular factors are generally constructed by ranking stocks on characteristics that initially gain the finance profession's attention by producing return anomalies. We also construct factors based on documented anomalies, but with a key difference. Rather than have each factor correspond to a single anomaly, as is typical, we construct factors by combining stocks' rankings with respect to 11 prominent anomalies. Specifically, we form two factors by averaging rankings within two clusters of anomalies whose long-short profits exhibit the greatest co-movement. We denote the resulting long-short return spreads as "mispricing" factors, motivated by evidence that anomalies in part reflect mispricing and possess common sentiment effects. Both of the mispricing factors exhibit a significant relation to lagged investor sentiment.

We combine the two mispricing factors with market and size factors to produce a four-factor model. We find that this four-factor model's ability to accommodate a wide range of anomalies exceeds that of both the four-factor model of Hou, Xue, and Zhang (2015a) and the five-factor model of Fama and French (2015). Also, if our two new factors are replaced by a single factor that simply averages rankings across our entire set of anomalies, rather than within clusters, the resulting three-factor model substantially outperforms the three-factor model of Fama and French (1993).

The typical approach to constructing a size factor using a two-way sort is to average across the categories of the other sorting variable, which in our case is a mispricing measure. We instead construct the size factor using stocks in neither extreme of a mispricing measure, in order to be less susceptible to asymmetric degrees of overpricing versus underpricing. The resulting size factor reveals a substantially larger small-firm premium than usual estimates.

Although mispricing factors can reflect common elements of mispricing, such as market-wide sentiment effects, a parsimonious factor model is unlikely to fully explain expected returns when mispricing is present. For example, factor models have difficulty accommodating the role idiosyncratic volatility (IVOL) plays as risk that deters price-correcting arbitrage. In fact, the well known IVOL anomaly of Ang, Hodrick, Xing, and Zhang (2006) appears to be explained by some of the factor models we consider. Such success is misleading, however. Alphas with respect to these factor models exhibit opposite and offsetting relations to IVOL, depending on whether the mispricing that the models fail to capture—the alphas—reflect relative underpricing or overpricing. In this sense, while parsimonious factor models are appealing and useful, there are limits to their abilities to explain expected returns. Nevertheless, among such models, those with mispricing factors appear to have greater ability than prominent alternatives.

Table 1
Factor Loadings and Alphas of Anomaly Strategies
Under the Mispricing-Factor Model

The table reports factor loadings and monthly alphas (in percent) for the long-short spread, long-leg, and short-leg corresponding to 12 anomalies. The long leg is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, where a high value of the measure is associated with lower return. The breakpoints are based on NYSE deciles, but all NYSE/AMEX/NASDAQ stocks with share prices of at least $5 are included. Data for the distress anomaly begin in October 1974, and data for the return-on-assets anomaly begin in November 1971. The other ten anomalies begin at the start of the sample period, which is from January 1967 through December 2013 (564 months). All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).

Anomaly	α	β_{MKT}	β_{SMB}	β_{UMO_1}	β_{UMO_2}	t_α	t_{MKT}	t_{SMB}	t_{UMO_1}	t_{UMO_2}
Panel A: Long-Short Spreads										
First Cluster (used to construct mispricing factor UMO_1)										
Net stock issues	0.06	0.02	-0.14	0.63	0.22	0.70	0.86	-3.64	17.21	8.85
Composite equity issues	0.07	-0.07	-0.06	0.85	0.05	0.70	-2.23	-1.22	18.12	1.72
Accruals	0.31	0.00	-0.28	0.38	0.02	2.08	0.12	-5.23	6.09	0.48
Net operating assets	0.22	0.11	-0.05	0.46	-0.01	1.70	2.72	-0.73	8.54	-0.28
Asset growth	-0.22	0.04	0.33	0.94	-0.02	-1.96	1.31	7.42	15.99	-0.54
Investment-to-assets	0.06	0.03	0.25	0.64	-0.09	0.54	1.12	5.40	11.83	-2.61
Average	0.08	0.02	0.01	0.65	0.03	0.63	0.65	0.33	12.96	1.27
Second Cluster (used to construct mispricing factor UMO_2)										
Distress	-0.16	-0.29	-0.35	0.31	1.17	-1.03	-7.13	-3.89	3.96	24.10
O-score	0.35	-0.15	-0.73	-0.09	0.23	2.42	-3.86	-14.43	-1.39	5.02
Momentum	0.12	0.12	0.16	0.25	1.21	0.47	1.78	1.44	1.71	12.15
Gross profitability	0.11	-0.14	-0.05	-0.32	0.66	0.92	-4.45	-1.29	-6.08	18.04
Return on assets	0.27	-0.02	-0.38	0.06	0.66	1.90	-0.41	-5.49	0.95	13.21
Average	0.14	-0.10	-0.27	0.04	0.79	0.94	-2.81	-4.73	-0.17	14.50
Book-to-market	-0.17	0.09	0.54	0.89	-0.35	-1.10	2.50	9.21	12.70	-7.52
Panel B: Long Legs										
First Cluster (used to construct mispricing factor UMO_1)										
Net stock issues	-0.06	1.04	-0.03	0.31	0.06	-1.39	83.49	-1.22	14.29	4.18
Composite equity issues	-0.01	0.98	0.05	0.48	-0.06	-0.18	33.81	0.98	11.13	-2.31
Accruals	0.19	1.05	0.02	-0.22	0.08	1.74	34.37	0.44	-4.64	2.37
Net operating assets	0.13	1.08	0.03	0.09	-0.08	1.44	44.02	0.86	2.49	-2.92
Asset growth	-0.15	1.11	0.35	0.34	-0.01	-1.58	43.33	11.25	6.99	-0.18
Investment-to-assets	-0.01	1.07	0.35	0.17	0.02	-0.13	50.21	10.80	5.52	0.83
Average	0.02	1.06	0.13	0.20	0.00	-0.02	48.21	3.85	5.96	0.33
Second Cluster (used to construct mispricing factor UMO_2)										
Distress	-0.22	0.98	0.11	0.04	0.39	-2.32	37.65	1.79	0.78	12.27
O-score	0.18	0.94	-0.12	-0.32	0.14	2.04	43.07	-3.38	-6.62	4.26
Momentum	0.10	1.15	0.38	-0.18	0.46	0.77	31.69	6.59	-2.40	9.48
Gross profitability	0.05	0.97	-0.01	-0.01	0.24	0.52	36.95	-0.28	-0.29	7.14
Return on assets	0.14	1.01	-0.06	-0.25	0.27	1.92	53.19	-2.03	-7.25	10.94
Average	0.05	1.01	0.06	-0.14	0.30	0.59	40.51	0.54	-3.16	8.82
Book-to-market	-0.10	1.09	0.38	0.54	-0.17	-0.91	38.00	8.42	10.38	-4.95

Table 1 (Continued)
Factor Loadings and Alphas of Anomaly Strategies
Under the Mispricing-Factor Model

Anomaly	α	β_{MKT}	β_{SMB}	β_{UMO_1}	β_{UMO_2}	t_α	t_{MKT}	t_{SMB}	t_{UMO_1}	t_{UMO_2}
Panel C: Short Legs										
First Cluster (used to construct mispricing factor UMO_1)										
Net stock issues	-0.13	1.02	0.11	-0.32	-0.16	-1.52	46.95	3.62	-8.82	-6.62
Composite equity issues	-0.09	1.05	0.11	-0.37	-0.11	-1.26	58.06	3.80	-11.80	-5.11
Accruals	-0.11	1.04	0.30	-0.61	0.06	-1.35	47.35	8.75	-16.11	2.43
Net operating assets	-0.09	0.97	0.08	-0.37	-0.07	-1.20	43.72	2.34	-11.45	-2.80
Asset growth	0.07	1.07	0.02	-0.60	0.01	1.05	55.02	0.60	-20.20	0.77
Investment-to-assets	-0.07	1.04	0.10	-0.47	0.11	-0.75	41.33	2.90	-9.14	3.21
Average	-0.07	1.03	0.12	-0.46	-0.03	-0.84	48.74	3.67	-12.92	-1.35
Second Cluster (used to construct mispricing factor UMO_2)										
Distress	-0.06	1.28	0.46	-0.27	-0.78	-0.52	39.36	8.75	-4.67	-23.10
O-score	-0.17	1.09	0.62	-0.23	-0.10	-1.80	40.74	13.34	-5.14	-3.05
Momentum	-0.02	1.03	0.21	-0.43	-0.75	-0.14	24.38	3.04	-4.91	-12.39
Gross profitability	-0.06	1.10	0.04	0.31	-0.42	-0.56	38.35	1.25	5.94	-13.00
Return on assets	-0.13	1.03	0.32	-0.32	-0.39	-0.99	28.53	4.69	-5.06	-8.69
Average	-0.09	1.11	0.33	-0.19	-0.49	-0.80	34.27	6.21	-2.77	-12.05
Book-to-market	0.07	1.00	-0.16	-0.35	0.18	0.92	51.01	-6.31	-11.45	7.87

Table 2
Investor Sentiment and the Factors

The table reports estimates of b in the regression

$$R_t \quad = \quad a + bS_{t-1} + u_t,$$

where R_t is the excess return in month t on either the long leg, the short leg, or the long-short difference for each of the factors, MKT, SMB, UMO_1 and UMO_2, and S_{t-1} is the previous month's level of the investor-sentiment index of Baker and Wurgler (2006). All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is from January 1967 through December 2013 (564 months).

	Long Leg		Short Leg		Long−Short	
Factor	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
MKT	-	-	-	-	-0.32	-1.37
SMB	-0.49	-1.72	-0.27	-1.17	-0.22	-1.60
UMO_1	-0.22	-0.98	-0.66	-2.06	0.44	2.81
UMO_2	-0.31	-1.29	-0.67	-2.05	0.36	2.02

Table 3
Anomaly Alphas Under Different Factor Models

For long-short returns corresponding to 12 anomalies, the table reports information about alphas computed under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are the average unadjusted return spreads (the alphas in a model with no factors). In constructing the long-short spreads, the long leg is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, where a high value of the measure is associated with lower return. The breakpoints are based on NYSE deciles, but all NYSE/AMEX/NASDAQ stocks with share prices of at least \$5 are included. Panel A reports the monthly alphas (in percent); Panel B reports their heteroskedasticity-consistent t-statistics based on White (1980).

Anomaly	Unadjusted	FF-3	FF-5	q-4	M-4
	Panel A: Alphas				
Net stock issues	0.56	0.66	0.32	0.37	0.06
Composite equity issues	0.58	0.54	0.34	0.51	0.07
Accruals	0.43	0.51	0.56	0.65	0.31
Net operating assets	0.53	0.53	0.50	0.43	0.22
Asset growth	0.52	0.32	0.06	0.08	-0.22
Investment-to-assets	0.53	0.42	0.35	0.32	0.06
Distress	0.44	1.21	0.62	0.20	-0.16
O-score	0.05	0.49	0.45	0.47	0.35
Momentum	1.26	1.59	1.35	0.48	0.12
Gross profitability	0.28	0.69	0.35	0.39	0.11
Return on assets	0.58	0.91	0.43	0.10	0.27
Book-to-market	0.43	-0.20	-0.14	-0.03	-0.17
	Panel B: t-statistics				
Net stock issues	4.77	6.60	3.42	3.54	0.71
Composite equity issues	3.88	4.93	2.94	4.10	0.70
Accruals	2.95	3.61	3.94	4.30	2.08
Net operating assets	4.32	4.10	3.63	3.03	1.70
Asset growth	3.69	2.83	0.58	0.72	-1.96
Investment-to-assets	4.28	3.48	3.04	2.72	0.54
Distress	1.54	5.03	2.29	0.78	-1.03
O-score	0.30	4.28	3.92	3.89	2.42
Momentum	4.58	5.70	4.12	1.40	0.47
Gross profitability	1.79	5.22	2.78	2.50	0.92
Return on assets	3.18	5.52	3.13	0.85	1.90
Book-to-market	2.39	-1.99	-1.33	-0.19	-1.10

Table 4
Summary Measures of Models' Abilities to Explain Anomalies

The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. In Panel A, two versions of the GRS test are reported. Data for the distress anomaly begin in October 1974, and data for the return-on-assets anomaly begin in November 1971. The other ten anomalies begin at the start of the sample period, which is from January 1967 through December 2013 (564 months). GRS_{10} tests whether the ten alphas for the full-sample anomalies equal zero, while GRS_{12} uses all 12 anomalies and begins the sample in October 1974. Panels B and C also report two versions of the GRS test: GRS_{51} uses 51 anomalies whose data are available by January 1967, while GRS_{72} uses those anomalies plus 21 others whose data are available by February 1986.

Measure	Unadjusted	FF-3	FF-5	q-4	M-4
		Panel A: 12 Anomalies, value-weighted, NYSE deciles			
Average $\|\alpha\|$	0.52	0.67	0.45	0.34	0.18
Average $\|t\|$	3.14	4.44	2.93	2.34	1.29
GRS_{10}	6.89	10.10	6.71	5.99	1.84
p_{10}	3.4×10^{-10}	1.1×10^{-15}	6.9×10^{-10}	1.2×10^{-8}	0.05
GRS_{12}	6.16	7.71	4.17	3.95	1.88
p_{12}	4.5×10^{-10}	4.2×10^{-13}	3.1×10^{-6}	8.3×10^{-6}	0.03
Number of $min\|\alpha\|$	-	0	1	2	9
		Panel B: 73 Anomalies, value-weighted, NYSE deciles			
Average $\|\alpha\|$	0.39	0.44	0.30	0.20	0.18
Average $\|t\|$	2.14	2.74	1.77	1.15	0.99
GRS_{51}	2.74	2.60	1.91	1.68	1.28
p_{51}	9.3×10^{-9}	6.5×10^{-8}	2.9×10^{-4}	3.2×10^{-3}	0.10
GRS_{72}	2.23	2.10	1.79	1.78	1.54
p_{72}	2.2×10^{-6}	1.3×10^{-5}	5.3×10^{-4}	5.8×10^{-4}	8.1×10^{-3}
Number of $min\|\alpha\|$	-	7	10	19	37
		Panel C: 73 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles			
Average $\|\alpha\|$	0.50	0.53	0.35	0.23	0.22
Average $\|t\|$	3.02	3.72	2.41	1.44	1.38
GRS_{51}	5.85	6.31	5.15	4.19	4.17
p_{51}	2.7×10^{-27}	6.2×10^{-30}	4.3×10^{-23}	2.3×10^{-17}	3.1×10^{-17}
GRS_{72}	2.95	3.25	2.64	2.41	2.68
p_{72}	1.4×10^{-10}	3.0×10^{-12}	1.1×10^{-8}	2.3×10^{-7}	6.2×10^{-9}
Number of $min\|\alpha\|$	-	7	11	23	32

Table 5
Summary Measures of Models' Abilities to Explain Anomalies Less Correlated with Factors in Models q-4 and M-4

The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. Panels A and B correspond to Panels B and C of Table 4, except the set of anomalies is reduced: For each of four factors—those in models q-4 and M-4 other than the market and size factors—the five anomalies (of the 73) whose long-short returns are most highly correlated with the factor are eliminated. This procedure leaves 57 anomalies in Panel A and 54 in Panel B. The sample period is from January 1967 through December 2013 (564 months). Two versions of the GRS test are reported: GRS_{41} in Panel A (or GRS_{40} in Panel B), uses the 41 (or 40) anomalies whose data are available by January 1967, while GRS_{56} in Panel A (or GRS_{53} in Panel B) uses the remaining anomalies whose data are available by February 1986.

Measure	Unadjusted	FF-3	FF-5	q-4	M-4
Panel A: 57 Anomalies, value-weighted, NYSE deciles					
Average $\|\alpha\|$	0.37	0.39	0.27	0.19	0.17
Average $\|t\|$	2.14	2.60	1.71	1.15	0.97
GRS_{41}	3.01	2.81	1.95	1.63	1.26
p_{41}	6.7×10^{-9}	6.1×10^{-8}	5.8×10^{-4}	9.3×10^{-3}	0.13
GRS_{56}	2.29	2.16	1.73	1.64	1.53
p_{56}	5.5×10^{-6}	2.5×10^{-5}	2.3×10^{-3}	5.2×10^{-3}	0.01
Number of $min\|\alpha\|$	-	4	7	15	31
Number of $min\|\alpha\|$, q-4 vs. M-4	-	-	-	21	36
Panel B: 54 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles					
Average $\|\alpha\|$	0.45	0.46	0.32	0.25	0.23
Average $\|t\|$	2.94	3.53	2.41	1.61	1.47
GRS_{40}	6.38	7.03	5.78	4.69	4.55
p_{40}	7.3×10^{-26}	5.0×10^{-29}	8.3×10^{-23}	2.9×10^{-17}	1.6×10^{-16}
GRS_{53}	3.36	4.07	3.12	2.82	3.03
p_{53}	3.6×10^{-11}	1.0×10^{-14}	6.7×10^{-10}	$2.0\mathrm{E}\times10^{-8}$	1.8×10^{-9}
Number of $min\|\alpha\|$	-	6	9	16	23
Number of $min\|\alpha\|$, q-4 vs. M-4	-	-	-	21	33

Table 6
Comparing Additional Factor Models

The table reports summary statistics for alphas computed under six different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the four-factor momentum model of Carhart (1997), denoted MOM-4; the four-factor liquidity-risk model of Pástor and Stambaugh (2003), denoted LIQ-4; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. The table reports each model's average absolute monthly (percent) alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. In Panel A, two versions of the GRS test are reported. Data for the distress anomaly begin in October 1974, and data for the return-on-assets anomaly begin in November 1971. The other ten anomalies begin at the start of the sample period, which is from January 1967 through December 2013 (564 months). GRS_{10} tests whether the ten alphas for the full-sample anomalies equal zero, while GRS_{12} uses all 12 anomalies and begins the sample in October 1974. Panels B and C also report two versions of the GRS test: GRS_{51} uses 51 anomalies whose data are available by January 1967, while GRS_{72} use those anomalies plus 21 others whose data are available by February 1986.

	FF-3	MOM-4	LIQ-4	FF-5	q-4	M-4
	Panel A: 12 Anomalies (value-weighted, NYSE deciles)					
Average $\|\alpha\|$	0.67	0.46	0.66	0.45	0.34	0.18
Average $\|t\|$	4.40	3.52	4.34	2.84	2.31	1.29
GRS_{10}	9.67	7.21	9.34	6.23	5.56	1.62
p_{10}	6.5×10^{-15}	9.9×10^{-11}	2.4×10^{-14}	4.8×10^{-9}	6.6×10^{-8}	0.10
GRS_{12}	7.71	6.09	7.77	4.17	3.95	1.88
p_{12}	4.2×10^{-13}	6.2×10^{-10}	3.2×10^{-13}	3.1×10^{-6}	8.3×10^{-6}	0.03
Number of $min\|\alpha\|$	0	0	0	1	2	9
	Panel B: 73 Anomalies, value-weighted, NYSE deciles					
Average $\|\alpha\|$	0.44	0.30	0.44	0.29	0.20	0.18
Average $\|t\|$	2.69	1.92	2.72	1.74	1.13	1.00
GRS_{51}	2.60	2.11	2.64	1.95	1.72	1.36
p_{51}	6.7×10^{-8}	2.7×10^{-5}	3.9×10^{-8}	1.8×10^{-4}	2.0×10^{-3}	0.05
GRS_{72}	2.10	1.96	2.15	1.79	1.78	1.54
p_{72}	1.3×10^{-5}	7.0×10^{-5}	6.8×10^{-6}	5.3×10^{-4}	5.8×10^{-4}	8.1×10^{-3}
Number of $min\|\alpha\|$	4	6	5	5	21	32
	Panel C: 73 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles					
Average $\|\alpha\|$	0.52	0.35	0.52	0.34	0.23	0.22
Average $\|t\|$	3.63	2.52	3.68	2.37	1.41	1.38
GRS_{51}	6.11	5.46	6.09	4.97	4.12	4.14
p_{51}	1.2×10^{-28}	7.5×10^{-25}	1.8×10^{-28}	5.9×10^{-22}	7.1×10^{-17}	5.9×10^{-17}
GRS_{72}	3.25	3.06	3.18	2.64	2.41	2.68
p_{72}	3.0×10^{-12}	4.1×10^{-11}	7.9×10^{-12}	1.1×10^{-8}	2.3×10^{-07}	6.2×10^{-9}
Number of $min\|\alpha\|$	3	7	4	7	24	28

Table 7
Models' Abilities to Explain Each Other's Factors

Panel A reports a factor's estimated monthly alpha (in percent) with respect to each of the other models (with White (1980) heteroskedasticity-consistent t-statistics in parentheses). Panel B computes the Gibbons-Ross-Shanken (1989) F-test of whether a given model produces zero alphas for the factors of an alternative model (with p-values in parentheses). The models considered are the five-factor model of Fama and French (2015), denoted FF-5, which includes the factors HML, RMW, and CMA; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4, which includes the factors I/A and ROE; and the four-factor mispricing-factor model, denoted M-4, which includes the factors UMO_1 and UMO_2. The sample period is from January 1967 through December 2013 (564 months).

	Alpha computed with respect to model		
Factors	FF-5	q-4	M-4
	Panel A: Alpha (t-statistic)		
Factors in FF-5			
HML	-	0.04	-0.03
		(0.43)	(-0.28)
RMW	-	0.04	0.11
		(0.55)	(1.35)
CMA	-	0.02	-0.03
		(0.47)	(-0.56)
Factors in q-4			
I/A	0.12	-	0.09
	(3.48)		(1.57)
ROE	0.45	-	0.36
	(5.53)		(4.00)
Factors in M-4			
UMO_1	0.33	0.36	-
	(4.93)	(4.54)	
UMO_2	0.64	0.35	-
	(4.17)	(2.24)	
	Panel B: GRS F-statistic (p-value)		
HML, RMW, CMA	-	0.23	0.65
		(0.87)	(0.58)
I/A, ROE	19.06	-	9.12
	(9.8×10^{-9})		(1.3×10^{-4})
UMO_1, UMO_2	25.35	15.66	-
	(2.9×10^{-11})	(2.4×10^{-7})	

Table 8
Comparison of Three-Factor Models

The table reports summary statistics for alphas computed under two three-factor models: the model of Fama and French (1993), denoted model FF-3; and a model that combines a market and size factor with a single mispricing factor, denoted model M-3. The mispricing factor is constructed using a composite mispricing measure that averages stocks' rankings across 11 anomalies. The table reports each model's average absolute monthly (percent) alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. In Panel A, two versions of the GRS test are reported. Data for the distress anomaly begin in October 1974, and data for the return-on-assets anomaly begin in November 1971. The other ten anomalies begin at the start of the sample period, which is from January 1967 through December 2013 (564 months). GRS_{10} tests whether the ten alphas for the full-sample anomalies equal zero, while GRS_{12} uses all 12 anomalies and begins the sample in October 1974. Panels B and C also report two versions of the GRS test: GRS_{51} uses 51 anomalies whose data are available by January 1967, while GRS_{72} use those anomalies plus 21 others whose data are available by February 1986.

	FF-3	M-3
Panel A: 12 Anomalies, value-weighted, NYSE deciles		
Average $\lvert\alpha\rvert$	0.67	0.28
Average $\lvert t\rvert$	4.44	1.78
GRS_{10}	10.10	2.50
p_{10}	1.1×10^{-15}	6.1×10^{-3}
GRS_{12}	7.71	3.03
p_{12}	4.2×10^{-13}	4.2×10^{-4}
Number of min $\lvert\alpha\rvert$	1	11
Panel B: 73 Anomalies, value-weighted, NYSE deciles		
Average $\lvert\alpha\rvert$	0.44	0.24
Average $\lvert t\rvert$	2.74	1.17
GRS_{51}	2.60	1.46
p_{51}	6.5×10^{-8}	0.02
GRS_{72}	2.10	1.67
p_{72}	1.3×10^{-5}	1.9×10^{-3}
Number of min $\lvert\alpha\rvert$	18	55
Panel C: 73 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles		
Average $\lvert\alpha\rvert$	0.53	0.30
Average $\lvert t\rvert$	3.72	1.61
GRS_{51}	6.31	4.09
p_{51}	6.2×10^{-30}	9.7×10^{-17}
GRS_{72}	3.25	2.48
p_{72}	3.0×10^{-12}	8.9×10^{-8}
Number of min $\lvert\alpha\rvert$	15	58

Table 9
Idiosyncratic Volatility Effects in Underpriced versus Overpriced Stocks

This table reports, for each of four models, the monthly percentage alphas on 25 value-weighted portfolios formed by an independent 5×5 sort on the composite mispricing measure—the average ranking across 11 anomalies—and IVOL—the previous month's daily volatility of residuals from the three-factor model of Fama and French (1993). Panel A reports alphas with respect to the three-factor model of Fama and French (1993), model FF-3; Panel B reports alphas for the five-factor model of Fama and French (2015), model FF-5; Panel C reports alphas for the four-factor model of Hou, Xing, and Zhang (2015a), model q-4; Panel D reports alphas for the four-factor mispricing-factor model, model M-4. Heteroskedasticity-consistent t-statistics based on White (1980) are shown in parentheses. The sample period is from January 1967 through December 2013 (564 months).

	Highest IVOL	Next 20%	Next 20%	Next 20%	Lowest IVOL	Highest -Lowest	All Stocks
				Panel A: FF-3 Alpha			
Most Overpriced	-1.87	-0.92	-0.77	-0.51	-0.23	-1.64	-0.78
(top 20%)	(-12.04)	(-6.89)	(-5.42)	(-4.13)	(-1.85)	(-8.46)	(-8.46)
Next 20%	-0.79	-0.39	-0.15	-0.23	-0.09	-0.70	-0.22
	(-5.18)	(-3.03)	(-1.51)	(-2.37)	(-1.02)	(-3.86)	(-3.88)
Next 20%	-0.22	-0.18	-0.01	-0.25	0.06	-0.28	-0.06
	(-1.43)	(-1.51)	(-0.09)	(-2.47)	(0.65)	(-1.42)	(-1.28)
Next 20%	-0.10	0.16	-0.02	0.19	0.15	-0.25	0.14
	(-0.58)	(1.35)	(-0.17)	(2.44)	(2.18)	(-1.32)	(3.24)
Most Underpriced	0.45	0.61	0.50	0.35	0.15	0.30	0.28
(bottom 20%)	(2.86)	(4.56)	(4.95)	(4.3)	(2.18)	(1.70)	(5.76)
Most Overpriced -	-2.32	-1.53	-1.26	-0.86	-0.38	-1.94	-1.06
Most Underpriced	(-10.80)	(-7.98)	(-6.75)	(-5.71)	(-2.51)	(-8.02)	(-8.20)
All Stocks	-0.72	-0.12	-0.02	0.02	0.10	-0.81	
	(-6.52)	(-1.61)	(-0.38)	(0.46)	(2.31)	(-6.04)	
				Panel B: FF-5 Alpha			
Most Overpriced	-1.40	-0.65	-0.55	-0.47	-0.17	-1.23	-0.52
(top 20%)	(-8.71)	(-4.63)	(-3.85)	(-3.54)	(-1.27)	(-6.15)	(-5.28)
Next 20%	-0.50	-0.22	-0.08	-0.26	-0.15	-0.35	-0.14
	(-3.26)	(-1.69)	(-0.73)	(-2.66)	(-1.59)	(-1.96)	(-2.24)
Next 20%	0.09	-0.07	0.01	-0.28	-0.06	0.15	-0.04
	(0.56)	(-0.56)	(0.10)	(-2.43)	(-0.71)	(0.78)	(-0.80)
Next 20%	0.09	0.20	-0.08	0.06	0.05	0.04	0.06
	(0.45)	(1.52)	(-0.81)	(0.79)	(0.61)	(0.21)	(1.46)
Most Underpriced	0.57	0.61	0.39	0.17	-0.07	0.64	0.12
(bottom 20%)	(3.44)	(4.03)	(3.75)	(1.99)	(-1.02)	(3.61)	(2.41)
Most Overpriced -	-1.97	-1.26	-0.94	-0.64	-0.10	-1.87	-0.64
Most Underpriced	(-8.42)	(-5.55)	(-5.11)	(-4.02)	(-0.61)	(-7.41)	(-4.74)
All Stocks	-0.36	0.01	-0.01	-0.08	-0.03	-0.33	
	(-3.55)	(0.19)	(-0.11)	(-1.44)	(-0.70)	(-2.69)	

Table 9 (continued)
Idiosyncratic Volatility Effects in Underpriced versus Overpriced Stocks

	Highest IVOL	Next 20%	Next 20%	Next 20%	Lowest IVOL	Highest -Lowest	All Stocks
				Panel C: q-4 Alpha			
Most Overpriced	-1.25	-0.44	-0.55	-0.45	-0.14	-1.11	-0.46
(top 20%)	(-7.57)	(-3.11)	(-3.38)	(-2.8)	(-0.85)	(-4.88)	(-4.14)
Next 20%	-0.37	-0.09	0.03	-0.24	-0.15	-0.22	-0.09
	(-2.14)	(-0.64)	(0.28)	(-2.19)	(-1.41)	(-1.05)	(-1.39)
Next 20%	0.12	0.01	0.09	-0.35	-0.05	0.16	-0.02
	(0.67)	(0.07)	(0.65)	(-2.68)	(-0.45)	(0.73)	(-0.46)
Next 20%	0.16	0.20	-0.08	0.01	0.05	0.10	0.06
	(0.71)	(1.44)	(-0.71)	(0.17)	(0.68)	(0.43)	(1.33)
Most Underpriced	0.47	0.59	0.32	0.07	-0.14	0.61	0.04
(bottom 20%)	(2.43)	(3.56)	(2.93)	(0.84)	(-1.65)	(2.96)	(0.81)
Most Overpriced -	-1.72	-1.03	-0.87	-0.52	0.00	-1.72	-0.50
Most Underpriced	(-6.87)	(-4.33)	(-4.12)	(-2.88)	(0.00)	(-6.51)	(-3.36)
All Stocks	-0.28	0.09	0.01	-0.13	-0.05	-0.23	
	(-2.40)	(1.13)	(0.13)	(-2.00)	(-1.05)	(-1.58)	
				Panel D: M-4 Alpha			
Most Overpriced	-0.96	-0.20	-0.16	-0.11	0.08	-1.04	-0.09
(top 20%)	(-6.33)	(-1.61)	(-1.05)	(-0.88)	(0.57)	(-4.40)	(-1.60)
Next 20%	-0.36	0.05	0.17	-0.06	-0.02	-0.34	0.06
	(-2.08)	(0.33)	(1.80)	(-0.57)	(-0.24)	(-1.64)	(1.07)
Next 20%	0.06	0.02	0.12	-0.25	-0.01	0.08	0.01
	(0.34)	(0.14)	(1.04)	(-2.03)	(-0.13)	(0.33)	(0.25)
Next 20%	-0.02	0.23	-0.06	0.02	-0.02	0.00	0.02
	(-0.09)	(1.66)	(-0.55)	(0.24)	(-0.26)	(0.01)	(0.49)
Most Underpriced	0.36	0.28	0.23	0.00	-0.26	0.62	-0.09
(bottom 20%)	(2.08)	(1.93)	(2.16)	(-0.05)	(-3.66)	(3.17)	(-2.50)
Most Overpriced -	-1.32	-0.48	-0.39	-0.10	0.34	-1.66	0.00
Most Underpriced	(-6.99)	(-2.67)	(-2.00)	(-0.75)	(2.16)	(-6.59)	(0.04)
All Stocks	-0.21	0.13	0.08	-0.06	-0.09	-0.12	
	(-1.75)	(1.60)	(1.22)	(-0.91)	(-1.80)	(-0.79)	

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APPENDIX A

A1. The 11 Anomalies Used to Construct the Mispricing Factors

Below we detail the construction of the anomaly measures used to construct mispricing scores and form anomaly portfolios and mispricing factors. The anomaly measures are computed at the end of each month. We exclude stocks with share prices less than \$5, primarily to avoid micro-structure effects, and we use ordinary common shares (CRSP codes 10 and 11). The anomaly portfolios are constructed using NYSE deciles as breakpoints. When constructing the mispricing factors, we require that a stock have non-missing values at the end of month $t-1$ for at least three of the (five or six) anomalies in a cluster in order to be included in that cluster's factor. Also, in order for an anomaly to be included in the mispricing measure for its cluster at the end of month $t-1$, we require at least 30 stocks to have non-missing values for that anomaly. The values computed at the end of month $t-1$ for each anomaly are constructed as follows:

1. *Net Stock Issues:* The stock issuing market has long been viewed as producing an anomaly arising from sentiment-driven mispricing: smart managers issue shares when sentiment-driven traders push prices to overvalued levels. Ritter (1991) and Loughran and Ritter (1995) show that, in post-issue years, equity issuers underperform matching nonissuers with similar characteristics. Motivated by this evidence, Fama and French (2008) show that net stock issues and subsequent returns are negatively correlated. Following Fama and French(2008), we measure net issuance as the annual log change in split-adjusted shares outstanding. Split-adjusted share equal shares outstanding (Compustat annual item CSHO) times the adjustment factor(Compustat annual item ADJEX_C). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$. Stocks with negative net issues are assigned to decile 1 and those with zero net issues are assigned to decile 2. The remaining stocks are assigned to the remaining eight deciles using NYSE breakpoints.

2. *Composite Equity Issues:* Daniel and Titman (2006) find that issuers underperform nonissuers using a measure they denote as composite equity issuance, defined as the growth in the firm's total market value of equity minus (i.e., not attributable to) the stock's rate of return. We compute this measure by subtracting the 12-month cumulative stock return from the 12-month growth in equity market capitalization. We lag the quantity four months, to make its timing more coincident with the above measure of net stock issues.

3. *Accruals:* Sloan (1996) shows that firms with high accruals earn abnormally lower average returns than firms with low accruals, and he suggests that investors overestimate the persistence of the accrual component of earnings when forming earnings expectations. Following Sloan (1996), we measure total accruals as the annual change in noncash working capital minus depreciation and amortization expense (Compustat annual item DP), divided by average total assets (item AT) for the previous two fiscal years. Noncash working capital is computed as the change in current asset (item ACT) minus the change in cash and short-term investment (item CHE), minus the change in current liabilities (item DLC), plus the change in debt included in current liabilities (item LCT), plus the change in income taxes payable (item TXP). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$.

4. *Net Operating Assets:* Hirshleifer, Hou, Teoh, and Zhang (2004) find that net operating assets, defined as the difference on the balance sheet between all operating assets and all operating liabilities, scaled by total assets, is a strong negative predictor of long-run stock returns. The authors suggest that investors with limited attention tend to focus on accounting profitability, neglecting information about cash profitability, in which case net operating assets (equivalently measured as the cumulative difference between operating income and free cash flow) captures such a bias. Following equations equations (4), (5), and (6) of that study, we measure net operation assets as operating assets minus operating liabilities, divided by lagged total assets (Compustat annual item AT). Operating assets equal total assets (item AT) minus cash and short-term investment (item CHE). Operating liabilities equal total assets minus debt included in current liabilities (item DLC), minus long-term debt (item DLTT), minus common equity (item CEQ), minus minority interests (item MIB), minus preferred stocks (item PSTK). (The last two items are zero if missing.) The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$.

5. *Asset Growth:* Cooper, Gulen, and Schill (2008) find that companies that grow their total assets more earn lower subsequent returns. They suggest that this phenomenon is due to investors' initial overreaction to changes in future business prospects implied by asset expansions. Asset growth is measured as the growth rate of total assets in the previous fiscal year. Following that study, we measure asset growth as the most recent year-over-growth rate annual growth rate of total assets (Compustat annual item AT). The most recent reporting year used is the one that ends (according to item

DATADATE) at least four months before the end of month $t-1$.

6. *Investment-to-Assets:* Titman, Wei, and Xie (2004) and Xing (2008) show that higher past investment predicts abnormally lower future returns. Titman, Wei, and Xie (2004) attribute this anomaly to investors' initial underreactions to the overinvestment caused by managers' empire-building behavior. Here, investment to assets is measured as the annual change in gross property, plant, and equipment, plus the annual change in inventories, scaled by lagged book value of assets. Following the above studies, we compute investment-to-assets as the changes in gross property, plant, and equipment (Compustat annual item PPEGT) plus changes in inventory (item INVT), divided by lagged total assets (item AT). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$.

7. *Distress:* Financial distress is often invoked to explain otherwise anomalous patterns in the cross-section of stock returns. However, Campbell, Hilscher, and Szilagyi (2008) find that firms with high failure probability have lower rather than higher subsequent returns. The authors suggest that their finding is a challenge to standard models of rational asset pricing. Failure probability is estimated with a dynamic logit model that uses several equity market variables, such as stock price, book-to-market, stock volatility, size relative to the S&P 500, and cumulative excess return relative to the S&P 500. Specifically, using the above study's equations (2) and (3) along with its Table IV (12-month column), we compute the distress anomaly measure—failure probability—as

$$\begin{aligned}\pi &= -20.26\, NIMTAAVG + 1.42\, TLMTA - 7.13\, EXRETAVG + 1.41\, SIGMA \\ &\quad -0.045\, RSIZE - 2.13\, CASHMTA + 0.075\, MB - 0.058\, PRICE - 9.16,\end{aligned}$$

where

$$\begin{aligned}NIMTAAVG_{t-1,t-12} &= \frac{1-\phi^3}{1-\phi^{12}}(NIMTA_{t-1,t-3} + \cdots + \phi^9 NIMTA_{t-10,t-12}) \\ EXRETAVG_{t-1,t-12} &= \frac{1-\phi}{1-\phi^{12}}(EXRET_{t-1} + \cdots + \phi^{11} EXRET_{t-12}),\end{aligned}$$

and $\phi = 2^{-1/3}$. *NIMTA* is net income (Compustat quarterly item NIQ) divided by firm scale, where the latter is computed as the sum of total liabilities (item LTQ) and market equity capitalization (data from CRSP). $EXRET_s$ is the stock's monthly log return in month s minus the log return on the S&P500 index. Missing values for *NIMTA* and *EXRET* are replaced by those quantities' cross-sectional means. *TLMTA* equals total liabilities divided by firm scale. *SIGMA* is the stock's daily standard deviation for the most recent three months, expressed on an annualized basis. At least five non-zero daily returns are required. *RSIZE* is the log of the ratio of the stock's market capitalization to that of the S&P500 index. *CASHMTA* equals cash and short-term investment (item CHEQ) divided by firm scale. *MB* is the market-to-book ratio. Following Campbell, Hilscher, and Szilagyi (2008), we increase book equity by 10% of the difference between market equity and book equity. If the resulting value of book equity is negative, then book equity is set to \$1. *PRICE* is the log of the share price, truncated above at \$15. All explanatory variables except *PRICE* are winsorized above and below at the 5% level in the cross section. CRSP based variables, *EXRETAVG*, *SIGMA*, *RSIZE* and *PRICE* are for month $t-1$. *NIQ* is for the most recent quarter for which the reporting date provided by Compustat (item RDQ) precedes the end of month $t-1$, whereas the items requiring information from the balance sheet (*LTQ*, *CHEQ* and *MB*) are for the prior quarter.

8. *O-score:* This distress measure, from Ohlson (1980), predicts returns in a manner similar to the measure above. It is the probability of bankruptcy estimated in a static model using accounting variables. Following Ohlson (1980), we construct it as:

$$\begin{aligned} O &= -0.407\, SIZE + 6.03\, TLTA - 1.43\, WCTA + 0.076\, CLCA - 1.72\, OENEG \\ &= -2.37\, NITA - 1.83\, FUTL + 0.285\, INTWO - 0.521\, CHIN - 1.32, \end{aligned}$$

where *SIZE* is the log of total assets (Compustat annual item AT), *TLTA* is the book value of debt (item DLC plus item DLTT) divided by total assets, *WCTA* is working capital (item ACT minus item LCT) divided by total assets, *CLCA* is current liabilities (item LCT) divided by current assets (item ACT), *ONEEG* is 1 if total liabilities (item LT) exceed total assets and is zero otherwise, *NITA* is net income (item NI) divided by total assets, *FUTL* is funds provided by operations (item PI) divided by total liabilities, *INTWO* is equal to 1 if net income (item NI) is negative for the last 2 years and zero otherwise, *CHIN* is $(NI_j - NI_{j-1})/(|NI_j| + |NI_{j-1}|)$, in which NI_j is the income (item NI) for year j, which is the most recent reporting year that ends (according to item DATADATE) at least four months before the end of month $t-1$.

9. *Momentum:* The momentum effect, discovered by Jegadeesh and Titman (1993), is one of the most robust anomalies in asset pricing. It refers to the phenomenon whereby high (low) past recent recent returns forecast high (low) future returns. The momentum ranking at the end of month t-1 uses the cumulative returns from month t-12 to month t-2. This is the choice of ranking variable used by Carhart (1997) to construct the widely used momentum factor.

10. *Gross Profitability Premium:* Novy-Marx (2013) shows that sorting on the ratio of gross profit to assets creates abnormal benchmark-adjusted returns, with more profitable firms having higher returns than less profitable ones. He argues that gross profit is the cleanest accounting measure of true economic profitability. The farther down the income statement one goes, the more polluted profitability measures become, and the less related they are to true economic profitability. Following that study, we measure gross profitability as total revenue (Compustat annual item REVT) minus the cost of goods sold (item COGS), divided by current total assets (item AT). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$.

11. *Return on Assets:* Fama and French (2006) find that more profitable firms have higher expected returns than less profitable firms. Chen, Novy-Marx, and Zhang (2010) show that firms with higher past return on assets earn abnormally higher subsequent returns. Return on assets is measured as the ratio of quarterly earnings to last quarter's assets. Wang and Yu (2010) find that the anomaly exists primarily among firms with high arbitrage costs and high information uncertainty, suggesting that mispricing is a culprit. Following Chen, Novy-Marx, and Zhang (2010), we compute return on assets as income before extraordinary items (Compustat quarterly item IBQ) divided by the previous quarter's total assets (item ATQ). Income is for most recent quarter for which the reporting date provided by Compustat (item RDQ) precedes the end of month $t-1$, and assets are for the prior quarter.

A2. The Larger Set of 73 Anomalies

We list here the 73 anomalies for which long-short returns were generously provided by the authors of Hou, Xue, and Zhang (2015a, 2015b). See those studies for detailed explanations and references. The anomalies are grouped into six categories:

1. *Momentum*

   SUE-1: Earnings surprise (1-month holding period)
   SUE-6: Earnings surprise (6-month holding period)
   Abr-1: Cumulative abnormal stock returns around earnings announcements (1-month holding period)
   Abr-6: Cumulative abnormal stock returns around earnings announcements (6-month holding period)
   RE-1: Revisions in analysts?earnings forecasts (1-month holding period)
   RE-6: Revisions in analysts?earnings forecasts (6-month holding period)

R6-1: Price momentum (6-month prior returns, 1-month holding period)

R6-6: Price momentum (6-month prior returns, 6-month holding period)

R11-1: Price momentum, (11-month prior returns, 1-month holding period)

I-Mom: Industry momentum

2. *Value-versus-growth*

   B/M: Book-to-market equity

   A/ME: Market Leverage

   Rev: Reversal

   E/P: Earnings-to-price

   EF/P: Analysts?earnings forecasts-to-price

   CF/P: Cash flow-to-price

   D/P: Dividend yield

   O/P: Payout yield

   NO/P: Net payout yield

   SG: Sales growth

   LTG: Long-term growth forecasts of analysts

   Dur: Equity duration

3. *Investment*

   ACI: Abnormal corporate investment

   I/A: Investment-to-assets

   NOA: Net operating assets

   ΔPI/A: Changes in property, plant, and equipment plus changes in inventory scaled by assets

   IG: Investment growth

   NSI: Net stock issues

   CEI: Composite issuance

   NXF: Net external financing

   IvG: Inventory growth

   IvC: Inventory changes

   OA: Operating accruals

   TA: Total accruals

   POA: Percent operating accruals

   PTA: Percent total accruals

4. *Profitability*

   ROE: Return on equity

   ROA: Return on assets

RNA: Return on net operating assets

PM: Profit margin

ATO: Asset turnover

CTO: Capital turnover

GP/A: Gross profits-to-assets

F: F-score

TES: Tax expense surprise

TI/BI: Taxable income-to-book income

RS: Revenue surprise

NEI: Number of consecutive quarters with earnings increases

FP: Failure probability

O: O-score

5. *Intangibles*

OC/A: Organizational capital-to-assets

BC/A: Brand capital-to-assets

Ad/M: Advertisement expense-to-market

RD/S: R&D-to-sales

RD/M: R&D-to-market

RC/A: R&D capital-to-assets

H/N: Hiring rate

OL: Operating leverage

G: Corporate governance

AccQ: Accrual quality

6. *Trading frictions*

ME: Market equity

Ivol: Idiosyncratic volatility

Tvol: Total volatility

Svol: Systematic volatility

MDR: Maximum daily return

β: Market beta

D-β: Dimsons beta

S-Rev: Short-term reversal

Disp: Dispersion of analysts?earnings forecasts

Turn: Share turnover

1/P: 1/share price

Dvol: Dollar trading volume

Illiq: Illiquidity as absolute return-to-volume

A3. Anomalies Eliminated in Producing Table 5

We eliminate the five anomalies from the above set of 73 that are most highly correlated with each factor other than the market and size factors, in both models q-4 and M-4. The two relevant factors in model q-4 are investment (I/A) and profitability (ROE), while in model M-4 they are the mispricing factors, UMO_1 and UMO_2. In Panel A of Table 5, the anomalies that each factor eliminates are as follows:

I/A: CEI, H/N, I/A, LTG, SG
ROE: Disp, FP, 1/P, ROA, ROE
UMO_1: CEI, LTG, NO/P, O/P, Turn
UMO_2: FP, R11-1, R6-1, R6-6, ROA

In Panel B of Table 5, the anomalies eliminated:

I/A: A/ME, B/M, H/N, I/A, SG
ROE: Disp, FP, NEI, ROA, ROE
UMO_1: CEI, LTG, NO/P, NXF, O/P
UMO_2: FP, 1/P, R11-1, R6-1, R6-6

APPENDIX B

This appendix contains the robusteness results discussed in subsection 3.3. The tables presented recompute Tables 4, 5, and 7 with the following modifications to the original procedure:

1. Reconstruct the M-4 factors using mispricing-measure breakpoints of 30% and 70% instead of 20% and 80% (Tables B1, B5, and B9).

2. Reconstruct the M-4 factors using mispricing-measure breakpoints for the NYSE instead of NYSE/AMEX/NASDAQ (Tables B2, B6, and B10).

3. Reconstruct the M-4 SMB factor by averaging across the three mispricing categories instead of using only stocks in the middle category (Table B3, B7, and B11).

4. Incorporate all of the above simultaneously (Tables B4, B8, and B12).

5. Reconstruct annual-data factors in models FF-3, FF-5, and q-4 with a minimum gap of 4 months after the end of the fiscal year instead of a gap of 6 to 18 months (Tables B13–B15).

Table B1
Summary Measures of Models' Abilities to Explain Anomalies,
Factors Constructed Using 30% and 70% Breakpoints

This table recomputes Table 4 with the factors constructed using mispricing-measure breakpoints of 30% and 70% instead of 20% and 80%. The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. In Panel A, two versions of the GRS test are reported. Data for the distress anomaly begin in October 1974, and data for the return-on-assets anomaly begin in November 1971. The other ten anomalies begin at the start of the sample period, which is from January 1967 through December 2013 (564 months). GRS_{10} tests whether the ten alphas for the full-sample anomalies equal zero, while GRS_{12} uses all 12 anomalies and begins the sample in October 1974. Panels B and C also report two versions of the GRS test: GRS_{51} uses 51 anomalies whose data are available by January 1967, while GRS_{72} use those anomalies plus 21 others whose data are available by February 1986.

Measure	Unadjusted	FF-3	FF-5	q-4	M-4
		Panel A: 12 Anomalies, value-weighted, NYSE deciles			
Average $\|\alpha\|$	0.52	0.67	0.45	0.34	0.16
Average $\|t\|$	3.14	4.44	2.93	2.34	1.18
GRS_{10}	6.89	10.10	6.71	5.99	1.84
p_{10}	3.4×10^{-10}	1.1×10^{-15}	6.9×10^{-10}	1.2×10^{-8}	0.05
GRS_{12}	6.16	7.71	4.17	3.95	1.73
p_{12}	4.5×10^{-10}	4.2×10^{-13}	3.1×10^{-6}	8.3×10^{-6}	0.06
Number of $min\|\alpha\|$	-	0	1	2	9
		Panel B: 73 Anomalies, value-weighted, NYSE deciles			
Average $\|\alpha\|$	0.39	0.44	0.30	0.20	0.18
Average $\|t\|$	2.14	2.74	1.77	1.15	0.99
GRS_{51}	2.74	2.60	1.91	1.68	1.34
p_{51}	9.3×10^{-9}	6.5×10^{-8}	2.9×10^{-4}	3.2×10^{-3}	0.06
GRS_{72}	2.23	2.10	1.79	1.78	1.60
p_{72}	2.2×10^{-6}	1.3×10^{-5}	5.3×10^{-4}	5.8×10^{-4}	4.1×10^{-3}
Number of $min\|\alpha\|$	-	10	10	23	30
		Panel C: 73 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles			
Average $\|\alpha\|$	0.50	0.53	0.35	0.23	0.21
Average $\|t\|$	3.02	3.72	2.41	1.44	1.30
GRS_{51}	5.85	6.31	5.15	4.19	4.11
p_{51}	2.7×10^{-27}	6.2×10^{-30}	4.3×10^{-23}	2.3×10^{-17}	6.7×10^{-17}
GRS_{72}	2.95	3.25	2.64	2.41	2.45
p_{72}	1.4×10^{-10}	3.0×10^{-12}	1.1×10^{-8}	2.3×10^{-7}	1.3×10^{-7}
Number of $min\|\alpha\|$	-	7	13	23	30

Table B2
Summary Measures of Models' Abilities to Explain Anomalies, Factors Constructed Using NYSE Breakpoints

This table recomputes Table 4 with the factors constructed using mispricing-measure breakpoints for the NYSE instead of NYSE/AMEX/NASDAQ. The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. In Panel A, two versions of the GRS test are reported. Data for the distress anomaly begin in October 1974, and data for the return-on-assets anomaly begin in November 1971. The other ten anomalies begin at the start of the sample period, which is from January 1967 through December 2013 (564 months). GRS_{10} tests whether the ten alphas for the full-sample anomalies equal zero, while GRS_{12} uses all 12 anomalies and begins the sample in October 1974. Panels B and C also report two versions of the GRS test: GRS_{51} uses 51 anomalies whose data are available by January 1967, while GRS_{72} use those anomalies plus 21 others whose data are available by February 1986.

Measure	Unadjusted	FF-3	FF-5	q-4	M-4
Panel A: 12 Anomalies, value-weighted, NYSE deciles					
Average $\lvert\alpha\rvert$	0.52	0.67	0.45	0.34	0.15
Average $\lvert t\rvert$	3.14	4.44	2.93	2.34	1.13
GRS_{10}	6.89	10.10	6.71	5.99	1.80
p_{10}	3.4×10^{-10}	1.1×10^{-15}	6.9×10^{-10}	1.2×10^{-8}	0.06
GRS_{12}	6.16	7.71	4.17	3.95	1.81
p_{12}	4.5×10^{-10}	4.2×10^{-13}	3.1×10^{-6}	8.3×10^{-6}	0.04
Number of $min\lvert\alpha\rvert$	-	0	1	2	9
Panel B: 73 Anomalies, value-weighted, NYSE deciles					
Average $\lvert\alpha\rvert$	0.39	0.44	0.30	0.20	0.18
Average $\lvert t\rvert$	2.14	2.74	1.77	1.15	0.98
GRS_{51}	2.74	2.60	1.91	1.68	1.24
p_{51}	9.3×10^{-9}	6.5×10^{-8}	2.9×10^{-4}	3.2×10^{-3}	0.13
GRS_{72}	2.23	2.10	1.79	1.78	1.55
p_{72}	2.2×10^{-6}	1.3×10^{-5}	5.3×10^{-4}	5.8×10^{-4}	7.3×10^{-3}
Number of $min\lvert\alpha\rvert$	-	10	11	20	32
Panel C: 73 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles					
Average $\lvert\alpha\rvert$	0.50	0.53	0.35	0.23	0.21
Average $\lvert t\rvert$	3.02	3.72	2.41	1.44	1.32
GRS_{51}	5.85	6.31	5.15	4.19	4.06
p_{51}	2.7×10^{-27}	6.2×10^{-30}	4.3×10^{-23}	2.3×10^{-17}	1.4×10^{-16}
GRS_{72}	2.95	3.25	2.64	2.41	2.59
p_{72}	1.4×10^{-10}	3.0×10^{-12}	1.1×10^{-8}	2.3×10^{-7}	2.2×10^{-8}
Number of $min\lvert\alpha\rvert$	-	7	10	25	31

Table B3
Summary Measures of Models' Abilities to Explain Anomalies,
***SMB* Constructed by Averaging Across Mispricing Categories**

This table recomputes Table 4 with the SMB factor constructed by averaging across the three mispricing categories instead of using only stocks in the middle category. The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. In Panel A, two versions of the GRS test are reported. Data for the distress anomaly begin in October 1974, and data for the return-on-assets anomaly begin in November 1971. The other ten anomalies begin at the start of the sample period, which is from January 1967 through December 2013 (564 months). GRS_{10} tests whether the ten alphas for the full-sample anomalies equal zero, while GRS_{12} uses all 12 anomalies and begins the sample in October 1974. Panels B and C also report two versions of the GRS test: GRS_{51} uses 51 anomalies whose data are available by January 1967, while GRS_{72} use those anomalies plus 21 others whose data are available by February 1986.

Measure	Unadjusted	FF-3	FF-5	q-4	M-4
	Panel A: 12 Anomalies, value-weighted, NYSE deciles				
Average $\lvert\alpha\rvert$	0.52	0.67	0.45	0.34	0.17
Average $\lvert t\rvert$	3.14	4.44	2.93	2.34	1.23
GRS_{10}	6.89	10.10	6.71	5.99	1.76
p_{10}	3.4×10^{-10}	1.1×10^{-15}	6.9×10^{-10}	1.2×10^{-8}	0.06
GRS_{12}	6.16	7.71	4.17	3.95	1.71
p_{12}	4.5×10^{-10}	4.2×10^{-13}	3.1×10^{-6}	8.3×10^{-6}	0.06
Number of $min\lvert\alpha\rvert$	-	0	1	2	9
	Panel B: 73 Anomalies, value-weighted, NYSE deciles				
Average $\lvert\alpha\rvert$	0.39	0.44	0.30	0.20	0.19
Average $\lvert t\rvert$	2.14	2.74	1.77	1.15	1.06
GRS_{51}	2.74	2.60	1.91	1.68	1.35
p_{51}	9.3×10^{-9}	6.5×10^{-8}	2.9×10^{-4}	3.2×10^{-3}	0.06
GRS_{72}	2.23	2.10	1.79	1.78	1.61
p_{72}	2.2×10^{-6}	1.3×10^{-5}	5.3×10^{-4}	5.8×10^{-4}	3.9×10^{-3}
Number of $min\lvert\alpha\rvert$	-	9	12	24	28
	Panel C: 73 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles				
Average $\lvert\alpha\rvert$	0.50	0.53	0.35	0.23	0.21
Average $\lvert t\rvert$	3.02	3.72	2.41	1.44	1.34
GRS_{51}	5.85	6.31	5.15	4.19	4.04
p_{51}	2.7×10^{-27}	6.2×10^{-30}	4.3×10^{-23}	2.3×10^{-17}	1.8×10^{-16}
GRS_{72}	2.95	3.25	2.64	2.41	2.38
p_{72}	1.4×10^{-10}	3.0×10^{-12}	1.1×10^{-8}	2.3×10^{-7}	3.2×10^{-7}
Number of $min\lvert\alpha\rvert$	-	8	13	21	31

Table B4
Summary Measures of Models' Abilities to Explain Anomalies,
Factors Constructed Using All Modifications in Tables B1–B3

This table recomputes Table 4 with the factors constructed using mispricing-measure breakpoints of 30% and 70% for the NYSE instead of 20% and 80% for NYSE/AMEX/NASDAQ. Also, the SMB factor is constructed by averaging across the three mispricing categories instead of using only stocks in the middle category. The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. In Panel A, two versions of the GRS test are reported. Data for the distress anomaly begin in October 1974, and data for the return-on-assets anomaly begin in November 1971. The other ten anomalies begin at the start of the sample period, which is from January 1967 through December 2013 (564 months). GRS_{10} tests whether the ten alphas for the full-sample anomalies equal zero, while GRS_{12} uses all 12 anomalies and begins the sample in October 1974. Panels B and C also report two versions of the GRS test: GRS_{51} uses 51 anomalies whose data are available by January 1967, while GRS_{72} use those anomalies plus 21 others whose data are available by February 1986.

Measure	Unadjusted	FF-3	FF-5	q-4	M-4
		Panel A: 12 Anomalies, value-weighted, NYSE deciles			
Average $\lvert\alpha\rvert$	0.52	0.67	0.45	0.34	0.16
Average $\lvert t\rvert$	3.14	4.44	2.93	2.34	1.22
GRS_{10}	6.89	10.10	6.71	5.99	2.26
p_{10}	3.4×10^{-10}	1.1×10^{-15}	6.9×10^{-10}	1.2×10^{-8}	0.01
GRS_{12}	6.16	7.71	4.17	3.95	2.14
p_{12}	4.5×10^{-10}	4.2×10^{-13}	3.1×10^{-6}	8.3×10^{-6}	0.01
Number of $min\lvert\alpha\rvert$	-	0	1	1	10
		Panel B: 73 Anomalies, value-weighted, NYSE deciles			
Average $\lvert\alpha\rvert$	0.39	0.44	0.30	0.20	0.18
Average $\lvert t\rvert$	2.14	2.74	1.77	1.15	1.02
GRS_{51}	2.74	2.60	1.91	1.68	1.34
p_{51}	9.3×10^{-9}	6.5×10^{-8}	2.9×10^{-4}	3.2×10^{-3}	0.07
GRS_{72}	2.23	2.10	1.79	1.78	1.59
p_{72}	2.2×10^{-6}	1.3×10^{-5}	5.3×10^{-4}	5.8×10^{-4}	4.8×10^{-3}
Number of $min\lvert\alpha\rvert$	-	10	9	21	33
		Panel C: 73 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles			
Average $\lvert\alpha\rvert$	0.50	0.53	0.35	0.23	0.22
Average $\lvert t\rvert$	3.02	3.72	2.41	1.44	1.38
GRS_{51}	5.85	6.31	5.15	4.19	4.29
p_{51}	2.7×10^{-27}	6.2×10^{-30}	4.3×10^{-23}	2.3×10^{-17}	6.2×10^{-18}
GRS_{72}	2.95	3.25	2.64	2.41	2.47
p_{72}	1.4×10^{-10}	3.0×10^{-12}	1.1×10^{-8}	2.3×10^{-7}	1.0×10^{-7}
Number of $min\lvert\alpha\rvert$	-	5	13	26	29

Table B5
Summary Measures of Models' Abilities to Explain Anomalies Less Correlated with Factors in Models q-4 and M-4, Factors Constructed Using 30% and 70% Breakpoints

This table recomputes Table 5 with the factors constructed using mispricing-measure breakpoints of 30% and 70% instead of 20% and 80%. The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. Panels A and B correspond to Panels B and C of Table 4, except the set of anomalies is reduced: For each of four factors—those in models q-4 and M-4 other than the market and size factors—the five anomalies (of the 73) whose long-short returns are most highly correlated with the factor are eliminated. This procedure leaves 56 anomalies in Panel A and 54 in Panel B. The sample period is from January 1967 through December 2013 (564 months). Two versions of the GRS test are reported: GRS_{41} in Panel A (or GRS_{40} in Panel B) uses the 41 (or 40) anomalies whose data are available by January 1967, while GRS_{55} in Panel A (or GRS_{53} in Panel B) uses the remaining anomalies whose data are available by February 1986.

Measure	Unadjusted	FF-3	FF-5	q-4	M-4
Panel A: 56 Anomalies, value-weighted, NYSE deciles					
Average $\|\alpha\|$	0.37	0.38	0.26	0.20	0.18
Average $\|t\|$	2.13	2.57	1.69	1.17	1.00
GRS_{41}	3.01	2.81	1.95	1.63	1.35
p_{41}	6.7×10^{-9}	6.1×10^{-8}	5.8×10^{-4}	9.3×10^{-3}	0.08
GRS_{55}	2.28	2.17	1.75	1.66	1.58
p_{55}	7.2×10^{-6}	2.5×10^{-5}	2.0×10^{-3}	4.5×10^{-3}	9.8×10^{-3}
Number of $min\|\alpha\|$	-	7	7	19	23
Number of $min\|\alpha\|$, q-4 vs. M-4	-	-	-	27	29
Panel B: 54 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles					
Average $\|\alpha\|$	0.45	0.46	0.32	0.25	0.22
Average $\|t\|$	2.94	3.53	2.41	1.61	1.42
GRS_{40}	6.38	7.03	5.78	4.69	4.54
p_{40}	7.3×10^{-26}	5.0×10^{-29}	8.3×10^{-23}	2.9×10^{-17}	1.8×10^{-16}
GRS_{53}	3.36	4.07	3.12	2.82	2.87
p_{53}	3.6×10^{-11}	1.0×10^{-14}	6.7×10^{-10}	2.0×10^{-8}	1.2×10^{-8}
Number of $min\|\alpha\|$	-	6	11	16	21
Number of $min\|\alpha\|$, q-4 vs. M-4	-	-	-	21	33

Table B6
Summary Measures of Models' Abilities to Explain Anomalies Less Correlated with Factors in Models q-4 and M-4, Factors Constructed Using NYSE Breakpoints

This table recomputes Table 5 with the factors constructed using mispricing-measure breakpoints for the NYSE instead of NYSE/AMEX/NASDAQ. The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. Panels A and B correspond to Panels B and C of Table 4, except the set of anomalies is reduced: For each of four factors—those in models q-4 and M-4 other than the market and size factors—the five anomalies (of the 73) whose long-short returns are most highly correlated with the factor are eliminated. This procedure leaves 56 anomalies in Panel A and 54 in Panel B. The sample period is from January 1967 through December 2013 (564 months). Two versions of the GRS test are reported: GRS_{40} uses the 40 anomalies whose data are available by January 1967, while GRS_{55} in Panel A (or GRS_{53} in Panel B) uses the remaining anomalies whose data are available by February 1986.

Measure	Unadjusted	FF-3	FF-5	q-4	M-4
Panel A: 56 Anomalies, value-weighted, NYSE deciles					
Average $\|\alpha\|$	0.36	0.38	0.26	0.20	0.17
Average $\|t\|$	2.13	2.58	1.70	1.17	0.95
GRS_{40}	3.08	2.89	2.00	1.66	1.15
p_{40}	3.9×10^{-9}	3.6×10^{-8}	4.0×10^{-4}	8.0×10^{-3}	0.25
GRS_{55}	2.28	2.14	1.70	1.61	1.42
p_{55}	7.3×10^{-6}	3.3×10^{-5}	3.3×10^{-3}	7.1×10^{-3}	0.04
Number of $min\|\alpha\|$	-	7	8	15	26
Number of $min\|\alpha\|$, q-4 vs. M-4	-	-	-	22	34
Panel B: 54 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles					
Average $\|\alpha\|$	0.45	0.46	0.32	0.25	0.22
Average $\|t\|$	2.94	3.53	2.41	1.61	1.42
GRS_{40}	6.38	7.03	5.78	4.69	4.40
p_{40}	7.3×10^{-26}	5.0×10^{-29}	8.3×10^{-23}	2.9×10^{-17}	8.8×10^{-16}
GRS_{53}	3.36	4.07	3.12	2.82	3.00
p_{53}	3.6×10^{-11}	1.0×10^{-14}	6.7×10^{-10}	2.0×10^{-8}	2.5×10^{-9}
Number of $min\|\alpha\|$	-	6	8	18	22
Number of $min\|\alpha\|$, q-4 vs. M-4	-	-	-	25	29

Table B7
Summary Measures of Models' Abilities to Explain Anomalies Less Correlated with Factors in Models q-4 and M-4, SMB Constructed by Averaging Across Mispricing Categories

This table recomputes Table 5 with the SMB factor constructed by averaging across the three mispricing categories instead of using only stocks in the middle category. The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "*GRS*" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. Panels A and B correspond to Panels B and C of Table 4, except the set of anomalies is reduced: For each of four factors—those in models q-4 and M-4 other than the market and size factors—the five anomalies (of the 73) whose long-short returns are most highly correlated with the factor are eliminated. This procedure leaves 57 anomalies in Panel A and 54 in Panel B. The sample period is from January 1967 through December 2013 (564 months). Two versions of the GRS test are reported: GRS_{41} in Panel A (or GRS_{40} in Panel B) uses the 41 (or 40) anomalies whose data are available by January 1967, while GRS_{56} in Panel A (or GRS_{53} in Panel B) uses the remaining anomalies whose data are available by February 1986.

Measure	Unadjusted	FF-3	FF-5	q-4	M-4
Panel A: 57 Anomalies, value-weighted, NYSE deciles					
Average $\lvert\alpha\rvert$	0.37	0.39	0.27	0.19	0.18
Average $\lvert t\rvert$	2.14	2.60	1.71	1.15	1.05
GRS_{41}	3.01	2.81	1.95	1.63	1.36
p_{41}	6.7×10^{-9}	6.1×10^{-8}	5.8×10^{-4}	9.3×10^{-3}	0.07
GRS_{56}	2.29	2.16	1.73	1.64	1.59
p_{56}	5.5×10^{-6}	2.5×10^{-5}	2.3×10^{-3}	5.2×10^{-3}	8.3×10^{-3}
Number of $min\lvert\alpha\rvert$	-	6	9	20	22
Number of $min\lvert\alpha\rvert$, q-4 vs. M-4	-	-	-	27	30
Panel B: 54 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles					
Average $\lvert\alpha\rvert$	0.45	0.46	0.32	0.25	0.23
Average $\lvert t\rvert$	2.94	3.53	2.41	1.61	1.47
GRS_{40}	6.38	7.03	5.78	4.69	4.55
p_{40}	7.3×10^{-26}	5.0×10^{-29}	8.3×10^{-23}	2.9×10^{-17}	1.6×10^{-16}
GRS_{53}	3.36	4.07	3.12	2.82	3.03
p_{53}	3.6×10^{-11}	1.0×10^{-14}	6.7×10^{-10}	2.0×10^{-8}	1.8×10^{-9}
Number of $min\lvert\alpha\rvert$	-	6	9	16	23
Number of $min\lvert\alpha\rvert$, q-4 vs. M-4	-	-	-	21	33

Table B8
Summary Measures of Models' Abilities to Explain Anomalies Less Correlated with Factors in Models q-4 and M-4, Factors Constructed Using All Modifications in Tables B5–B7

This table recomputes Table 5 with the factors constructed using mispricing-measure breakpoints of 30% and 70% for the NYSE instead of 20% and 80% for NYSE/AMEX/NASDAQ. Also, the SMB factor is constructed by averaging across the three mispricing categories instead of using only stocks in the middle category. The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. Panels A and B correspond to Panels B and C of Table 4, except the set of anomalies is reduced: For each of four factors—those in models q-4 and M-4 other than the market and size factors—the five anomalies (of the 73) whose long-short returns are most highly correlated with the factor are eliminated. This procedure leaves 56 anomalies in Panel A and 55 in Panel B. The sample period is from January 1967 through December 2013 (564 months). Two versions of the GRS test are reported: GRS_{41} in Panel A (or GRS_{40} in Panel B) uses the 41 (or 40) anomalies whose data are available by January 1967, while GRS_{55} in Panel A (or GRS_{54} in Panel B) uses the remaining anomalies whose data are available by February 1986.

Measure	Unadjusted	FF-3	FF-5	q-4	M-4
Panel A: 56 Anomalies, value-weighted, NYSE deciles					
Average $\|\alpha\|$	0.37	0.38	0.26	0.20	0.18
Average $\|t\|$	2.13	2.57	1.69	1.17	1.03
GRS_{41}	3.01	2.81	1.95	1.63	1.34
p_{41}	6.7×10^{-9}	6.1×10^{-8}	5.8×10^{-4}	9.3×10^{-3}	0.08
GRS_{55}	2.28	2.17	1.75	1.66	1.58
p_{55}	7.2×10^{-6}	2.5×10^{-5}	2.0×10^{-3}	4.5×10^{-3}	0.01
Number of $min\|\alpha\|$	-	7	6	17	26
Number of $min\|\alpha\|$, q-4 vs. M-4	-	-	-	27	29
Panel B: 55 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles					
Average $\|\alpha\|$	0.45	0.47	0.32	0.25	0.23
Average $\|t\|$	2.96	3.57	2.42	1.61	1.49
GRS_{40}	6.38	7.03	5.78	4.69	4.69
p_{40}	7.3×10^{-26}	5.0×10^{-29}	8.3×10^{-23}	2.9×10^{-17}	3.1×10^{-17}
GRS_{54}	3.33	3.99	3.07	2.78	2.88
p_{54}	3.8×10^{-11}	1.9×10^{-14}	9.5×10^{-10}	2.6×10^{-8}	8.1×10^{-9}
Number of $min\|\alpha\|$	-	4	10	18	23
Number of $min\|\alpha\|$, q-4 vs. M-4	-	-	-	25	30

Table B9
Models' Abilities to Explain Each Other's Factors, Factors Constructed Using 30% and 70% Breakpoints

This table recomputes Table 7 with the factors constructed using mispricing-measure breakpoints of 30% and 70% instead of 20% and 80%. Panel A reports a factor's estimated monthly alpha (in percent) with respect to each of the other models (with White (1980) heteroskedasticity-consistent t-statistics in parentheses). Panel B computes the Gibbons-Ross-Shanken (1989) F-test of whether a given model produces zero alphas for the factors of an alternative model(with p-values in parentheses). The models considered are the five-factor model of Fama and French (2015), denoted FF-5, which includes the factors HML, RMW, and CMA; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4, which includes the factors I/A and ROE; and the four-factor mispricing-factor model, denoted M-4, which includes the factors UMO_1 and UMO_2. The sample period is from January 1967 through December 2013 (564 months).

	Alpha computed with respect to model		
Factors	FF-5	q-4	M-4
	Panel A: Alpha (t-statistic)		
Factors in FF-5			
HML	-	0.04	0.05
		(0.43)	(0.50)
RMW	-	0.04	0.11
		(0.55)	(1.26)
CMA	-	0.02	-0.02
		(0.47)	(-0.43)
Factors in q-4			
I/A	0.12	-	0.09
	(3.48)		(1.57)
ROE	0.45	-	0.36
	(5.53)		(4.00)
Factors in M-4			
UMO_1	0.22	0.22	-
	(4.23)	(3.55)	
UMO_2	0.48	0.26	-
	(4.15)	(2.15)	
	Panel B: GRS F-statistic (p-value)		
HML, RMW, CMA	-	0.23	0.53
		(0.87)	(0.66)
I/A, ROE	19.06	-	6.67
	(9.8×10^{-9})		(1.4×10^{-3})
UMO_1, UMO_2	22.25	11.39	-
	(5.1×10^{-10})	(1.4×10^{-5})	

Table B10
Models' Abilities to Explain Each Other's Factors,
Factors Constructed Using NYSE Breakpoints

This table recomputes Table 7 with the factors constructed using mispricing-measure breakpoints for the NYSE instead of NYSE/AMEX/NASDAQ. Panel A reports a factor's estimated monthly alpha (in percent) with respect to each of the other models (with White (1980) heteroskedasticity-consistent t-statistics in parentheses). Panel B computes the Gibbons-Ross-Shanken (1989) F-test of whether a given model produces zero alphas for the factors of an alternative model(with p-values in parentheses). The models considered are the five-factor model of Fama and French (2015), denoted FF-5, which includes the factors HML, RMW, and CMA; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4, which includes the factors I/A and ROE; and the four-factor mispricing-factor model, denoted M-4, which includes the factors UMO_1 and UMO_2. The sample period is from January 1967 through December 2013 (564 months).

	Alpha computed with respect to model		
Factors	FF-5	q-4	M-4
	Panel A: Alpha (t-statistic)		
Factors in FF-5			
HML	-	0.04	0.03
		(0.43)	(0.29)
RMW	-	0.04	0.13
		(0.55)	(1.50)
CMA	-	0.02	-0.04
		(0.47)	(-0.63)
Factors in q-4			
I/A	0.12	-	0.09
	(3.48)		(1.57)
ROE	0.45	-	0.36
	(5.53)		(4.00)
Factors in M-4			
UMO_1	0.29	0.31	-
	(4.72)	(4.38)	
UMO_2	0.60	0.33	-
	(4.46)	(2.26)	
	Panel B: GRS F-statistic (p-value)		
HML, RMW, CMA	-	0.23	0.70
		(0.87)	(0.55)
I/A, ROE	19.06	-	7.56
	(9.8×10^{-9})		(5.7×10^{-4})
UMO_1, UMO_2	26.84	16.02	-
	(7.5×10^{-12})	(1.7×10^{-7})	

Table B11
Models' Abilities to Explain Each Other's Factors, SMB Constructed by Averaging Across Mispricing Categories

This table recomputes Table 7 with the SMB factor constructed by averaging across the three mispricing categories instead of using only stocks in the middle category. Panel A reports a factor's estimated monthly alpha (in percent) with respect to each of the other models (with White (1980) heteroskedasticity-consistent t-statistics in parentheses). Panel B computes the Gibbons-Ross-Shanken (1989) F-test of whether a given model produces zero alphas for the factors of an alternative model(with p-values in parentheses). The models considered are the five-factor model of Fama and French (2015), denoted FF-5, which includes the factors HML, RMW, and CMA; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4, which includes the factors I/A and ROE; and the four-factor mispricing-factor model, denoted M-4, which includes the factors UMO_1 and UMO_2. The sample period is from January 1967 through December 2013 (564 months).

	Alpha computed with respect to model		
Factors	FF-5	q-4	M-4
	Panel A: Alpha (t-statistic)		
Factors in FF-5			
HML	-	0.04	-0.02
		(0.43)	(-0.19)
RMW	-	0.04	0.10
		(0.55)	(1.16)
CMA	-	0.02	-0.02
		(0.47)	(-0.40)
Factors in q-4			
I/A	0.12	-	0.09
	(3.48)		(1.57)
ROE	0.45	-	0.36
	(5.53)		(4.00)
Factors in M-4			
UMO_1	0.33	0.36	-
	(4.93)	(4.54)	
UMO_2	0.64	0.35	-
	(4.17)	(2.24)	
	Panel B: GRS F-statistic (p-value)		
HML, RMW, CMA	-	0.23	0.49
		(0.87)	(0.69)
I/A, ROE	19.06	-	8.89
	(9.8×10^{-9})		(1.6×10^{-4})
UMO_1, UMO_2	25.35	15.66	-
	(2.9×10^{-11})	(2.4×10^{-7})	

Table B12
Models' Abilities to Explain Each Other's Factors, Factors Constructed Using All Modifications in Tables B9–B11

This table recomputes Table 7 with the factors constructed using mispricing-measure breakpoints of 30% and 70% for the NYSE instead of 20% and 80% for NYSE/AMEX/NASDAQ. Also, the SMB factor is constructed by averaging across the three mispricing categories instead of using only stocks in the middle category. Panel A reports a factor's estimated monthly alpha (in percent) with respect to each of the other models (with White (1980) heteroskedasticity-consistent t-statistics in parentheses). Panel B computes the Gibbons-Ross-Shanken (1989) F-test of whether a given model produces zero alphas for the factors of an alternative model(with p-values in parentheses). The models considered are the five-factor model of Fama and French (2015), denoted FF-5, which includes the factors HML, RMW, and CMA; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4, which includes the factors I/A and ROE; and the four-factor mispricing-factor model, denoted M-4, which includes the factors UMO_1 and UMO_2. The sample period is from January 1967 through December 2013 (564 months).

	Alpha computed with respect to model		
Factors	FF-5	q-4	M-4
	Panel A: Alpha (t-statistic)		
Factors in FF-5			
HML	-	0.04	0.09
		(0.43)	(1.02)
RMW	-	0.04	0.13
		(0.55)	(1.47)
CMA	-	0.02	-0.02
		(0.47)	(-0.30)
Factors in q-4			
I/A	0.12	-	0.09
	(3.48)		(1.57)
ROE	0.45	-	0.36
	(5.53)		(4.00)
Factors in M-4			
UMO_1	0.19	0.19	-
	(3.90)	(3.32)	
UMO_2	0.49	0.28	-
	(4.65)	(2.48)	
	Panel B: GRS F-statistic (p-value)		
HML, RMW, CMA	-	0.23	0.91
		(0.87)	(0.44)
I/A, ROE	19.06	-	7.79
	(9.8×10^{-9})		(4.6×10^{-4})
UMO_1, UMO_2	23.74	12.12	-
	(1.3×10^{-10})	(7.1×10^{-6})	

Table B13
Summary Measures of Models' Abilities to Explain Anomalies, Annual-Data Factors for Models FF-3, FF-5, and q-4 Reconstructed with Minimum Four-Month Gap

This table recomputes Table 4 after reconstructing factors in models FF-3, FF-5, and q-4 that use annual data. A minimum gap of 4 months after the end of the fiscal year (instead of a gap of 6 to 18 months) is required before using an annual variable in the factor construction, while using immediate prior-month values of market capitalization. We apply this change to SMB and HML in model FF-3, to SMB, HML, RMW, and CMA in model FF-5, and to I/A in model q-4. The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. In Panel A, two versions of the GRS test are reported. Data for the distress anomaly begin in October 1974, and data for the return-on-assets anomaly begin in November 1971. The other ten anomalies begin at the start of the sample period, which is from January 1967 through December 2013 (564 months). GRS_{10} tests whether the ten alphas for the full-sample anomalies equal zero, while GRS_{12} uses all 12 anomalies and begins the sample in October 1974. Panels B and C also report two versions of the GRS test: GRS_{51} uses 51 anomalies whose data are available by January 1967, while GRS_{72} use those anomalies plus 21 others whose data are available by February 1986.

Measure	Unadjusted	FF-3	FF-5	q-4	M-4
	Panel A: 12 Anomalies, value-weighted, NYSE deciles				
Average $\lvert\alpha\rvert$	0.52	0.68	0.45	0.30	0.18
Average $\lvert t\rvert$	3.14	4.55	2.85	2.17	1.29
GRS_{10}	6.89	11.47	7.59	5.83	1.84
p_{10}	3.4×10^{-10}	5.5×10^{-10}	2.2×10^{-11}	2.2×10^{-8}	0.05
GRS_{12}	6.16	8.38	4.56	3.73	1.88
p_{12}	4.5×10^{-10}	2.2×10^{-14}	5.8×10^{-7}	2.1×10^{-5}	0.03
Number of $min\lvert\alpha\rvert$	-	0	1	3	8
	Panel B: 73 Anomalies, value-weighted, NYSE deciles				
Average $\lvert\alpha\rvert$	0.39	0.44	0.32	0.21	0.18
Average $\lvert t\rvert$	2.14	2.73	1.90	1.20	0.99
GRS_{51}	2.74	2.66	2.10	1.75	1.28
p_{51}	9.3×10^{-9}	3.0×10^{-8}	3.3×10^{-5}	1.6×10^{-3}	0.10
GRS_{72}	2.23	2.14	1.67	1.83	1.54
p_{72}	2.2×10^{-6}	7.2×10^{-6}	2.0×10^{-3}	3.3×10^{-4}	8.1×10^{-3}
Number of $min\lvert\alpha\rvert$	-	8	6	22	37
	Panel C: 73 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles				
Average $\lvert\alpha\rvert$	0.50	0.53	0.38	0.24	0.22
Average $\lvert t\rvert$	3.02	3.76	2.66	1.45	1.38
GRS_{51}	5.85	6.43	5.43	4.28	4.17
p_{51}	2.7×10^{-27}	1.2×10^{-30}	8.9×10^{-25}	6.5×10^{-18}	3.1×10^{-17}
GRS_{72}	2.95	3.41	2.75	2.46	2.68
p_{72}	1.4×10^{-10}	3.3×10^{-13}	2.6×10^{-9}	1.1×10^{-7}	6.2×10^{-9}
Number of $min\lvert\alpha\rvert$	-	7	6	27	33

Table B14

Summary Measures of Models' Abilities to Explain Anomalies Less Correlated with Factors in Models q-4 and M-4, Annual-Data Factors for Models FF-3, FF-5, and q-4 Reconstructed with Minimum Four-Month Gap

This table recomputes Table 5 after reconstructing factors in models FF-3, FF-5, and q-4 that use annual data. A minimum gap of 4 months after the end of the fiscal year (instead of a gap of 6 to 18 months) is required before using an annual variable in the factor construction, while using immediate prior-month values of market capitalization. We apply this change to SMB and HML in model FF-3, to SMB, HML, RMW, and CMA in model FF-5, and to I/A in model q-4. The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the four-factor mispricing-factor model introduced in this study, denoted M-4. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. Panels A and B correspond to Panels B and C of Table 4, except the set of anomalies is reduced: For each of four factors—those in models q-4 and M-4 other than the market and size factors—the five anomalies (of the 73) whose long-short returns are most highly correlated with the factor are eliminated. This procedure leaves 57 anomalies in Panel A and 54 in Panel B. The sample period is from January 1967 through December 2013 (564 months). Two versions of the GRS test are reported: GRS_{41} in Panel A (or GRS_{40} in Panel B) uses the 41 (or 40) anomalies whose data are available by January 1967, while GRS_{56} in Panel A (or GRS_{53} in Panel B) uses the remaining anomalies whose data are available by February 1986.

Measure	Unadjusted	FF-3	FF-5	q-4	M-4
Panel A: 57 Anomalies, value-weighted, NYSE deciles					
Average $\lvert\alpha\rvert$	0.37	0.39	0.28	0.21	0.17
Average $\lvert t\rvert$	2.14	2.56	1.83	1.23	0.97
GRS_{41}	3.01	2.87	2.15	1.71	1.26
p_{41}	6.7×10^{-9}	3.2×10^{-8}	7.7×10^{-5}	4.7×10^{-3}	0.13
GRS_{56}	2.29	2.22	1.67	1.68	1.53
p_{56}	5.5×10^{-6}	1.2×10^{-5}	4.0×10^{-3}	3.5×10^{-3}	0.01
Number of $min\lvert\alpha\rvert$	-	6	4	17	30
Number of $min\lvert\alpha\rvert$, q-4 vs. M-4	-	-	-	22	35
Panel B: 54 Anomalies, equally weighted, NYSE/AMEX/NASDAQ deciles					
Average $\lvert\alpha\rvert$	0.45	0.47	0.34	0.26	0.23
Average $\lvert t\rvert$	2.94	3.54	2.63	1.62	1.47
GRS_{40}	6.38	7.19	6.25	4.80	4.55
p_{40}	7.3×10^{-26}	8.7×10^{-30}	3.9×10^{-25}	7.8×10^{-18}	1.6×10^{-16}
GRS_{54}	3.36	4.29	3.31	2.85	3.03
p_{54}	3.6×10^{-11}	7.8×10^{-16}	6.9×10^{-11}	1.4×10^{-8}	1.8×10^{-9}
Number of $min\lvert\alpha\rvert$	-	6	4	21	23
Number of $min\lvert\alpha\rvert$, q-4 vs. M-4	-	-	-	24	30

Table B15
Models' Abilities to Explain Each Other's Factors, Annual-Data Factors for Models FF-3, FF-5, and q-4 Reconstructed with Minimum Four-Month Gap

This table recomputes Table 7 after reconstructing factors in models FF-3, FF-5, and q-4 that use annual data. A minimum gap of 4 months after the end of the fiscal year (instead of a gap of 6 to 18 months) is required before using an annual variable in the factor construction, while using immediate prior-month values of market capitalization. We apply this change to SMB and HML in model FF-3, to SMB, HML, RMW, and CMA in model FF-5, and to I/A in model q-4. Because the FF-5 factor CMA then becomes identical to the q-4 factor I/A, we omit the comparisons involving those factors. Panel A reports a factor's estimated monthly alpha (in percent) with respect to each of the other models (with White (1980) heteroskedasticity-consistent t-statistics in parentheses). Panel B computes the Gibbons-Ross-Shanken (1989) F-test of whether a given model produces zero alphas for the factors of an alternative model(with p-values in parentheses). The models considered are the five-factor model of Fama and French (2015), denoted FF-5, which includes the factors HML, RMW, and CMA; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4, which includes the factors I/A and ROE; and the four-factor mispricing-factor model, denoted M-4, which includes the factors UMO_1 and UMO_2. The sample period is from January 1967 through December 2013 (564 months).

	Alpha computed with respect to model		
Factors	FF-5	q-4	M-4
	Panel A: Alpha (t-statistic)		
Factors in FF-5			
HML	-	-0.01	-0.07
		(-0.10)	(-0.69)
RMW	-	0.10	0.15
		(1.07)	(1.61)
CMA	-	-	-0.08
			(-1.38)
Factors in q-4			
I/A	-	-	-0.08
			(-1.38)
ROE	0.49	-	0.36
	(5.92)		(4.00)
Factors in M-4			
UMO_1	0.32	0.33	-
	(5.53)	(4.67)	
UMO_2	0.64	0.24	-
	(4.18)	(1.55)	
	Panel B: GRS F-statistic (p-value)		
HML, RMW, CMA	-	-	1.45
			(0.23)
I/A, ROE	-	-	8.29
			(2.8×10^{-4})
UMO_1, UMO_2	28.84	16.88	-
	(1.2×10^{-12})	(7.7×10^{-8})	